

# Open-Set Test-Time Adaptation in VLMs via Noise-Immune Self-Purification

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## Abstract

Unlike test-time adaptation (TTA), open-set TTA (OSTTA) aims to robustly adapt to in-distribution (ID) domain shifts while suppressing the detrimental impact of out-of-distribution (OOD) samples encountered at test time. To this end, we propose a novel OSTTA approach named Noise-Immune Self-Purification (NISP). By exploiting the zero-shot priors of pre-trained vision-language models (VLMs), NISP advances from coarse pseudo-labeling to fine-grained, noise-resilient adaptation. Technically, we first introduce a dual-cluster Bayesian Gaussian mixture model to fit VLMs-derived scores, achieving coarse pseudo-ID/OOD separation via posterior-risk thresholding. Subsequently, NISP constructs a noise-immune fine-grained adaptation where the adapter enforces consensus-discrepancy constraints to refine coarse pseudo-labels and suppress noise propagation. We then devise the Jaccard Consistency Score for OOD discrimination. Overall the coarse-to-fine pipeline enables rigorous self-purification and robust online adaptation. Theoretically we show that consensus-discrepancy losses mitigate the deleterious effects of noise. Empirically, NISP achieves state-of-the-art results across multiple OSTTA benchmarks, validating its efficacy. The code is available at <https://github.com/njustkmg/IJCAI26-NISP>.

## 1 Introduction

Despite the remarkable generalization of deep learning models, they still suffer performance degradation when encountering distribution shifts during testing. Test-time adaptation (TTA) has been introduced to mitigate this issues [Shu *et al.*, 2022; Ma *et al.*, 2023; Jia *et al.*, 2024]. Nevertheless, TTA is vulnerable in open-world scenarios, where out-of-distribution (OOD) samples bias the optimization direction, thereby undermining the discriminability of known classes [Li *et al.*, 2023b; Yang *et al.*, 2024]. This motivates the open-set TTA (OSTTA) challenge, which aims to robustly adapt to in-distribution (ID) shifts while mitigating

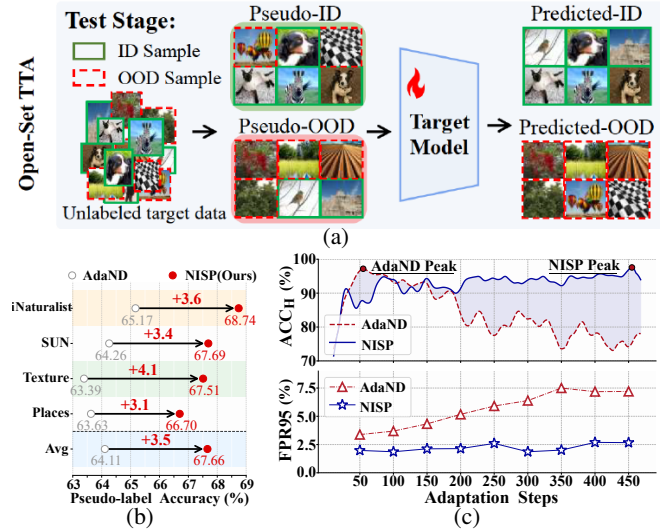


Figure 1: (a) Open-Set TTA pipeline for pseudo-labeling and adaptation. (b) Pseudo-label accuracy evaluation on ImageNet under varying data distributions. (c) Classification ( $ACC_H$ ) and OOD detection (FPR95) performance in different steps on ImageNet.

the detrimental impact of OOD samples [Gao *et al.*, 2024; Yang and Xu, 2025; Dong *et al.*, 2025; Zhao *et al.*, 2025].

