CYFLOD: Cyclic Filtering and Loss Damping for Alleviating Noisy Labels in Fine-grained Visual Classification

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ABSTRACT

We propose CYFLOD, a transfer-learning-based framework to tackle noisy labels in fine-grained visual classification (FGVC). CYFLOD integrates two components: (i) **cyclic filtering to remove high-loss samples iteratively**, and (ii) **loss damping using a SmoothStep function to mitigate gradient spikes from mislabeled samples**. We evaluated on datasets like Stanford Cars, Aircraft, CIFAR-10, and Food-101N, CYFLOD consistently outperforms state-of-the-art (SOTA) methods under both synthetic (**symmetric** and **asymmetric**) and **real-world** noise conditions.

Problem Statement

Fine-grained datasets (e.g., Stanford Cars, Aircraft) are more prone to label noise than generic datasets due to high visual similarity between classes.

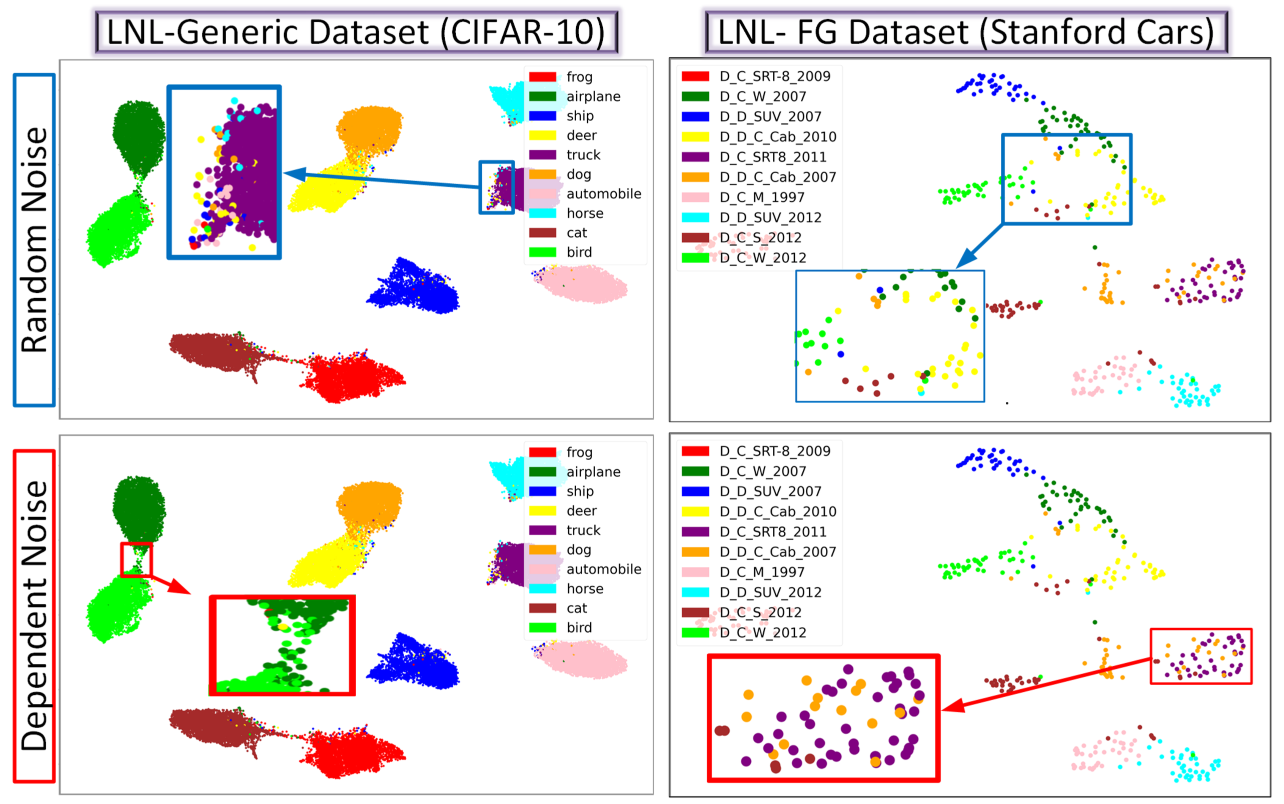


Figure 1. **Challenges in LNL**: LNL-FG is more challenging than generic classification. **Blue** rectangles show random noise; **red** rectangles indicate dependent noise (e.g., class confusion).

