SHUFFLE PATCHMIX AUGMENTATION WITH CONFIDENCE-MARGIN WEIGHTED PSEUDO-LABELS FOR ENHANCED SOURCE-FREE DOMAIN ADAPTATION

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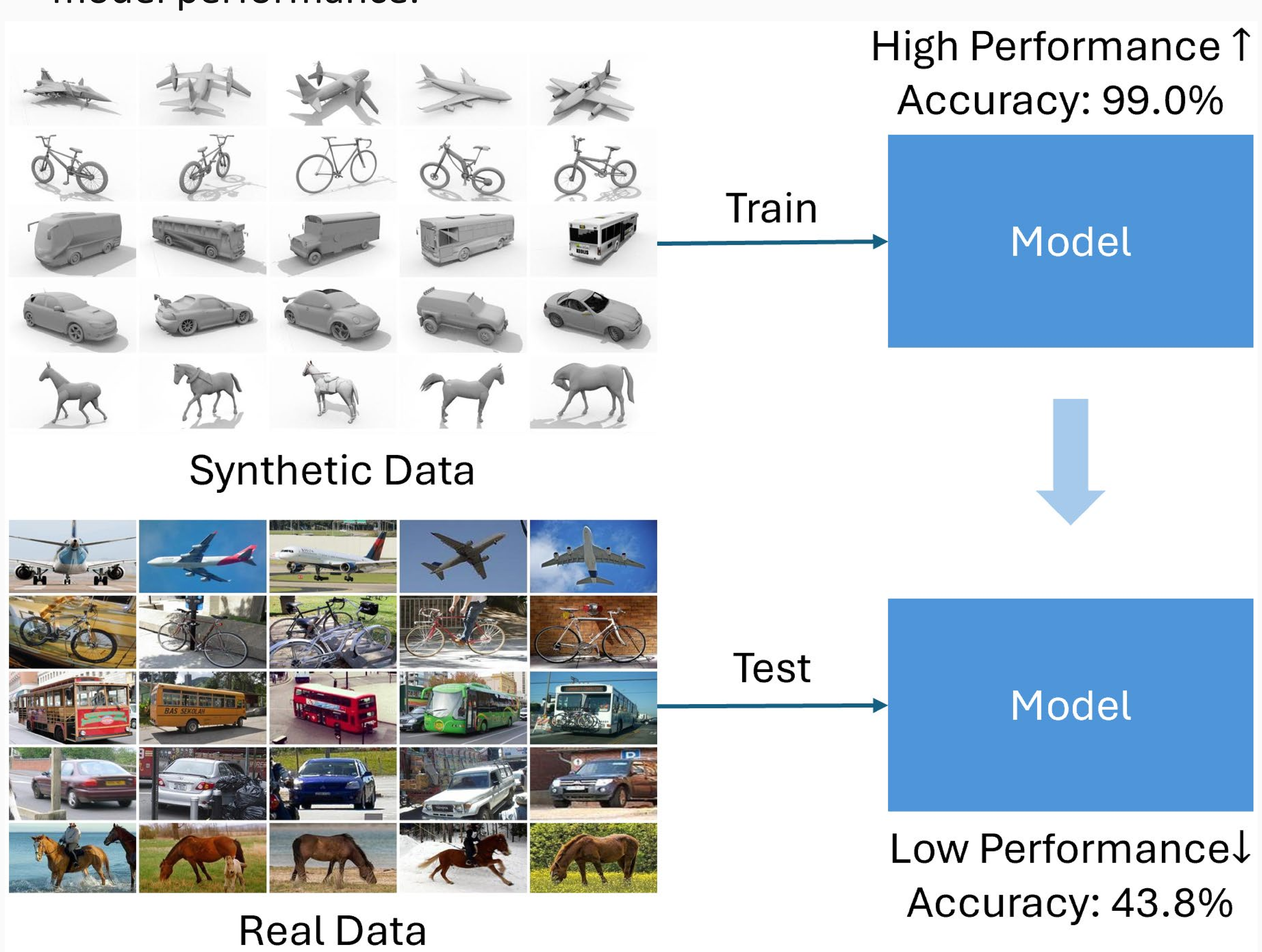
Introduction

- **Motivation:**
  Domain shift occurs when the data distribution in the training domain differs from that in the testing domain, leading to degraded model performance.



[1] Peng, Xingchao, et al. "Syn2real: A new benchmark for synthetic-to-real visual domain adaptation." arXiv:1806.09755 (2018).

- **Source-Free Domain Adaptation (SFDA):**
  We tackle SFDA, where a pre-trained source model adapts to a target domain without access to the source data.
- **Challenges:**
  Existing SFDA methods depend on the quality of pseudo-labels, and noisy pseudo-labels negatively impact adaptation performance.

