Bayesian Statistics Guided Label Refurbishment
Mechanism: Mitigating Label Noise in Medical Image Classification

Mengdi Gao¹,²,³,⁴, Ximeng Feng¹,²,³,⁴, Mufeng Geng¹,²,³,⁴, Zhe Jiang¹,²,³,⁴, Lei Zhu¹,²,³,⁴, Xiangxi Meng⁵, Chuanqing Zhou⁴, Qiushi Ren¹,²,³,⁴, Yanye Lu²,³

¹ Department of Biomedical Engineering, College of Future Technology, Peking University, Beijing 100871, China
² Institute of Medical Technology, Peking University Health Science Center, Peking University, Beijing 100191, China
³ Institute of Biomedical Engineering, Peking University Shenzhen Graduate School, Shenzhen 518055, China
⁴ Institute of Biomedical Engineering, Shenzhen Bay Laboratory 5F, Shenzhen 518071, China
⁵ Key Laboratory of Carcinogenesis and Translational Research (Ministry of Education), Key Laboratory for Research and Evaluation of Radiopharmaceuticals (National Medical Products Administration), Department of Nuclear Medicine, Beijing Cancer Hospital & Institute, Beijing, China

Corresponding author: Yanye Lu, e-mail: yanye.lu@pku.edu.cn

Abstract

Purpose: Deep neural networks (DNNs) have been widely applied in medical image classification, benefiting from its powerful mapping capability among medical images. However, these existing deep learning-based methods depend on an enormous amount of carefully labeled images. Meanwhile, noise is inevitably introduced in the labeling process, degrading the performance of models. Hence, it is significant to devise robust training strategies to mitigate label noise in the medical image classification tasks.

Methods: In this work, we propose a novel Bayesian statistics guided label refurbishment mechanism (BLRM) for DNNs to prevent overfitting noisy images. BLRM utilizes maximum a posteriori probability (MAP) in the Bayesian statistics and the exponentially time-weighted technique to selectively correct the labels of noisy images. The training images are purified gradually with the training epochs when BLRM is activated, further improving classification performance.

Results: Comprehensive experiments on both synthetic noisy images (public OCT & Messidor datasets) and real-world noisy images (ANIMAL-10N) demonstrate that BLRM refurbishes the noisy labels selectively, curbing the adverse effects of noisy data. Also, the anti-noise BLRM integrated with DNNs are effective at different noise ratio and are independent of backbone DNN architectures. In addition, BLRM is superior...
to state-of-the-art comparative methods of anti-noise.

**Conclusions:** These investigations indicate that the proposed BLRM is well capable of mitigating label noise in medical image classification tasks.

**KEYWORDS:** deep learning, noisy label, label refurbishment, medical image classification
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1. Introduction

Over the past decade, learning-based computer vision algorithms have been widely explored and have contributed to medical imaging research. Artificial intelligence especially DNNs have exhibited impressive performance in numerous medical imaging tasks, such as image classification\(^1\), object detection\(^2\), semantic segmentation\(^3\) and image synthesis\(^4\), etc. While the remarkable medical image classification results achieved by various deep learning methods\(^1,5,6\), highly depend on large-scale datasets with reliable labels. However, it is costly and time-consuming to collect and label datasets. In the medical scenarios, the annotations of images strongly rely on professional and experienced specialists and double-blinded even muti-blinded annotations are necessary. Meanwhile, some ineluctable labeling mistakes from annotators may generate noisy labels that may deviate from ground-truth labels. It has been reported that the ratio of noisy labels in real-world datasets ranges from 8.0% to 38.5\(^%\)^5,^7,^8,^9,^10.

Fig. 1 describes the performance of optical coherence tomography images classification on noisy labeled training datasets. The details of dataset can be referred in Dataset description of section D. The noise ratio ranges from 0 to 40% with step 10%. The train accuracies, converging to optimal value 100% or nearly 100% in Fig. 1 (a), prove that DNNs can easily fit the entire training dataset with any ratio of corrupted labels. This viewpoint was also demonstrated in the existing computer vision literatures\(^11,12\). Fig. 1 (c) and (d) indicate that DNNs are capable of memorizing noise data, leading to poor generalization on the test dataset and the generalization performance degrades as the noise ratio increases. Zhang et al.\(^13\) has also drawn the similar conclusions in the classic image recognition tasks. In addition, the curves of test accuracy, especially at the heavy noise rate (30% and 40%), shows initially increased and then an downward trend which supports that DNNs tend to prioritize learning simple patterns first then memorize the remaining data including noisy data\(^11,12\). Hence, it is meaningful to mitigate label noise to enhance the generalization performance of DNNs in medical image classification. Hence, the critical issue is how to train DNNs robustly even with noisy labels in the training data. Unfortunately, the above issue has not been settled completely through the popular regularization techniques, such as data augmentation\(^14\), dropout\(^15\), weight decay\(^16\), and batch normalization\(^17\).