NOISE GENERATION

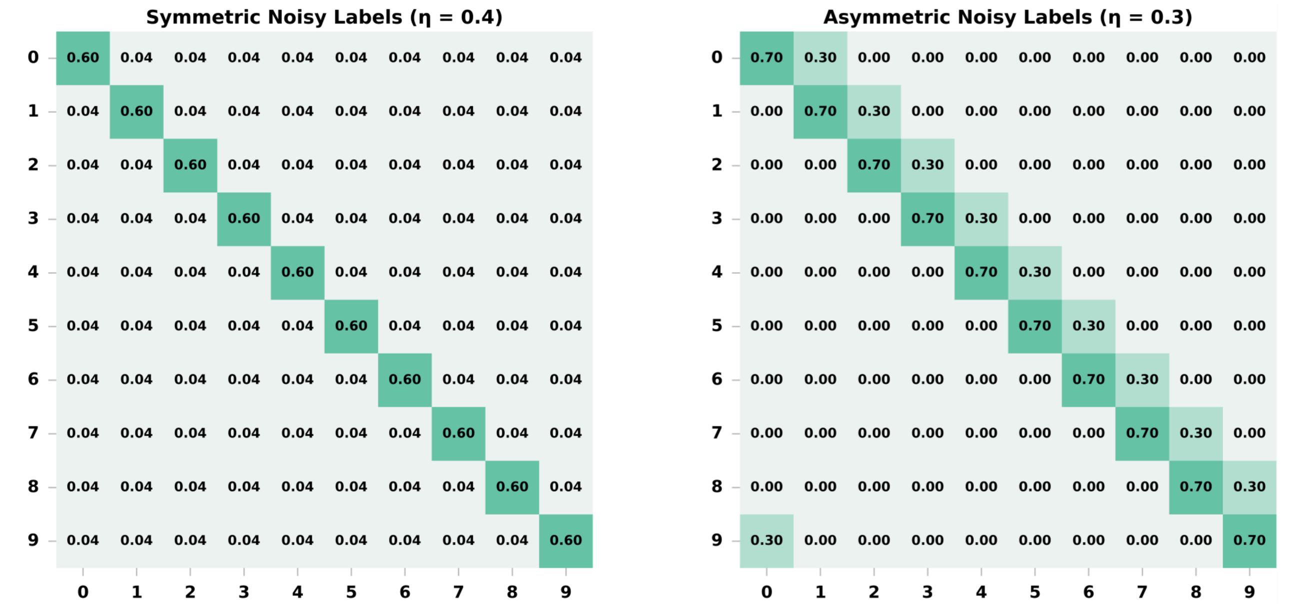


Figure 2: **Transition matrix** : Left : Symmetric Noise ($\eta = 0.4$), and Right: Asymmetric Noise ($\eta = 0.3$).

