Robust Asymmetric Loss for Multi-Label Long-Tailed Learning

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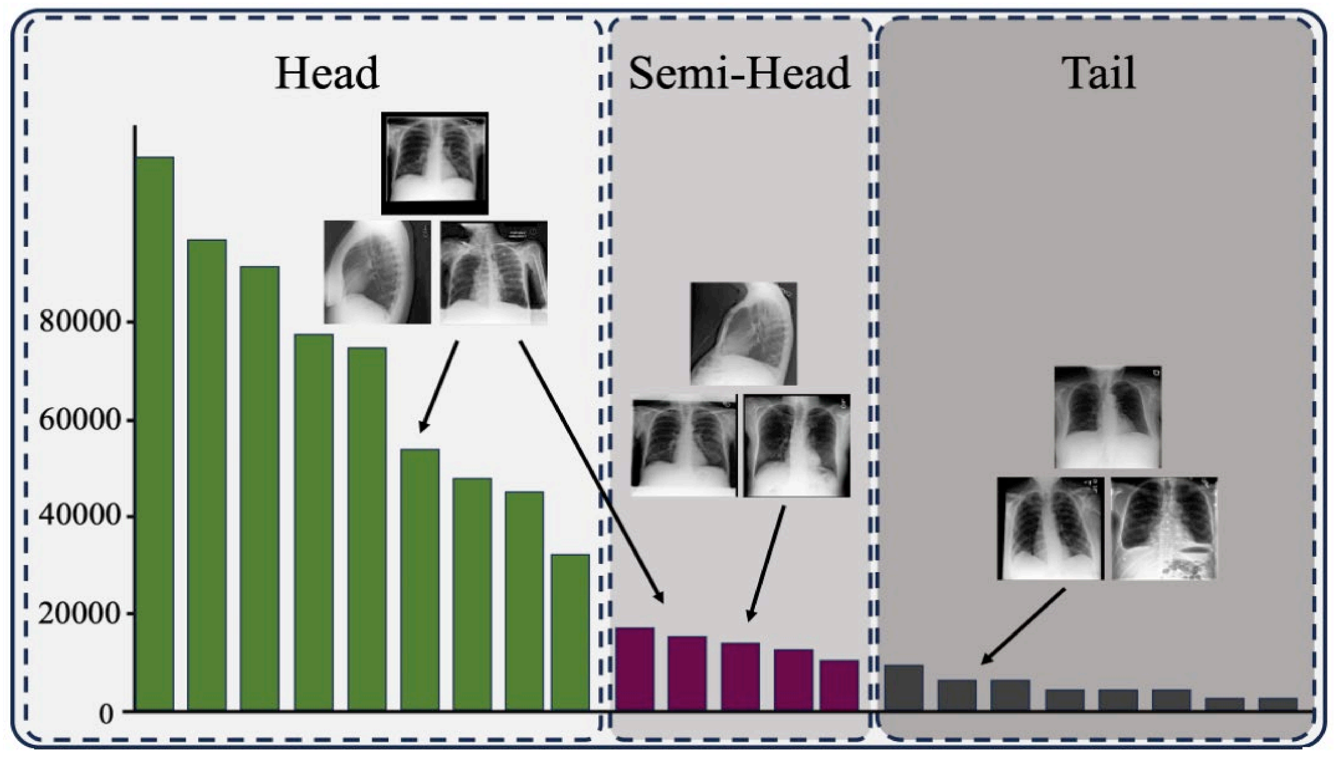
Overview

- We propose robust asymmetric loss, which is effective for long-tailed multi-label classification.
- We improve the performance of long-tailed multi-label classification.
- We achieved Top-5 results in the CVAMD2023 competition on the long-tailed multi-label CXR-LT dataset.