To tackle the OSTTA challenge, existing methods typically adopt a filtering-then-adaptation paradigm, i.e., Figure 1(a): thresholding OOD scores to generate pseudo-labels, and then supervising the model via discriminative losses. State-of-the-art (SOTA) approaches like AdaND [Cao *et al.*, 2025] and Open-IRT [Peng *et al.*, 2025] enhance this pipeline by leveraging vision-language models’ (VLMs) zero-shot generalization [Chao *et al.*, 2025] to derive OOD scores. However, their thresholding schemes rely on idealized priors (e.g., balanced bimodality) that fail under complex real-world distributions, leading to erroneous pseudo-labeling. Figure 1(b) reveals that AdaND fails to maintain robust OOD filtering across diverse evaluation datasets. Crucially, this filtering failure triggers a cascading error accumulation. Instead of rejecting noise, the model is compelled to overfit to the mislabeled samples during updates, distorting learned decision boundaries [Wang *et al.*, 2019; Zhang *et al.*, 2023]. This results in the catastrophic collapse observed in Figure 1(c): performance de-

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grades severely after an initial transient peak as noise dominates the adaptation process, highlighting the inability to sustain robustness.

Motivated by these limitations, we propose a novel OSTTA framework named Noise-Immune Self-Purification (NISP) that implements self-purification of OOD samples to safeguard adaptation quality. First, we propose a dual-cluster Bayesian Gaussian mixture model (BGMM) with posterior-risk thresholding to extract high-fidelity pseudo-labels. As illustrated in Figure 1(b), our strategy yields superior pseudo-label accuracy and maintains exceptional robustness regardless of the dataset variations. Second, we develop a noise-resilient adaptation governed by consensus-discrepancy constraints to refine coarse pseudo-labels. The synergistic regularization effectively mitigates noise interference from pseudo-labels and prevents error accumulation. Capitalizing on this adaptation dynamic, we derive the Jacard Consistency Score (JCS) to enable precise test-time OOD discrimination. As evidenced in Figure 1(c), NISP exhibits a sustained performance trajectory: ascending and then stabilizing, validating its efficacy in noise-robust adaptation. Furthermore, theoretical analysis substantiates that the collaborative optimization of consensus and discrepancy objectives can significantly reduce the deleterious impact of pseudo-label noise, thereby enhancing the robustness of the model in open-world scenarios.

The contributions of this work are summarized as follows:

- **Technically**, we propose NISP, a coarse-to-fine self-purification framework that leverages VLMs to safeguard adaptation against open-set noise.
- **Theoretically**, we prove that our optimization objective provides an upper-bound on Bayes risk under noisy supervision, ensuring rigorous denoising adaptation.
- **Empirically**, NISP attains state-of-the-art (SOTA) performance across multiple OSTTA benchmarks, validating its efficacy in open-world settings.

## 2 Related Work

### 2.1 Open-Set Test-Time Adaptation

Test-Time Adaptation (TTA) aims to address performance degradation caused by the distribution shifts. Traditional TTA methods adapt models to target domains via self-supervised objectives, such as entropy minimization [Niu *et al.*, 2022; Wu *et al.*, 2025], or updating internal normalization statistics [Schneider *et al.*, 2020; Yuan *et al.*, 2023; Lim *et al.*, 2023]. Recent studies have exploited the zero-shot generalization of VLMs for TTA, like TPT [Shu *et al.*, 2022], DiffTPT [Feng *et al.*, 2023], and TDA [Karmanov *et al.*, 2024], which facilitate online calibration via prompt optimization or key-value caching. However, these methods overlook the presence of OOD samples in open-world deployments, which gives rise to the open-set TTA (OSTTA) challenge. While approaches such as SoTTA [Gong *et al.*, 2023], UniEnt [Gao *et al.*, 2024] and AEO [Dong *et al.*, 2025] incorporate OOD detection into TTA, they do not leverage the VLMs for adaptation. Prior work, such as AdaND [Cao *et al.*, 2025], utilizes VLMs to generate pseudo-labels, updating

only the OOD detector at test time with BCE loss. Yet, without addressing the inherent noise in pseudo-labels, the model could overfit to erroneous signals during adaptation.

### 2.2 Vision-Language Models

Pretrained vision-language models (VLMs) typically consist of image and text encoders, which are jointly trained on billions of image-text pairs to align cross-modal representations. For instance, ALIGN [Jia *et al.*, 2021] leverages a trillion-scale noisy web dataset to improve alignment precision and scalability. CLIP [Radford *et al.*, 2021] establishes a standardized contrastive pretraining framework using templated text prompts and four million image-text pairs, setting a new paradigm for zero-shot transfer tasks. BLIP [Li *et al.*, 2023a] introduces cross-modal attention into the contrastive loss and combines generative and discriminative objectives, enhancing fine-grained semantic understanding and generation. EVA-CLIP [Sun *et al.*, 2023] augments the CLIP architecture with a more powerful visual backbone and richer pretraining goals, employing LAMB [You *et al.*, 2020] optimization to reduce computational overhead while boosting downstream task performance. Empowered by large-scale pretraining data and contrastive learning, VLMs exhibit exceptional zero-shot generalization capacities.