As summarized by Song et al.\(^10\), the noisy label problem has been addressed based on
deep learning in five ways. 1) Sample selection: sample selection\textsuperscript{12,18,19} aimed to identify true-label samples from noisy training data. MentorNet\textsuperscript{12} introduced a collaborative learning paradigm where a pre-trained MentorNet would supervise the training of StudentNet. MentorNet guided StudentNet to focus on the sample where the label was probably correct, based on the low-loss trick. Sample selection excludes unreliable samples according to designed selection criterion, but it eliminates obscure yet useful training samples as well. 2) Robust architecture: robust architecture\textsuperscript{5,20,21} attempted to design a new dedicated architecture or added a noise adaptation layer at the top of the SoftMax layer. However, the dedicated architecture lacks flexibility for extending to other architectures and the noise adaptation layer hinders a model’s generalization to complex label noise. 3) Robust regularization: robust regularization\textsuperscript{14,15,16,17} aimed to enforce a DNN to overfit less to false-labeled samples. This technique introduces additional hyperparameters and is sensitive to both noise and data type, but unable to promote the model performance remarkably. 4) Robust loss function: robust loss function\textsuperscript{22,23,24,25} aimed to modify the loss function and achieved a small risk for unseen clean data with the presence of noisy labels in the training data. Symmetric cross entropy (SCE)\textsuperscript{24} was to integrate a noise tolerance term, namely reverse cross entropy loss, into the standard categorical cross entropy (CCE) loss. Nevertheless, the defect of the kind of technique is that it cannot combat the heavy and complex noise. 5) Loss adjustment: loss adjustment\textsuperscript{26,27,28,29} was intended to mitigate the adverse effects of noisy labels by adjusting the loss of training samples before updating the DNNs. Active bias\textsuperscript{30} emphasized hard samples with inconsistent label predictions and took prediction variances as the weights during training. Despite a full exploration of the training data when adjusting the loss of each sample, the error incurred by false correction is accumulated, particularly when the numbers of classes and noise samples are large. In addition, SELeCTively reFurbIsh unclEan samples (SELFIE) is a hybrid approach that combined advantages of both sample selection and loss adjustment\textsuperscript{9}. The refurbished label of a training sample is determined by the most frequently predicted label for previous certain epochs when the sample satisfies the refurbished condition in SELFIE. Although it reduces the possibility of false correction while exploiting the full training data, it deals with predicted labels during time-period equally.

In this work, we propose a novel anti-noise training method (BLRM) which can integrate with DNNs, aiming to selectively refurbish noisy labels of the training data and update model parameters with the refurbished data and clean data. This BLRM combines the advantages
of both loss adjustment and sample selection. BLRM determines the refurbished label of each sample through Bayesian statistics on predicted labels during the latest $T$ epochs. We hypothesize that the predicted labels, derived from the well-trained models at the epoch of stable rising in performance before overfitting situation, are more credible. Based on the hypothesis, we propose an exponentially time-weighted technique to the predicted labels during the latest $T$ epochs, referring to from $(k - T)^{th}$ to $(k - 1)^{th}$ epochs when refurbished label of a sample at the $k^{th}$ epoch is counted. Then, the refurbished label is calculated through counting exponentially time-weighted predicted labels from $(k - T)^{th}$ to $(k - 1)^{th}$ epochs and the predicted label at the $k^{th}$ epoch according to the maximum a posteriori probability (MAP) in the Bayesian statistics (as illustrated in Fig. 2). In addition, the start-up condition of BLRM is put forward to prevent refurbishing labels prematurely, which hinges on the gradient of accuracy and loss of test dataset. We validated the superiority of BLRM on public OCT$^6$ and Messidor$^{31}$ dataset, enhancing the medical image classification under simulated and different noisy rate. Besides, BLRM also contributed to the performance improvement of classification on a real-world and natural images set ANIMAL-10N$^9$. In summary, the contributions of this paper are as follows:

1. Our proposed anti-noise BLRM integrated with DNNs is effective to mitigate the label noise. BLRM combines exponentially time-weighted and MAP in the Bayesian statistics techniques to purify the actual training data. Also, the start-up condition of BLRM is analyzed.

2. BLRM is proved to be independent of the backbone DNN and resistant to different noise rate from 10% to 40%.

3. Not only simulated noisy public available OCT dataset$^6$ and Messidor dataset$^{31}$, but also a real-world ANIMAL-10N dataset validate the superiority of BLRM.

4. Both binary classification and multi-class classification of medical images are conducted to demonstrate the efficiency of BLRM in curbing adverse effects of noisy labels.