CYFLOD FRAMEWORK

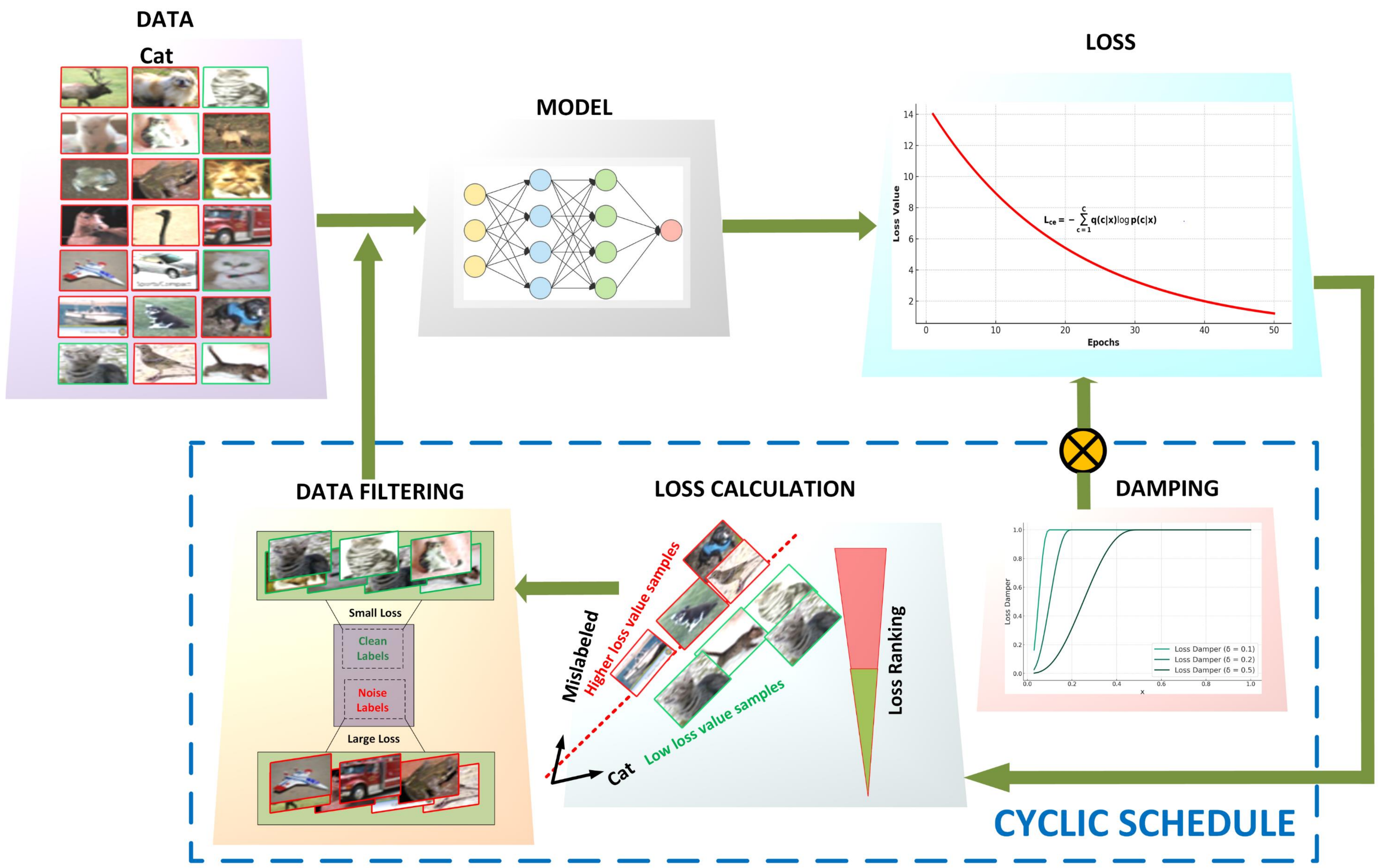


Figure 3. CYFLOD Framework. The model is trained on noisy data using a two-stage strategy: (1) **Cyclic Filtering** removes high-loss (likely noisy) samples each cycle and reintroduces them later to recover edge cases; (2) **Loss Damping** applies SmoothStep-based gradient suppression, modulated per epoch as to reduce early influence of mislabeled data. This iterative pipeline effectively isolates and mitigates label noise during training

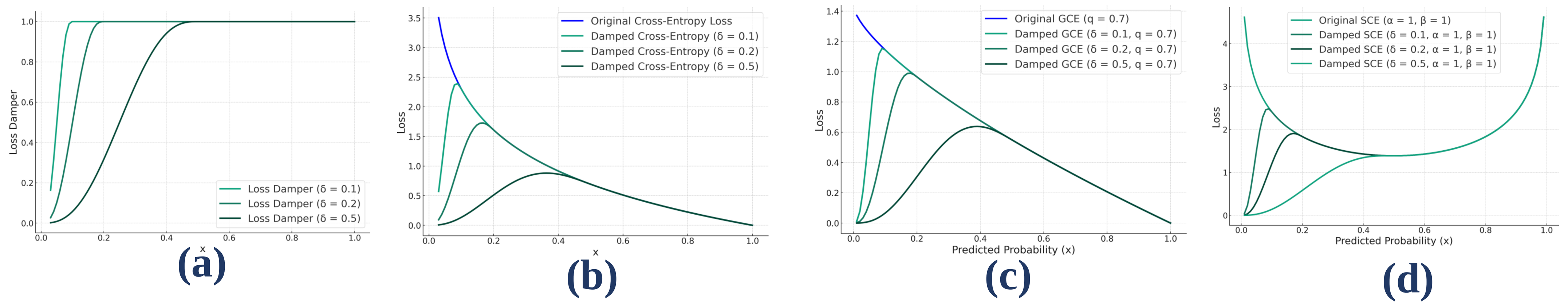


Figure 4. Effect of Loss Damping: For various δ values, (a) loss damping functions, (b) effect on **CE** loss (c) effect on **GCE,** and (d) effect on **SCE** .