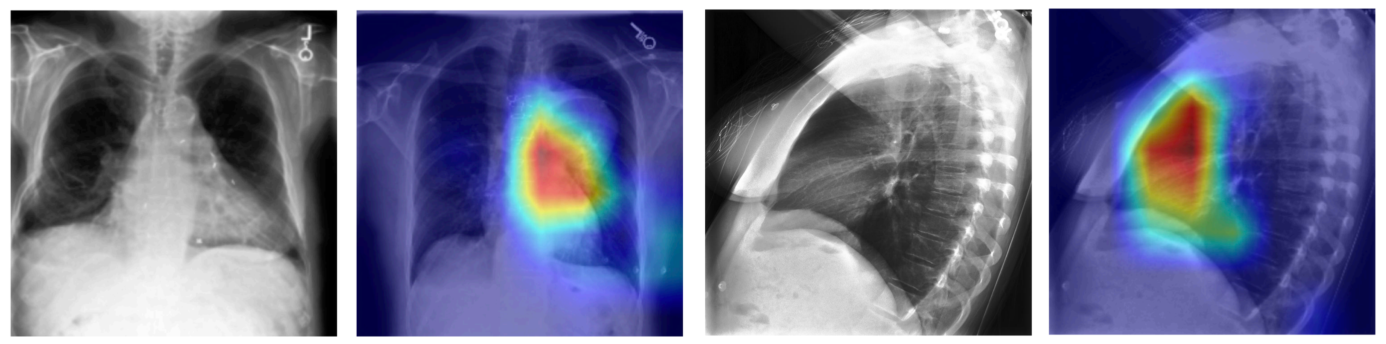
Long-tailed Dataset



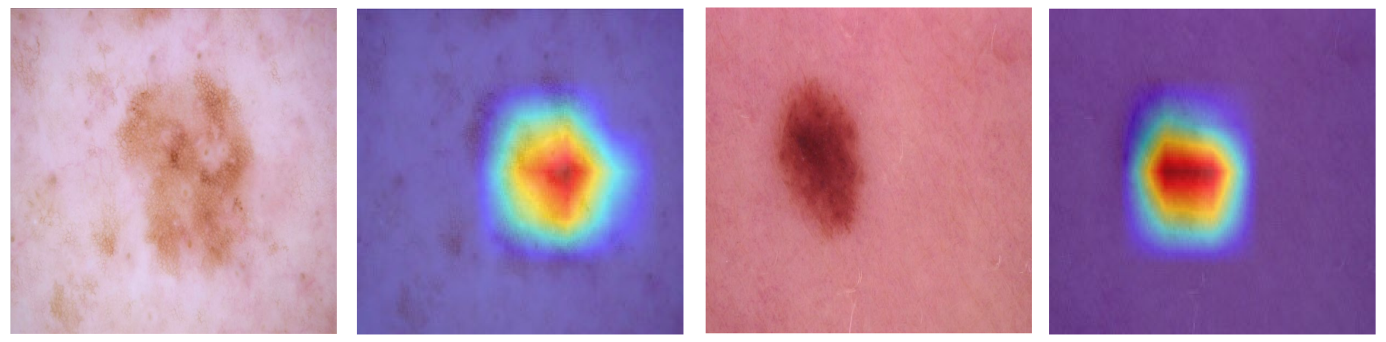
Label distribution of the CXR-LT Dataset

Dataset	classes	Samples	Imbalance Ratio
CXR-LT	26	377,110	142
APTOS2019	7	10,015	58
ISIC2018	5	3,662	10

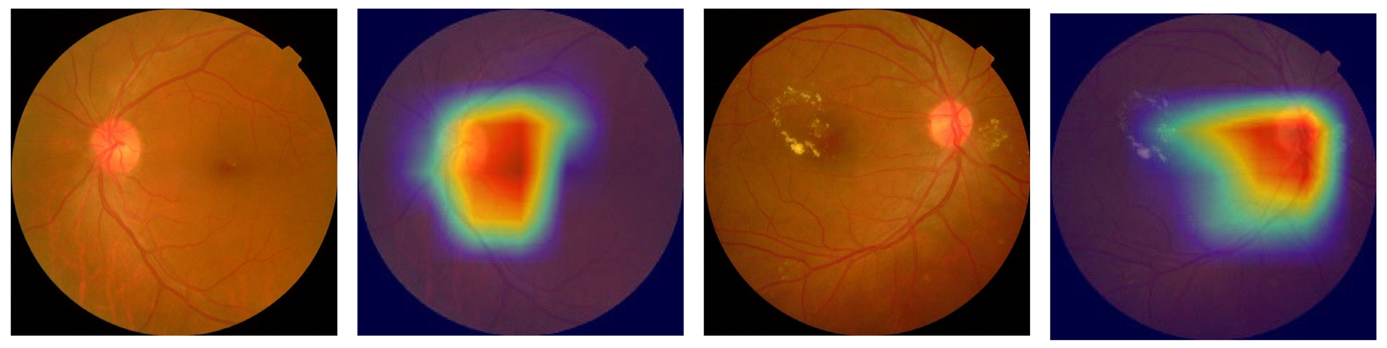
The details of long-tailed medical datasets.



CXR-LT Dataset.



ISIC2018 Dataset.



APTOS2019 Dataset.

Method

Existing loss function Problem

- **Escessively focuses on learning the head classes.**
- **Positive and negative losses share the same focusing parameter γ.**
- **Optimizing such a large number of hyper-parameters can be a time-consuming process and often leads to overfitting the models.**

RAL Loss (Ours)

$$\mathcal{L} = -\sum_{i=1}^{K} (y_i L_i^{+} + (1 - y_i) L_i^{-})$$

Our RAL is robust to the change of numerous hyperparameters due to the less sensitive negative loss in the training process. Our RAL loss regularizes the gradient of these hard negative samples to make them less sensitive to hyper-parameters.

$$\begin{cases} \mathcal{L}_{RAL}^{+} = y \sum_{m=1}^{M} \alpha_m (1-\hat{y})^{m+\gamma^{+}} \\ \mathcal{L}_{RAL}^{-} = \psi(\hat{y}) \cdot (1-y) \sum_{n=1}^{N} \beta_n \hat{y}_{\tau}^{n+\gamma^{-}} \end{cases}$$

$$\psi(\hat{y}) = \lambda - \hat{y}\ , \quad \hat{y}_{\tau} = max(\hat{y} - \tau, 0)$$

Focal Loss	Asymmetric	Hill	mAP	mAUC
✓			0.295	0.803
✓	✓		0.307	0.815
✓	✓	✓	0.323	0.817

Effectiveness of each module in RAL Loss.