The rest of the paper is organized as follows. Section II presents the background and details of the proposed approach. Section III shows the results of the proposed methods on
Algorithm 1 Pseudocode of the proposed BLRM

INPUT: $D$: train data, $B$: mini-batch data, $\epsilon$: uncertainty threshold, $\gamma$: noise rate, $T$: window width

OUTPUT: $\theta$: model parameters, $\psi$: refurbished data, $C$: clean data

1: $\psi \leftarrow \emptyset$
2: $t \leftarrow 1$
3: $\theta_t \leftarrow$ Initialize the model parameters;
4: for $i = 1$ to $\text{epochs}$ do
5:   for $j = 1$ to $|D|/|B|$ do
6:     Extract a mini-batch $B$ from $D$;
7:     if $i$ belongs to warm-up period then
8:       $\theta_{t+1} = \theta_t - \alpha \nabla \frac{1}{|B|} \sum_{x \in B} L(x, y; \theta_t)$ /* $\theta_t$ updated by Eq. (1)*/
9:     else $i$ reaches start-up condition of BLRM
10:       $C \leftarrow (1 - \gamma) \times 100\%$ of low-loss data in $B$ /* Clean samples selection*/
11:      for each $x \in B$ do
12:        if Entropy $(x, T) \leq \epsilon$ or $x \in \psi$ then
13:           Calculate $y^{\text{refurb}}$ based on BLRM
14:           $\psi \leftarrow \psi \cup (x, y^{\text{refurb}})$ /* $\theta_t$ updated by Eq. (2)*/
15:           $\theta_{t+1} = \theta_t - \alpha \nabla \frac{\sum_{x \in \psi} L(x, y^{\text{refurb}}; \theta_t) + \sum_{x \in C \cap \psi'} L(x, y; \theta_t)}{|\psi \cup C|}$
16:        $t \leftarrow t + 1$
17:      end for
18:    end for
19:   end for
20: end for

three public datasets. Section IV discusses relevant issues. Finally, Section V concludes the paper.

II. MATERIAL AND METHODS

II.A. Problem Definition and Algorithm Description

In a typical medical image classification task, the training dataset $D = \{(x_i, y_i) | 1 \leq i \leq N\}$ consisting of the sample $x_i$, and corresponding label $y_i$ is collected. The paired $(x_i, y_i)$ is i.i.d. The goal of the task is to learn a function which maps the feature space of $x_i$ to the ground-truth label space $y_i$. In this work, a mapping function $y = F(x; \theta)$ is learned by DNN to classify the retinal fundus images, where $\theta$ is the parameter of $F$. The parameter $\theta$ is learned by minimizing the empirical risk loss function and is updated along the descent direction of the expected loss on the mini-batch samples $B$, where $B$ is the subset of $D$. 

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\[
\theta_{t+1} = \theta_t - \alpha \nabla \frac{1}{|B|} \sum_{x \in B} L(x, y; \theta_t), \tag{1}
\]

where \(\alpha\) and \(L\) are the learning rate and loss function respectively. Considering the possible corruption of sample labels in many real-world scenarios, this study aims to modify the update equation (1) to render the network more robustness on noisy labels. Algorithm 1 describes the overall procedure of our proposed BLRM to handle the noisy labels. First, in the warm-up period, which is the initial \(n\) epochs of training, the network is trained on the whole training dataset in the default manner as shown in equation (1) (Algorithm 1, Lines 6–8). Notwithstanding the existence of noisy data, the memorization effects\(^{11,12}\) indicate that DNNs will initially ‘memorize’ the training samples with clean labels and then those of noisy labels. Subsequently, the start-up condition of label refurbishment mechanism is reached, and the training samples in the mini-batch \(B\) are separated into clean samples, refurbished samples and the remaining samples. Let \(C \subset B\) be the clean samples and \(\psi \subset B\) be the refurbished samples. Subset \(C\) covers \((1 - \gamma) \times 100\%\) of low-loss instances\(^{12}\) and \(\gamma\) is the noise rate (Algorithm 1, Lines 9–10). If \(\gamma\) is unknown, it can be reconstructed through cross-validation\(^{32}\). In this period, each train sample is identified through checking the predictive uncertainty that uses the entropy to measure the consistency of label prediction in the \(T\) epochs (Algorithm 1, Line 12). The detailed calculation of entropy can refer to the previous research\(^9\). Our proposed BLRM is applied to determine the refurbished labels of samples in \(\psi\) (Algorithm 1, Line 13). Then the refurbished samples are aggregated into \(\psi\) for reuse (Algorithm 1, Line 14). Notably, the intersection of \(C\) and \(\psi\) is not necessarily a nonempty set. If a sample \(x \in \psi \cap C\), being refurbished precedes being clean because mislabeled instances could be included even in \(C\). The parameters \(\theta\) of the DNN will be updated based on the clean samples along with refurbished samples. We correct the backward loss of the refurbished sample \(x \in \psi\) by replacing its corrupted label \(y\) with the refurbished label \(y^{\text{refurb}}\) and backpropagate the losses for the refurbished and clean samples to update the network (Algorithm 1, Lines 15-16), which can be described as:

\[
\theta_{t+1} = \theta_t - \alpha \nabla \left( \frac{1}{|\psi \cup C|} \left( \sum_{x \in \psi} L(x, y^{\text{refurb}}; \theta_t) + \sum_{x \in C \cap \psi'} L(x, y; \theta_t) \right) \right), \tag{2}
\]

where \(\psi'\) represents the complement set of \(\psi\).
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II.B. Techniques of Label Refurbishment Mechanism

Fig. 2 describes the overall procedure of our proposed Bayesian statistics guided label refurbishment mechanism. Each mini-batch of medical images are fed into the base DNN to train the image classification model. Through the training process, predicted labels with corresponding probabilities of all training samples at each epoch are recorded to calculate likelihood function for the optimal label selection. At the early stage of training, original given labels should be used for loss calculation and start-up condition of BLRM should be judged simultaneously. When the start-up condition of BLRM is reached, the optimal label selection module will be activated and calculates the estimated labels $y^\text{refurb}$ to replace the original given labels $y$. The technical details are illustrated in the following parts.