Key Contributions

1. **Shuffle PatchMix (SPM)**, an intra-image patch shuffle-and-blend augmentation technique that enriches target-domain data with diverse and challenging transformations.
2. **Confidence–Margin Reweighting** strategy that prioritizes reliable pseudo-labels using both the top-1 probability and the margin between the top-1 and top-2 classes.
3. Together they deliver state-of-the-art performance on PACS, VisDA-C, and DomainNet-126, especially on smaller datasets prone to overfitting and label noise.

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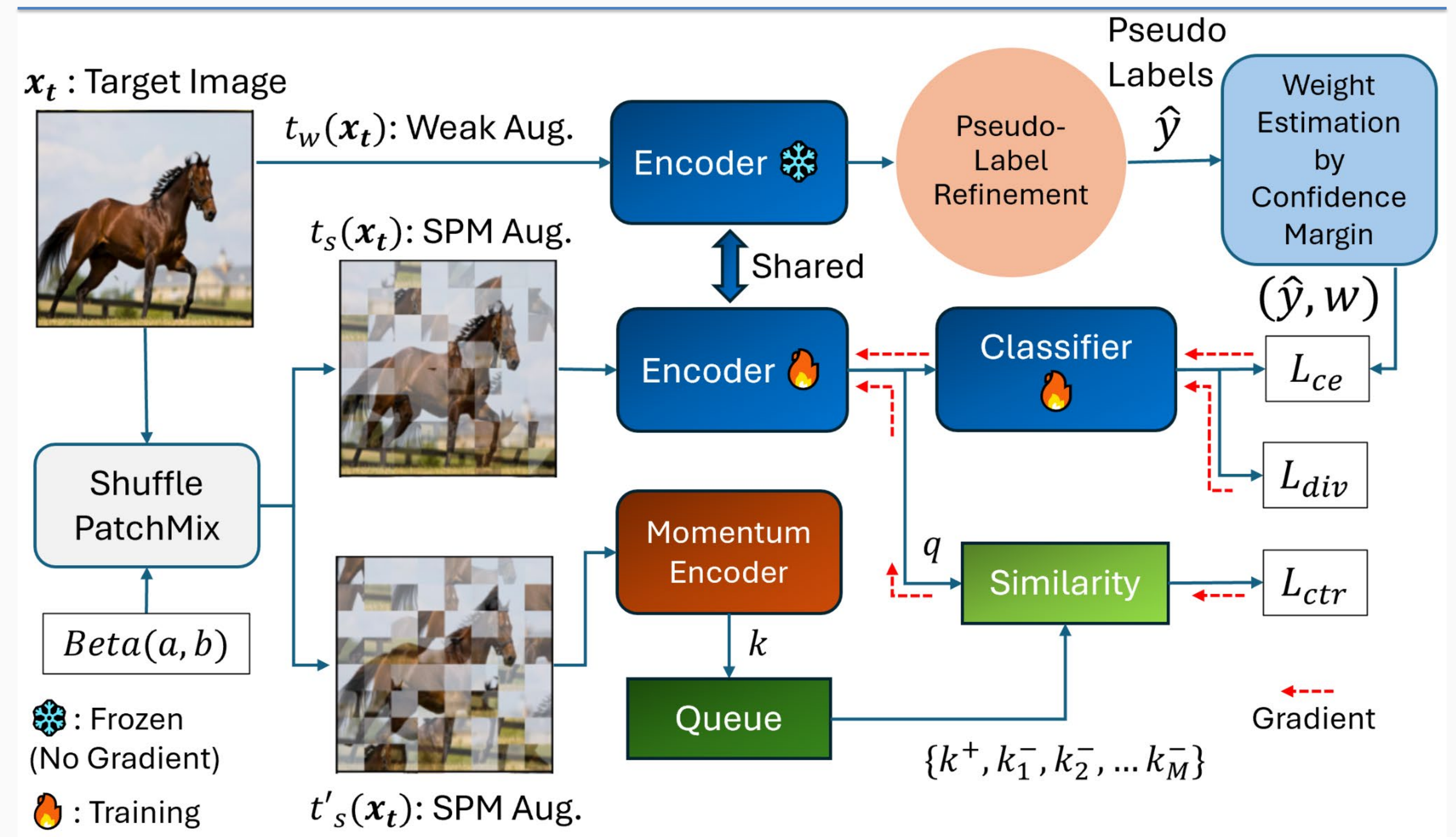
Method Overview



- Weak Augmentation → Features → Nearest-Neighbor soft voting → Refined Pseudo-Label $\hat{y}$ and Weight w;
- Strong Augmentation (SPM) → Contrastive Queue; Train with Weighted Cross-Entropy Loss, Diversity Loss, and Contrastive Loss.