Result on CVAMD2023 Competition

Model : ConvNeXt-Base
Optimizer : Adam
Loss : RAL (Ours)
Epoch :20

Image Size : 1024
Augmentation
- HorizontalFlip
- RandomRotation
- RandomErasing
- Sharpness

Submit	mAP	mAUC	mF1
# 1	0.351	0.837	0.256
# 2	0.317	0.814	0.061
# 3	0.318	0.814	0.143

Experimental result of submissions of test phase of the CVAMD 2023 competition.

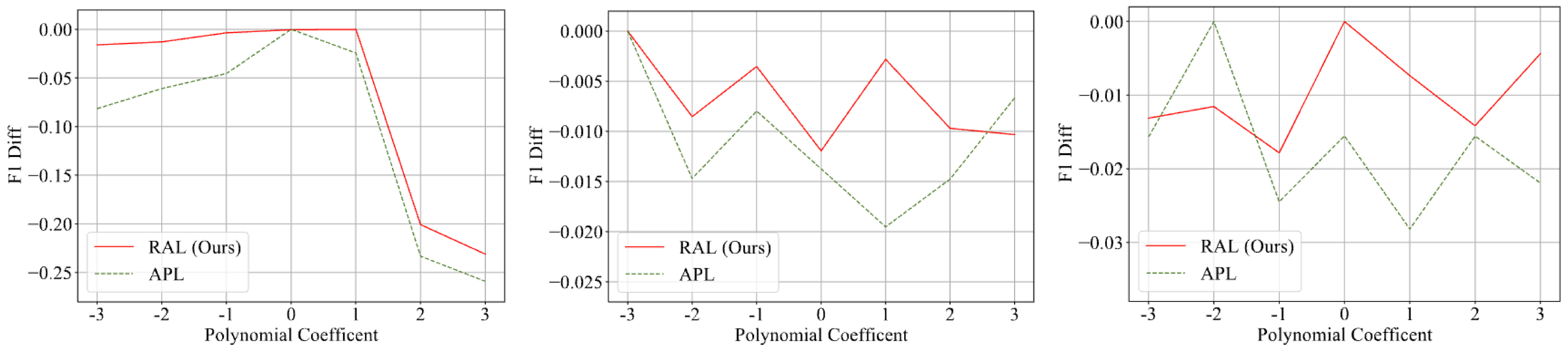
Experiments

Methods	mAP	mAUC	mF1
CE	0.314	0.813	0.227
Focal Loss	0.295	0.803	0.224
ASL	0.317	0.811	0.237
RAL (Ours)	0.323	0.817	0.233

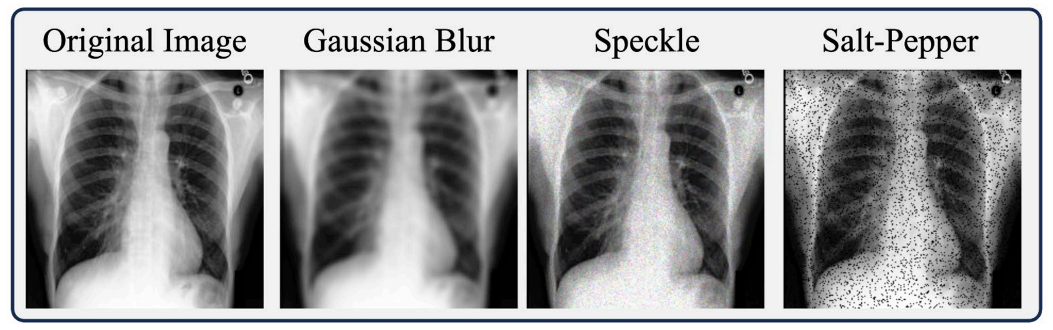
Experimental results of the CXR-LT dataset.

Methods	ISIC2018		APTOS2019	
	Accuracy	F1-score	Accuracy	F1-score
CE	0.850	0.716	0.812	0.608
Focal Loss	0.861	0.735	0.815	0.629
LDAM	0.849	0.728	0.813	0.620
ASL	0.854	0.734	0.820	0.660
RAL (Ours)	0.852	0.740	0.826	0.673

Experimental results of the ICIS2018 and APTOS2019 datasets.



CXR-LT **ISIC2018** **APTOS2019**



Methods	Img	Blur	Speckle	SaltPepper
BCE	0.789	0.718	0.502	0.501
ASL	0.791	0.734	0.512	0.513
RAL (Ours)	0.796	0.547	0.534	0.745

Experimental result on the noisy conditions. Our RAL shows better performance compared to the others consistently.

Reference

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- Ridnik, Tal, et al. "Asymmetric loss for multi-label classification." ICCV. 2021.
- Zhang, Youcai, et al. "Simple and robust loss design for multi-label learning with missing labels." arXiv. 2021.
- Huang, Yusheng, et al. "Asymmetric Polynomial Loss for Multi-Label Classification." ICASSP. 2023.

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