**Start-up condition of label refurbishment mechanism.** Before BLRM takes into effect, a warm-up period is necessary for ensuring the performance of the training model reaching into relatively steady state. In the warm-up stage of training, the performance of the model is unstable or under-fitting, which leads to large deviations of the computation results of refurbished labels. Therefore, an appropriate start-up condition of BLRM should be devised carefully, which can prevent the refurbished labels from fluctuating or unchanging unacceptably. In this study, we propose two prerequisites to activate BLRM. First, the average loss value of samples in validation dataset should step into a range $[L_a, L_b]$, in which our training model may acquire the best performance on validation dataset. Obviously, the value of $L_a$ is zero in an ideal situation. As the output of the last layer should be normalized by a SoftMax function, the minimum probability of the ground truth (GT) label for a correct predicted sample would be no less than $1/M$, where $M$ is the number of categories. According to the formula of cross-entropy, $L_b$ can be calculated as:

$$
L_b = \max_{(1/M < P_{GT} \leq 1)} L|L = -ln(P_{GT}) = -ln(1/M),
$$

(3)

where $P_{GT}$ represents the probability of the GT label. Second, our model has not been suspected of over-fitting or under-fitting. In the training process, the accuracy of validation dataset should satisfy following condition,

$$
\rho_{\text{val}} > 100\% - \gamma - \phi,
$$

(4)

where $\rho_{\text{val}}$ represents accuracy on validation dataset during training and $\gamma$ is the original noise rate of training dataset. $\phi$ is a hyperparameter that is named as the relaxation factor.
in our study and is used to control the base accuracy to trigger BLRM. In our study, the value of $\phi$ was pre-set to 5%.

**Bayesian statistics for optimal label selection.** The Bayesian statistics formula is utilized in our study to estimate the optimal label for each sample, which is shown as follows:

$$p(Y_{\theta(k)}|Y_{\theta(k-1)}\sim\theta(k-T)) = \frac{p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)})p(Y_{\theta(k)})}{Z}. \quad (5)$$

Inside:

$$Z = \sum_{Y_{\theta(k)}=1}^{M} p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)})p(Y_{\theta(k)}). \quad (6)$$

$$\sum_{i=1}^{M} p(Y_{\theta(k)} = i) = 1, \quad (7)$$

where $Y_{\theta(k)} \in \{1, \ldots, M\}$ expresses the label of a sample used in $k^{th}$ epoch, and $Y_{\theta(k-1)}\sim\theta(k-T)$ represents the label sequences ranging from the $(k-T)^{th}$ and the $(k-1)^{th}$ epoch. Besides, $T$ and $Z$ stand for the window width epoch for Bayesian statistics and the normalized constant, respectively.

The prior probability $p(Y_{\theta(k)})$ is obtained by the training model of the $k^{th}$ epoch. We need to make sure what statistical parameter to use to calculate the likelihood function $p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)})$. Referring to our hypothesis that the estimated label of a current sample is related to its past learning effects, we regard $p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)})$ as a weighted mean statistic to incorporate past knowledge into current label estimation. The likelihood function can be computed by the following formula:

$$p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)}) = \sum_{i=1}^{T} \omega_i p(Y_{\theta(k+i-T-1)} = Y_{\theta(k)}). \quad (8)$$

Inside:

$$\omega_i = \frac{e^{\frac{i}{\eta}}}{Z'}, \quad (9)$$

where $\omega_i$ denotes the weight of one label of $i^{th}$ epoch in window $T$; $Z'$ is a normalization constant where $Z' = \sum_{i=1}^{T} e^{\frac{i}{\eta}}$; and $\eta$ is an adjustable parameter that controls the distribution of $\omega_i$. In this study, we assigned a bigger weight to a more recently learned label, as the latest knowledge has the greatest impact on the decisions. In our study, $\eta$ was equal to the length of window width. Then the posterior probability $p(Y_{\theta(k-1)}\sim\theta(k-T)|Y_{\theta(k)})$ can be calculated.
The refurbished label $y^{\text{refurb}}$ is corresponding to the class index that maximized the posterior probability.