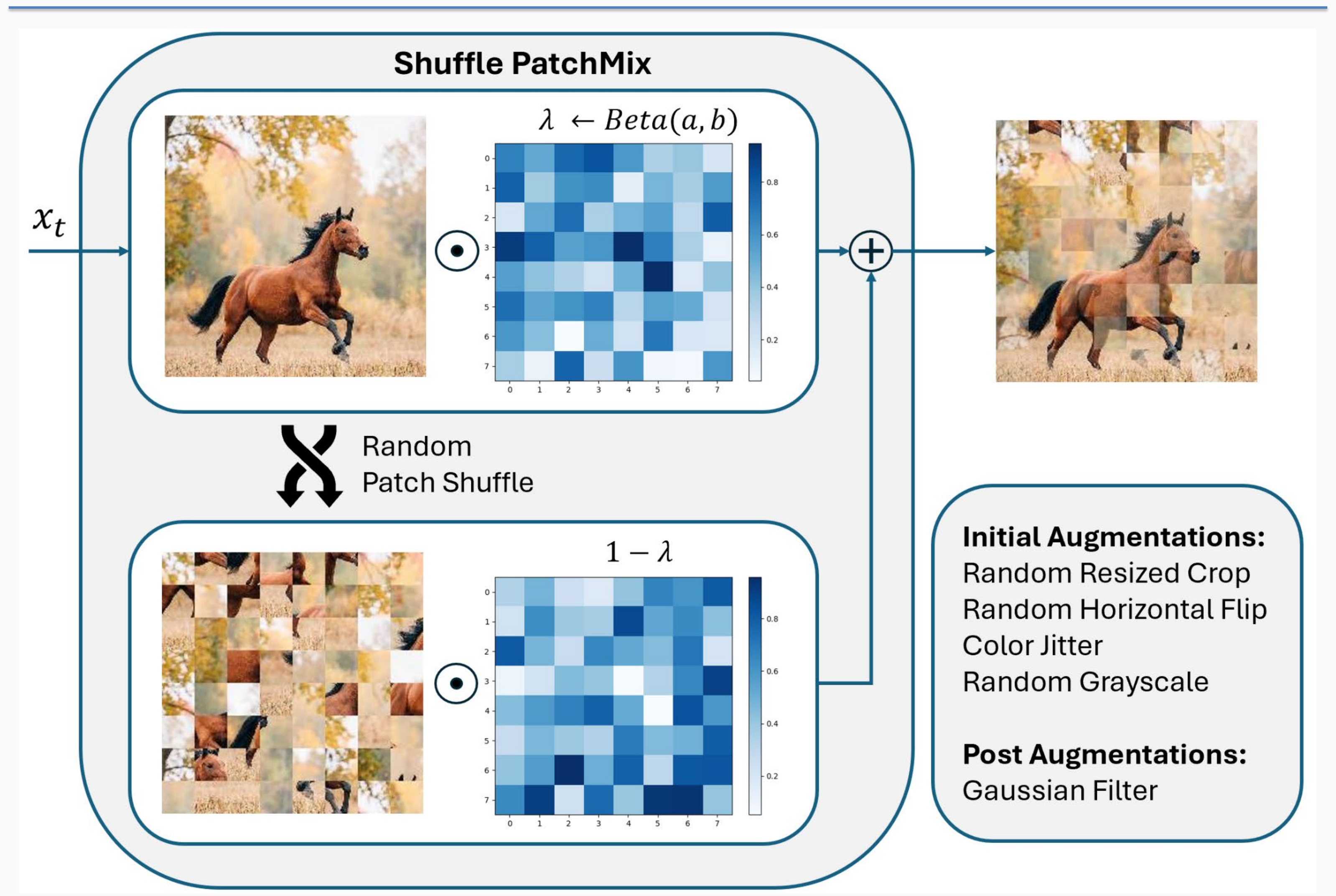
Core Equations

Pseudo-label weight: $w = p_{top1} \cdot \Delta \cdot \exp(\Delta)$,

where $\Delta = p_{top1} - p_{top2}$.