## 3 Proposed Method

### 3.1 Preliminaries

In OSTTA, we consider an unlabeled test stream  $\mathcal{X} = \{\mathbf{x}_i\}_{i=1}^N$ , where each sample is from an underlying distribution with an unobserved ground-truth label  $y_i$ . The universal label space  $\mathcal{Y}$  comprises two disjoint subsets: the ID categories  $\mathcal{Y}_{\text{id}}$  and OOD categories  $\mathcal{Y}_{\text{ood}}$ , such that  $\mathcal{Y} = \mathcal{Y}_{\text{id}} \cup \mathcal{Y}_{\text{ood}}$  and  $\mathcal{Y}_{\text{id}} \cap \mathcal{Y}_{\text{ood}} = \emptyset$ . During the adaptation phase, the model has access solely to the unlabeled images in  $\mathcal{X}$  and the ID class name set  $\mathcal{Y}_{\text{id}} = \{y_1, y_2, \dots, y_C\}$ . Our objective is to leverage the VLM’s zero-shot generalization to assign each  $\mathbf{x}_i$  an OOD score, thereby facilitating precise ID/OOD discrimination. Standard VLMs utilize a dual-encoder architecture consisting of an image encoder  $f(\cdot)$  and a text encoder  $g(\cdot)$ . For an image  $\mathbf{x}_i$  and a set of class-specific prompts  $\{\mathbf{t}_k\}_{k=1}^C$  (e.g., “a photo of a  $y_k$ ”), we obtain the corresponding embeddings as  $\mathbf{v}_i = f(\mathbf{x}_i)$  and  $\mathbf{u}_k = g(\mathbf{t}_k)$ .

### 3.2 Unsupervised Coarse Pseudo-Labeling

With the extracted embeddings, we adopt the Maximum Concept Matching (MCM) score [Ming *et al.*, 2022] to assign the coarse OOD score to each test sample:

$$S(\mathbf{x}_i) = \max_{1 \leq k \leq C} \frac{\exp(\text{sim}(\mathbf{v}_i, \mathbf{u}_k)/\tau)}{\sum_{j=1}^C \exp(\text{sim}(\mathbf{v}_i, \mathbf{u}_j)/\tau)}, \quad (1)$$

where  $\text{sim}(\cdot, \cdot)$  denotes the cosine similarity and  $\tau$  is the temperature hyperparameter. Then, we propose an unsupervised strategy to partition the test data into coarse pseudo-ID/OOD subsets. This is achieved by modeling the MCM score distribution as a mixture of Gaussian components, identifying their semantics (ID vs. OOD) and minimizing the decision risk.

To capture the complex data structure without pre-specifying the number of components, we introduce BGMM