II.C. Network Architecture and Implementation

To validate the effectiveness of BLRM, we integrated BLRM into the DNN architecture and compared the performance between the DNNs with and without BLRM based on the same train and test dataset. With new network architectures constantly emerging, the compatibility of the proposed BLRM with any type of DNNs is important. Flexibility ensures that the proposed method can quickly adapt to the different architectures. In the comparative experiments, three popular DNNs (VGG-16$^{33}$, Inception-V3$^{34}$, Resnet-50$^{35}$) were used to demonstrate the flexibility of BLRM. The training procedure utilized the Adam optimizer with a learning rate of 0.0001, a cross-entropy loss function, and a minibatch size of 32.

II.D. Dataset Accumulation and Transformation

Dataset description. In this study, we sought to develop an effective noise reduction technique (BLRM) to enhance the performance of noisy medical image classification. The primary illustration of this technique involves optical coherence tomography (OCT) images of the retina. The public OCT dataset$^{6}$ covers choroidal neovascularization (short as 1), diabetic macular edema (2), drusen (3), and normal cases (0). We randomly sampled 1,000 images for each category as training dataset and utilized the available validation dataset (250 images for each category).

The BLRM was also tested in DR retinal fundus images to validate the generalization of this technique across multiple imaging modalities. We performed the binary image classification tasks on a public dataset Messidor$^{31}$. Detailed grading information is listed in Table 1 and NMA, NHE, and NNV refer to the number of microaneurysms, hemorrhages and neovascularization, respectively. Fundus images with DR0 and DR1 are categorized as routine referrals (short as 0). These conditions would demand regular follow-up. While fundus images with DR2 and DR3 are categorized as urgent referrals (short as 1) where

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1The code will be released at https://github.com/neugmd/BLRM
the patients demand relatively urgent referral to ophthalmologists for timely treatment. We
referred to the errata available and then deleted 13 duplicate images and adjusted labels of
4 images with inconsistent grading.

**Noise injection.** As the both datasets contained only clean samples, we need to arti-
ficially corrupt sample labels to generate noisy labels. Frénay and Verleysen\textsuperscript{36} summarized
the taxonomy of label noise in detail. As shown in Fig. 3 (a), noise transition matrix \(T_{ij}\)
describes the probability of ground-truth label \(i\) being flipped to the noisy labels \(j\). For \(M\
classes, symmetry noise satisfies

\[
T_{ij} = \frac{\gamma}{M - 1},
\]

where a ground-truth label is flipped into other labels with equal probability and the noise
rate \(\gamma \in [0, 1]\).

In our work, symmetry noise was introduced respectively to construct researchable
datasets with noise. To evaluate the robustness on varying noise rates from light noise
to heavy noise, according to the real-world noise rate, we tested five noise rates, varying
from 0 to 40\% with step 10\%, to validate the robustness of our proposed method.

II.E. Quantitative Evaluation Metrics and Comparative Study

**Quantitative evaluation metrics.** The performance of BLRM is quantitatively evaluated
by test accuracy. The test dataset has unbiased and clean samples that are not used in
training. The test accuracy degrades drastically when the DNN overfitted samples with noisy
labels\textsuperscript{13}. Furthermore, area under curve (AUC) is also calculated as the metric. Meanwhile,
data purity could be utilized as an indicator of the proportion of samples with ground-truth
labels in the whole training dataset.

\[
Data\ purity = \frac{|\{(x_i, y_i) \in D : \tilde{y}_i = y_i\}|}{|D|},
\]

Where \(D\) is the whole training dataset and \(y_i\) is the GT label and \(\tilde{y}_i\) is the resulting label
of the \(i\)\textsuperscript{th} samples in \(D\). \(y_i\) is either original label or refurbished label. Data purity may be
updated after each epoch when BLRM worked. Cohen’s kappa (kappa)\textsuperscript{37} is further employed
to measure the agreement between ground-truth labels and noisy labels of training dataset.

**Comparative study methods.** We compared our proposed method with a benchmark
model (marked as Default) and four robust training algorithms (Coteaching\textsuperscript{38}, JoCoR\textsuperscript{39},
AdaCorr, and SELFIE). We re-implemented with the same network backbone architecture to ensure the fairness of the comparison. Although they were designed and evaluated for natural images classification tasks, we re-adapted them with fine-tune hyper-parameters on medical datasets for a fair comparison. Compared methods adapted different strategies to mitigate label noise in the medical image classification. Hence, we cannot compare the data purity of all the comparison methods. The compared methods include:

1. **Default** This is the common training procedure without any processing strategy of the noisy labels.

2. **Coteaching** This is the method proposed by. Coteaching selected the clean samples by the loss-based separation and adopted the co-training mechanism to confront noisy annotations.

3. **SELFIE** This is the method proposed by. SELFIE combined loss correction with the sample selection strategy to improve the robustness.

4. **JoCoR** This method was to train two classifiers simultaneously with small-loss instances, using both regular supervised loss and co-regularized loss.

5. **AdaCorr** This anti-noise method proposed a label correction algorithm to combat label noise.