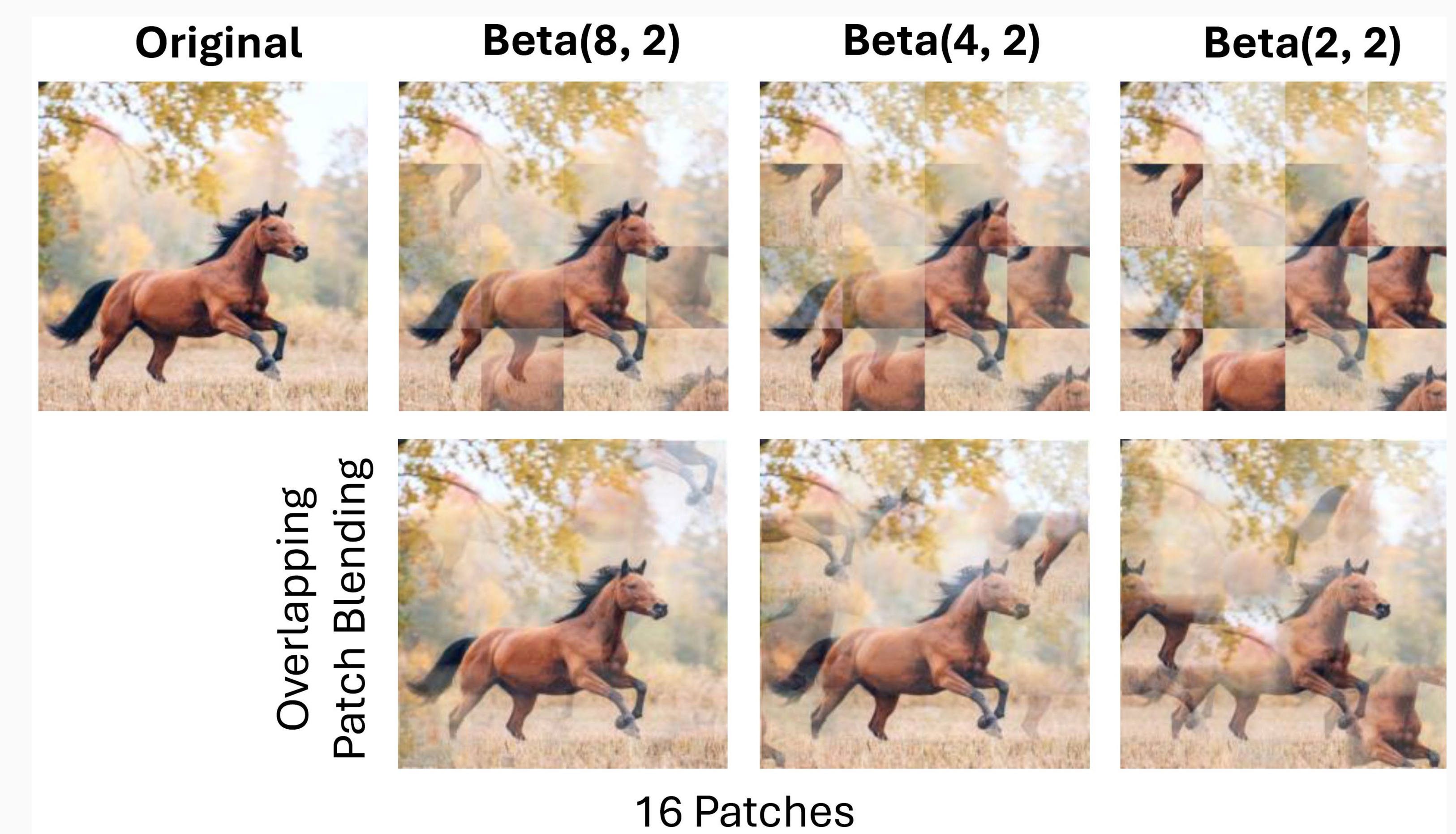
Total loss: $L = L_{ce}\,(weighted) + L_{ctr} + L_{div}$.

Shuffle PatchMix (SPM) Augmentation



Results

- PACS (ResNet-18): Single-target avg **86.7%** (**↑7.3 %** over AdaContrast baseline); Multi-target avg **82.6%** (**↑7.2 %**).
- VisDA-C (ResNet-101): **89.4%** avg (best overall; best/2nd-best in 8/12 classes).
- DomainNet-126 (ResNet-50): **71.1%** avg (**↑2.8 %** over prior SOTA).
- Ablations: each component (SPM, overlap, reweighting) contributes; all combined give the best results.



Ablations (Summary)

- Confidence–Margin Reweighting strategy alone improves over AdaContrast baseline (DomainNet **+1.3 %**, PACS **+2.4 %**).
- SPM with patch overlap reduces artifacts and adds further gains.
- Combining all: best overall (DomainNet **71.1 %** (**↑3.3%** over AdaContrast baseline), PACS **86.7 %** (**↑7.3%** over baseline)).

GitHub Code, Paper and Demo

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