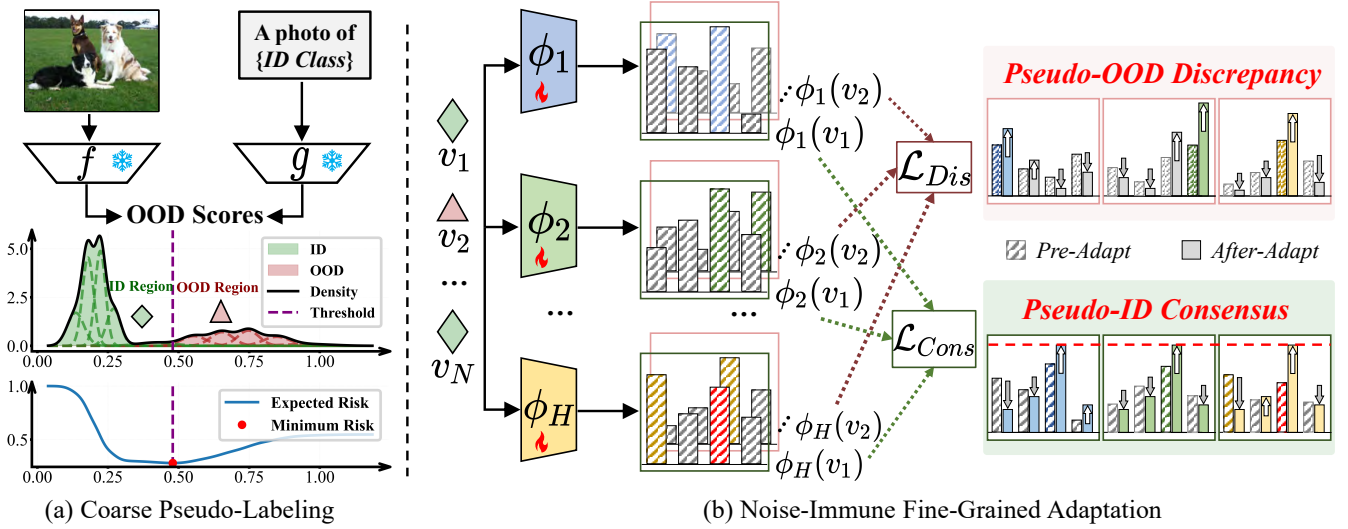


Figure 2: Illustration of the proposed NISP. (a) *Coarse Pseudo-Labeling*: OOD scores derived from VLMs are modeled by Bayesian GMM, enabling coarse pseudo-label assignment through component-level clustering and posterior-risk thresholding. (b) *Noise-Immune Fine-Grained Adaptation*: A multi-head adapter is trained using jointly designed consensus and discrepancy losses to refine the pseudo-labels and suppress label noise in a modality-aware manner.

with a Dirichlet Process prior [Blei and Jordan, 2004] fit the score distribution, defined as an infinite mixture:

$$p(S; \Theta) = \sum_{m=1}^{\infty} \pi_m \mathcal{N}(S | \mu_m, \sigma_m^2), \quad (2)$$

where  $\Theta = \{\pi_m, \mu_m, \sigma_m\}_{m=1}^{\infty}$  comprises the mixture weights  $\pi_m$ , the component means  $\mu_m$ , and variances  $\sigma_m$ . The weights  $\pi_m$  follow a stick-breaking process. To ensure computational tractability, we approximate Eq. (2) using a variational truncation bound  $M$ . Parameters  $\Theta$  are estimated via variational inference by maximizing the evidence lower bound, where negligible components with weights below  $\epsilon_w$  (empirically set to 0.001) are pruned.

Once the density is modeled, the next objective is to distinguish ID-dominant components from OOD-dominant ones. Each Gaussian component is characterized by its statistical moments, represented as a bivariate feature vector  $\mathbf{f}_m = (\mu_m, \sigma_m) \in \mathbb{R}^2$ . We apply K-means clustering [Likas *et al.*, 2003] on these vectors to categorize the component index set  $\mathcal{M} = \{1, \dots, M\}$  into mutually exclusive ID subset  $\mathcal{C}_{\text{id}}$  and OOD subset  $\mathcal{C}_{\text{ood}}$ . The clustering objective minimizes:

$$\mathcal{J}_{\text{cluster}} = \sum_{m \in \mathcal{C}_{\text{id}}} \|\mathbf{f}_m - \mathbf{c}_{\text{id}}\|^2 + \sum_{m \in \mathcal{C}_{\text{ood}}} \|\mathbf{f}_m - \mathbf{c}_{\text{ood}}\|^2, \quad (3)$$

where  $\mathbf{c}_{\text{id}}, \mathbf{c}_{\text{ood}} \in \mathbb{R}^2$  denote the cluster centroids.