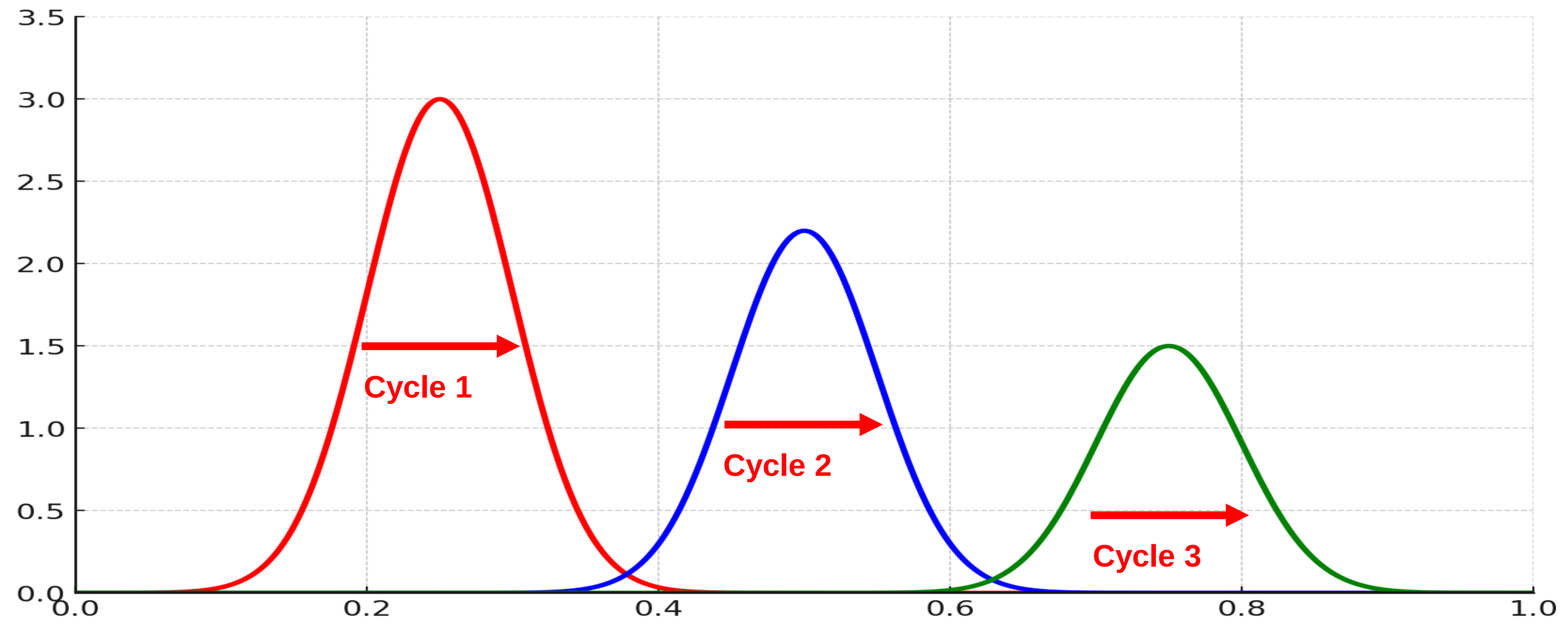


Figure 5. Repeated cycles and effects, reduces the losses from cycle 1 to cycle 3.