### III. EXPERIMENT AND RESULTS

We initially verified the validity of the proposed BLRM through four-class OCT images classification experiments based on public OCT dataset. After that, generalization was proven through binary DR images classification with the public Messidor dataset. Two classes refer to routine referral (DR0 and DR1) and urgent referral (DR2 and DR3) treatment group. The sizes of routine referral and urgent referral treatment groups are 550 and 380 for the training dataset, and 146 and 111 for test dataset, respectively. The division details of training and test set can be referred in Table 1. All experiments were performed on an NVIDIA RTX3090 GPU with 24 GB of memory. In this work, we did not apply any data augmentation or pre-processing procedures.
III.A. Hyperparameter Selection

The proposed DNN with BLRM receives two hyperparameters: the window width $T$ and the uncertainty threshold $\varepsilon$. To determine the optimal combination of hyperparameters, we trained Inception-V3 on the noisy OCT dataset at a rate of 40% noise with two hyperparameters set in a grid with $T \in \{4, 5, 6\}$ and $\varepsilon \in \{0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5\}$. Similarly, we repeated the grid-search experiments on the noisy Messidor dataset at a rate of 40% noise with two hyperparameters set in a grid with $T \in \{5, 10, 15\}$ and $\varepsilon \in \{0.3, 0.325, 0.35, 0.375, 0.4, 0.425, 0.45\}$. Fig. 4 illustrates the test accuracy obtained by the grid search on the two noisy datasets, respectively. Regarding the uncertainty threshold, the best test accuracy cannot be achieved with both small and large thresholds. The performance generally involves a compromise between the correctly refurbished samples in the $\psi$ and wrongly refurbished samples in the $C$. The small threshold corresponds to the small rate of both the above two cases while the large threshold corresponds to the high rate of both the above two cases. In Fig. 4 (a), as for the window width, although there is no clear winner among the 4, 5, and 6, the $T$ of value 5 achieves the highest test accuracy when the threshold $\varepsilon$ was 0.25. Therefore, in the following experiments on the OCT dataset (Messidor dataset), we set the uncertainty threshold $\varepsilon$ to 0.25 (0.4) and the window width $T$ to 5 (5).

III.B. Performance of Four-class OCT Images Classification

The flexibility of the proposed BLRM. The flexibility of BLRM ensures the capability of supporting any type of DNN architectures. BLRM were separately integrated with three popular DNNs (VGG-16, Resnet50, Inception-V3) to perform comparative experiments on the public OCT dataset. Here, the noise rate was fixed at 20%. The detailed performance metrics are shown in Table 2. Three DNNs architecture integrated with BLRM all enhance the generalization performance and reduce the influence of noisy labels. Compared with the benchmark VGG16, the test accuracy and data purity of VGG16-BLRM improve from 0.82 and 79.90% to 0.86 and 81.13%, respectively. Resnet50 and Inception-V3 with BLRM share the similar promoted trend. In general, the results prove that the proposed BLRM can improve the performance of DNNs and the promotion is independent of specific models.

Tolerance to different proportions of noise. We selected Inception-V3 as the
benchmark model and set the noise level from 0 to 40% with a step size of 10% to test the tolerance of the proposed BLRM to different proportions of noise. The comparison metrics of OCT dataset are listed in Table 3. We can see that the performance of the model without BLRM becomes worser with the increase of noise ratio. In the case of no noise containing only clean training samples, BLRM produces hardly any side effects to the performance of the well-trained models. Generally, under the noise level from 10% to 40%, BLRM achieves better metrics than benchmark model on OCT dataset. For example, at the relatively heavy noise rate of 30%, the data purity, ACC, and Kappa increase 2.80%, 8.50%, and 11.06%, respectively. The Fig. 5 (a) and (b) illustrate the confusion matrices comparing test accuracy for OCT images classification without and with BLRM at the noise of 40%, respectively. We could observe that the BLRM improves the test accuracy obviously and enhances performance of each category, especially for the normal cases (short as label 0).

III.C. Performance of Two-class DR Images Classification

Generalization on the public Messidor dataset. We also verified the generalization of BLRM based on the corrupted Messidor dataset. Considering that the size of Messidor was relatively small (less than 1200), we did not conduct the image grading experiment, but trained the two-class DR images classification model based on the pretrained models derived from ImageNet. We still adopted Inception-V3 as the backbone network and utilized hyperparameters determined by grid-search experiments above. Messidor was corrupted with different noise levels of 10%, 20%, 30% and 40%, respectively. The test accuracy and train data purity of comparative experiments are displayed in Table 4. Similarly, the Inception-V3 with BLRM weakens the influences of noisy labels on the Messidor dataset. The Inception-V3 with BLRM achieves improvement on test accuracy of 3.51%, 6.62%, 2.33%, and 5.84% under the noise rate raising from 10% to 40%, respectively. The Fig. 6 from (a) to (d) display the ROC curves using Inception-v3 with or without BLRM at each noise rate. The area under the ROC curve of Inception v3 with BLRM is larger at each noise rate , indicating BLRM improving the performance of Inception-v3. In addition, from the confusion matrices comparing test accuracy for DR images classification at the noise rate 40% without and with BLRM (Fig. 7), our proposed technique promotes the generalization performance of classification model. In brief, BLRM optimizes the performance of models and improves
purity of training data when learning from the noisy Messidor dataset.