With the components identified, we determine the optimal decision boundary by leveraging the component-wise posterior probabilities. The posterior responsibility  $\gamma_m(S)$  of component  $m$  for a score  $S$  is calculated via Bayesian inversion:

$$\gamma_m(S) = \frac{\pi_m \mathcal{N}(S | \mu_m, \sigma_m^2)}{\sum_{j=1}^M \pi_j \mathcal{N}(S | \mu_j, \sigma_j^2)}. \quad (4)$$

Subsequently, given the score sequence  $\{S_{(i)}\}_{i=1}^N$  sorted in ascending order, we seek a cut-off index  $d$  that minimizes the cumulative misclassification risk  $\mathcal{R}(d)$ , balancing the error of rejecting ID samples against accepting OOD samples:

$$\mathcal{R}(d) = \sum_{i=1}^d \sum_{m \in \mathcal{C}_{\text{id}}} \gamma_m(S_{(i)}) + \sum_{i=d+1}^N \sum_{n \in \mathcal{C}_{\text{ood}}} \gamma_n(S_{(i)}). \quad (5)$$

The optimal index  $d^* = \arg \min_d \mathcal{R}(d)$  is efficiently computed via prefix sums [Martinez and Raschia, 2024]. Finally, the decision threshold is set to the midpoint  $\xi = \frac{1}{2}(S_{(d^*)} + S_{(d^*+1)})$ , yielding binary pseudo-labels:

$$\hat{y}_i = \begin{cases} 0 & S_i \leq \xi, \\ 1 & S_i > \xi, \end{cases} \quad (6)$$

where  $\hat{y}_i = 0$  and  $\hat{y}_i = 1$  denote pseudo-ID and pseudo-OOD labels, respectively.

### 3.3 Noise-Immune Fine-Grained Adaptation

At each adaptation step, let  $\mathbf{V} = \{\mathbf{v}_i\}_{i=1}^B$  denote the image embeddings set of current batch with pseudo-labels  $\{\hat{y}_i\}_{i=1}^B$ . A binary mask partitions indices into ID set  $\mathcal{I} = \{i : \hat{y}_i = 0\}$  and OOD set  $\mathcal{O} = \{i : \hat{y}_i = 1\}$ . Subsequently, we introduce a lightweight adapter to perform noise-resilient adaptation, thereby refining the coarse pseudo-labels. The adapter consists of  $H$  parallel prediction heads  $\{\phi_h\}_{h=1}^H$ , where each  $\phi_h$  is an independent two-layer MLP with non-linear activation.

The adapter is optimized via a dual-path objective that separately handles pseudo-ID and pseudo-OOD samples. To promote predictive consistency among classifier heads on pseudo-ID samples, we minimize the pairwise mean squared error [Xue *et al.*, 2013] across all unique head pairs:

$$\mathcal{L}_{\text{Cons}} = \frac{1}{|\mathcal{I}| \binom{H}{2}} \sum_{i \in \mathcal{I}} \sum_{\substack{h, h' \in \mathcal{H} \\ h < h'}} \|\phi_h(\mathbf{v}_i) - \phi_{h'}(\mathbf{v}_i)\|_2^2, \quad (7)$$

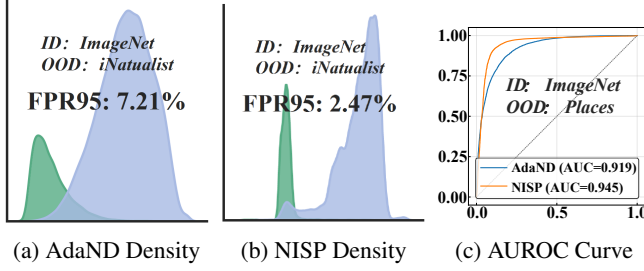


Figure 3: OOD Detection Performance.

where  $\mathcal{H} = \{1, \dots, H\}$  denotes the set of head indices,  $|\mathcal{I}|$  is the number of pseudo-ID samples, and  $\binom{H}{2}$  enumerates all unordered head pairs. This objective reduces prediction variance across heads on pseudo-ID samples, yielding more consistent and robust outputs.