RESULTS

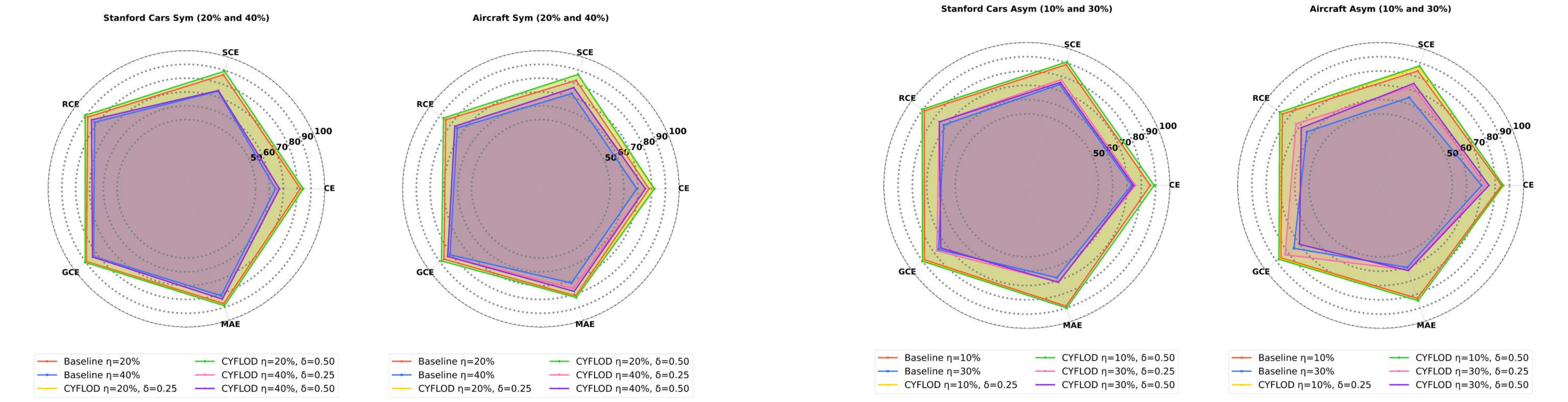


Figure 6. Baseline vs. CYFLOD with loss functions (CE, SCE, RCE, GCE, MAE), on Stanford Cars and Aircraft datasets, where **symmetric noise** $\eta = \{20\%, 40\%\}$ and $\delta = \{0.25, 0.50\}$ and **asymmetric noise** with same losses, and same δ values, but different $\eta=\{10\%, 30\%\}$.

Table 1. SOTA comparison with SNSCL Qi et al. [1] on **Cars** and **Aircraft**

Dataset	Method	Sym. (20%)	Sym. (40%)
Stanford Cars	CE+SNSCL	83.24	76.72
	GCE+SNSCL	73.78	58.11
	SCE+SNSCL	84.59	79.07
	DivideMix+SNSCL	86.29	80.09
	CYFLOD (RCE + $\delta = 0.5$)	**90.46**	**84.79**
Aircraft	CE+SNSCL	76.45	70.48
	GCE+SNSCL	72.67	60.19
	SYM+SNSCL	79.64	74.02
	DivideMix+SNSCL	82.31	76.22
	CYFLOD (GCE + $\delta = 0.25$)	**88.74**	**83.19**

Dataset	Method	Asym. (10%)	Asym. (30%)
Stanford Cars	CE+SNSCL	83.73	70.04
	GCE+SNSCL	80.33	64.64
	SYM+SNSCL	86.71	78.98
	DivideMix+SNSCL	88.18	**81.44**
	CYFLOD (RCE + $\delta = 0.25$)	**90.27**	77.81
Aircraft	CE+SNSCL	78.28	65.44
	GCE+SNSCL	73.85	64.33
	SYM+SNSCL	82.30	69.61
	DivideMix+SNSCL	84.17	74.80
	CYFLOD (GCE + $\delta = 0.25$)	**88.32**	**76.50**

Table 4. SOTA Comparison on **Food-101N** dataset. (~20% noisy)

Method	Accuracy (%)
CleanNet [17]	83.47
MWNet [43]	84.72
NRank [41]	85.20
SMP [9]	85.11
PLC [75]	85.28
WarPI [49]	85.91
CE+SNSCL [65]	85.44
DivideMix [18]	85.88
DivideMix+SNSCL [65]	86.40
CYFLOD (SCE + $\delta = 0.5$)	**88.50**