### III.D. Comparison Study

The comparative methods including Default, Coteaching, SELFIE, JoCoR, and AdaCorr were employed on OCT dataset and Messidor dataset, respectively, to compare with our proposed BLRM. Fig. 8 shows the test accuracy of the compared methods with varying symmetry noise rates, ranging from 0 to 40%. And the test accuracy of all methods at the noise rate of 30% are summarized in Table 5.

In the OCT dataset (Fig. 8 (a)), BLRM surpasses reference methods at high noise rate, except JoCoR. We speculate that four-class learning task, identifying choroidal neovascularization, diabetic macular edema, drusen, and normal cases, possesses relatively sufficient training samples (1000 images for each category) relative to task complexity. Hence, JoCoR works well thanks to a joint loss with co-regularization for each training example. However, JoCoR has two classifiers to train which doubles the quantity of parameters, raising the computing resources and training time considerably. Both AdaCorr and our method belong to label refurbishment for the noisy data. Our proposed Bayesian statistics guided label refurbishment mechanism performs more stably while AdaCorr is inferior at the noise rate of 30% and 40%. When compared with Default group, with the increase of noise ratio, the improvement of BLRM is more significant and the maximum increment reaches 14% when the noise rate is 40%. Both Coteaching and SELFIE reduce the influence of noise label but there is no clear winner between Coteaching and SELFIE. SELFIE is superior to Coteaching in presence of light noise (10% and 20%) while SELFIE is inferior to Coteaching in presence of heavy noise (30% and 40%).

In the Messidor dataset (Fig. 8 (b)), as DNNs were trained based on the pretrained models derived from ImageNet due to the dearth of training data, the effectiveness of methods for resisting noisy label is relatively limited. Regarding Messidor dataset, our proposed method is superior to others generally, under high noise levels in particular. Although JoCoR outperforms ours at noise rate of 10%, its performance degenerates sharply with the increase of noise ratio. Limited instances together with serious noisy labels interference in the Messidor dataset, caused JoCoR is indeed difficult to derive the joint loss including regular supervised part and co-regularized part, accurately. To sum up, our proposed
BLRM can improve the robustness of models across different noise patterns and is superior to the comparison method in most cases.

IV. Discussion

IV.A. Result with Realistic Noise

In addition to manually induced noise, ANIMAL-10N with realistic noise was further utilized to conduct image classification experiments to validate the proposed BLRM method. ANIMAL-10N consists of 10-class animal images with 50,000 training images and 5,000 test images. Notably, training dataset in ANIMAL-10N has realistic noise corrupted with noisy labels naturally by human mistakes and the noise rate is estimated at 8%. And the test dataset in ANIMAL-10N is free from noisy labels.

Further, the superiority of BLRM is proved by comparing with five comparative methods (Default, Coteaching, SELFIE, JoCoR, and AdaCorr). As the correct ground-truth labels of the training dataset in ANIMAL-10N are unknown, the data purity and Kappa metrics of the training dataset cannot be calculated. The test accuracy is illustrated in the bar chart in Fig. 9. Our proposed BLRM ranks first reaching 82.6% and Default ranks the last reaching 79.4%. BLRM increases the accuracy by 1.6% and 2.4% compared with SELFIE and Coteaching, respectively. ANIMAL-10N possesses more categories and large-scale small-sized natural images. JoCoR is not competent for this scenario, with very limited promotion while AdaCorr achieves high test accuracy of 81.6%, with merely 1% lower than ours. In brief, BLRM also works well when dealing with realistic noise.

IV.B. BLRM Applied in Weak Supervision Learning

DNNs for image classification is sensitive to the quantity of training data to some extent in the case of a fixed model. When lacking training data, enriching training data is an effective way to improve the performance of the model. Self-training exploits unlabeled data with pseudo-labels to achieve better model performance. Inspired by self-training, we apply BLRM to self-training to refurbish the pseudo-labels. We carried out three comparative experiments on the Messidor dataset and Fig. 10 illustrates the test accuracy against the
percentage of training dataset with ground-truth labels fed to DNNs. The differences among the three groups of comparative experiments depend on the training data and strategies of the training model. Taking $x$ value being 10% for example, in the control group experiment, 10% training data with the ground-truth label are utilized for training the DR image dichotomy task. While the self-training group contains the 10% training dataset above, as well as 10% dataset with pseudo-labels, the self-training with BLRM group shares a similar training data pattern as the self-training and applies BLRM to enhance the performance of the DNNs. In Fig. 10, all the three groups verify that test accuracy becomes higher along with the increase (from 10% to 30%) of the training dataset. The self-training group can indeed utilize the unlabeled samples and improve the test accuracy compared with the control group. Self-training with BLRM surpasses the other two groups and increases 3.2%, 5.9%, 2.5%, 2.9%, and 2.8% compared with the control group from the 10% to 30% percentage of the training dataset. It proves that BLRM can leverage the features’ information of unlabeled data and boost performance in weak supervision learning task.