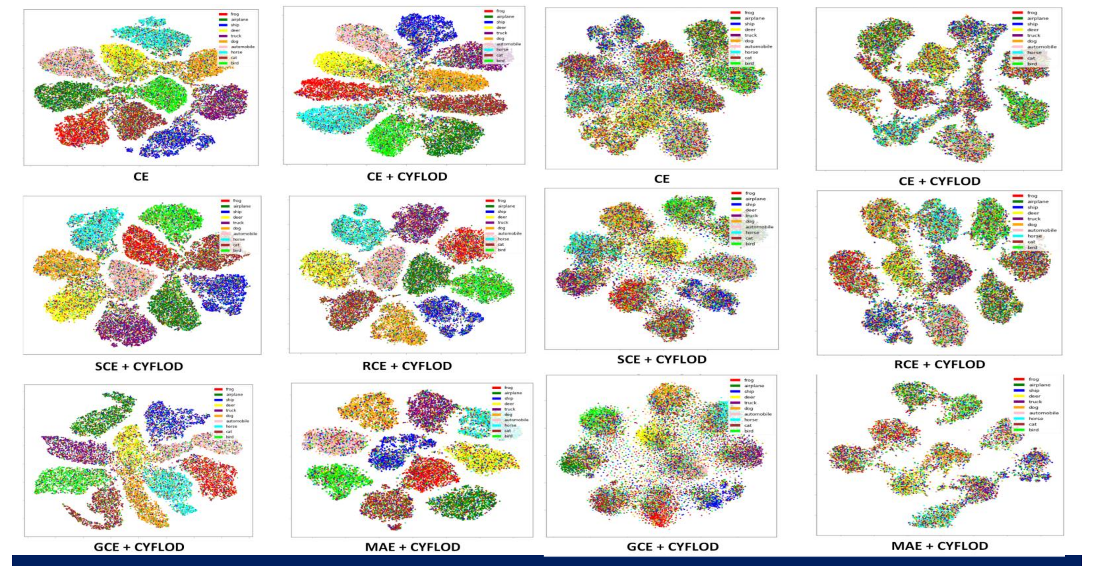
Table 2. SOTA Comparison with SNSCL Qi et al. [1] on CIFAR-10

Methods	Sym. (50%)	Sym. (80%)	Asym. (40%)
MoPro [19]	95.60	90.10	93.00
CMW-Net [44]	–	92.10	94.51
SLCLNL [1]	–	91.13	93.17
SNSCL [65]	95.20	91.70	94.90
CYFLOD (RCE + $\delta = 0.25$)	**96.71**	**92.25**	**95.23**
CYFLOD (MAE + $\delta = 0.25$)	**96.57**	**91.86**	**95.96**

Table 3. F1 score Comparison on **CIFAR-10** with recent DynaCor [2].

Noise Type	Sym. (60%)	Asym. (30%)
Avg. Encoder [81]	94.1 ± 0.14	85.4 ± 0.19
AUM [37]	75.4 ± 0.22	46.4 ± 0.30
CL [33]	88.7 ± 0.56	91.9 ± 0.12
CORES [4]	92.9 ± 0.17	26.7 ± 0.44
SIMIFEAT-V [79]	94.6 ± 0.06	84.7 ± 0.17
SIMIFEAT-R [79]	92.9 ± 1.84	84.0 ± 0.13
DynaCor[13]	93.6 ± 0.18	94.2 ± 0.45
CYFLOD (EfficientNet-B4+CE + $\delta = 0.25$)	93.66	**96.21**
CYFLOD (EfficientNet-B4+MAE + $\delta = 0.25$)	**95.71**	**96.31**
CYFLOD (EfficientNet-B4+RCE + $\delta = 0.25$)	**95.56**	**96.81**
CYFLOD (ResNet-34+RCE + $\delta = 0.25$)	94.15	93.80

Figure 7. **CIFAR-10** t-SNE visualization under symmetric noise 50% ,80%.



CONCLUSION

CYFLOD introduces a lightweight, plug-and-play strategy to combat noisy labels in fine-grained visual classification. By combining **cyclic filtering** with **loss damping**, it effectively suppresses noise during early training and gradually restores challenging samples.

References

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[2] S. Kim, D. Lee, S.K. Kang, S. Chae, S. Jang, and H. Yu. Learning discriminative dynamics with label corruption for noisy label detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 22477–22487, 2024. 1, 3, 7

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