IV.C. The Interpretability of the Model

The class activation maps (CAM) suggest that the sensitive areas which causes the high response of our model are consistent with the suspicious areas in a clinical diagnosis. CAM can prove the superiority of the DNNs with BLRM, which is shown as Fig. 11. The leftmost column shows the color retinal fundus images with corresponding ground-truth label in the upper left corner. The middle and rightmost columns are the CAMs with predicted labels and probabilities in the upper left corner from Inception-V3 with and without BLRM, respectively. In Fig. 11 (a), the predominant lesions including multiple hemorrhages lesions are located on the nasal side of the foveal location. Microaneurysms and hemorrhages lesions can be observed between superior and inferior vascular arcades in Fig. 11 (b). The model without BLRM fails to detect the lesions, resulting in false-negative misjudgment in both cases. However, our proposed method can accurately localize the lesions and obtain correct positive predicted labels. Fig. 11 (c) is a negative case. The model without BLRM treat the reflection of nerve fiber as lesions mistakenly, leading to a false-positive prediction with high probability of 0.9755.
IV.D. Limitations and Future Direction

This study still has some limitations. Firstly, our study initially carried out all the experiments based on the dataset with limited symmetry noise. In the clinical settings, the distribution of label noise is unknown. It is worth exploring the taxonomy of label noise such as asymmetric (or label-dependent) noise\textsuperscript{36}. Asymmetric noise means that a ground-truth label is more likely to be mislabeled into a particular label, which is more reasonable in a real sense. Secondly, the features of noisy samples need to be further mined so that more noisy samples can be refurbished to correct ones and fewer clean samples can be refurbished to wrong ones. Thirdly, datasets from other medical modalities such as CT, MRI and PET can be utilized to further validate the effectiveness of our proposed BLRM.

V. Conclusion

We propose a novel BLRM for robust training of DNNs classification models with noisy labels. A selectively refurbished sample can be corrected through analyzing the former predicted labels with the Bayesian maximum a posteriori probability and exponentially time-weighted technology. We conducted extensive experiments of four-class OCT images classification and two-class DR images classification on public OCT and Messidor datasets with varying noise levels. Our experiment results show that BLRM can improve the robustness of the DNNs when dealing with corrupted labels. BLRM guides the network to avoid noise accumulation and allows it to take advantage of the full exploration of training data. In summary, the proposed BLRM has demonstrated its capability of reducing the adverse effects of noisy labels in medical image classification based on deep learning.

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Conflict of Interest

The authors have no conflicts to disclose.
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Fig. 1. Plots depicting performance of optical coherence tomography images classification in the training and validation datasets using tensorboard. The training datasets include corrupted noisy label. Training accuracies are compared for different noisy corruption percentage (0, 10%, 20%, 30%, 40%) (a) with cross-entropy loss plotted against the training epoch (b). Test accuracies are compared (c) with the associated cross-entropy loss (d). Plots are normalized with a smoothing factor 0.6 in order to clearly visualize trends.

Fig. 2. The workflow diagram of DNN with plug-and-play BLRM module. The blue part above indicates the training process of benchmark DNN, and the green part below displays the procedure of refurbishing labels with BLRM. The training dataset is gradually purified after BLRM working.

Fig. 3. Confusion matrices comparing the training data purity for OCT images classification before (a) and after (b) correction at the noise rate of 40%.

Fig. 4. The test accuracy with different combinations of window width ($T$) and uncertainty threshold ($\varepsilon$), performed as a grid search to determine the optimized combination of hyperparameters for the OCT dataset (a) and the Messidor dataset (b).

Fig. 5. Confusion matrices comparing test accuracy for OCT images classification without (a) and with (b) BLRM.

Fig. 6. The ROC curves using Inception-v3 or Inception v3 integrated with BLRM. (a) to (d) is at 10%, 20%, 30%, and 40% noise rate, respectively. Inception v3 with BLRM: red. Inception v3 without BLRM: blue.

Fig. 7. Confusion matrices comparing test accuracy for DR images classification without (a) and with (b) BLRM.

Fig. 8. The best test accuracy of the comparative training methods of anti-noise on medical datasets under different noise settings.

Fig. 9. The best test accuracy of the comparative methods of combating noisy labels on ANIMAL-10N.

Fig. 10. Investigation of self-training with BLRM on the Messidor dataset. The X-
axis represents the percentage of training data with ground-truth labels fed to DNNs in the Messidor dataset and Y-axis represents test accuracy of DNNs.

Fig. 11. Examples of class activation maps from Inception-V3 with or without BLRM. (a) and (b) are positive cases where blue bounding boxes mark the lesions on the images, and (c) is a negative case. The second and third columns are CAMs with and without BLRM with predicted labels and probabilities in the upper left corner.