In contrast, pseudo-OOD samples are expected to exhibit prediction disagreement. To achieve this, a hinge-activated margin is applied to maximize their pairwise divergence:

$$\mathcal{L}_{\text{Dis}} = \frac{1}{|\mathcal{O}| \binom{H}{2}} \sum_{j \in \mathcal{O}} \sum_{\substack{h, h' \in \mathcal{H} \\ h < h'}} \left[ \delta - \|\phi_h(\mathbf{v}_j) - \phi_{h'}(\mathbf{v}_j)\|_2^2 \right]_+, \quad (8)$$

where  $[\cdot]_+ = \max(0, \cdot)$  is the hinge operator and  $\delta > 0$  denotes a predefined divergence margin (set to 0.1 in all experiments). Gradient flow is selectively activated only when head disagreement falls below the margin, allowing the model to preserve uncertainty on OOD samples. The overall adaptation objective is defined to minimize a weighted sum:

$$\mathcal{L} = \mathcal{L}_{\text{Cons}} + \lambda \cdot \mathcal{L}_{\text{Dis}}, \quad (9)$$

where the coefficient  $\lambda$  balances the two terms. As shown in Lemma 1, the discrepancy and consensus losses jointly suppress unreliable gradients and reduce gradient variance, resulting in a tighter bound in Theorem 1.

### 3.4 Inference Phase

Inspired by this adaptation process, we adopt a novel OOD scoring metric, termed the *Jaccard Consistency Score* (JCS), to enhance the separation between ID and OOD samples. Let  $\mathcal{A}$  denote a set of percentile thresholds (typically set to  $\{5, 10, \dots, 55\}$ ). For any granularity  $\alpha \in \mathcal{A}$ , the corresponding subset size is defined as  $K = \lceil \alpha \cdot C \rceil$ . Given an image embedding  $\mathbf{v}_i$ , the set of top- $K$  classes predicted by head  $h$  is defined as:

$$Y_h(\mathbf{v}_i; \alpha) = \left\{ c_k \mid c_k \in \text{argsort}^{(K)}(\phi_h(\mathbf{v}_i)) \right\}, \quad (10)$$

where  $\text{argsort}^{(K)}(\cdot)$  returns the indices of the top- $K$  highest confidence classes, and  $|Y_h(\mathbf{v}_i)| = K$ .

We compute the aggregates pairwise Jaccard similarity at this granularity  $\alpha$  across all head pairs  $(p, q)$ :

$$\bar{J}(\mathbf{v}_i; \alpha) = \frac{1}{\binom{H}{2}} \sum_{1 \leq p < q \leq H} \frac{|Y_p(\mathbf{v}_i; \alpha) \cap Y_q(\mathbf{v}_i; \alpha)|}{|Y_p(\mathbf{v}_i; \alpha) \cup Y_q(\mathbf{v}_i; \alpha)|}. \quad (11)$$

The final JCS score is obtained by identifying the maximum consensus achieved across the spectrum of granularities:

$$\text{JCS}(\mathbf{v}_i) = \max_{\alpha \in \mathcal{A}} \bar{J}(\mathbf{v}_i; \alpha). \quad (12)$$

This metric provides a compact measure of cross-head prediction consistency. Higher JCS values indicate strong agreement among heads, which is characteristic of ID samples, while lower values reflect prediction dispersion typical of OOD samples. Empirical effectiveness of this metric is demonstrated in Figure 3.

### 3.5 Theoretical Understanding

We theoretically justify the effectiveness of our method in suppressing overfitting to noisy pseudo-labels under test-time adaptation. Under the standard assumptions of  $L$ -smoothness [Seccia *et al.*, 2025] and the  $\mu$ -PL condition [Plassier *et al.*, 2025], we analyze the convergence behavior in the presence of pseudo-label noise.

**Theorem 1** (Excess Risk Bound). *Let  $\theta_T$  be the model after  $T$  steps of adaptation with learning rate  $\eta \leq 1/L$ , and let  $\bar{\sigma}_{\text{eff}}^2$  denote the average gradient variance over noisy samples. Then the expected excess risk satisfies:*

$$\mathbb{E}[\mathcal{L}(\theta_T) - \mathcal{L}(\theta^*)] \leq (1 - \eta\mu)^T \cdot (\mathcal{L}(\theta_0) - \mathcal{L}(\theta^*)) + \frac{L\eta}{2\mu} \cdot \rho \cdot \bar{\sigma}_{\text{eff}}^2. \quad (13)$$

The key to controlling generalization error lies in reducing  $\bar{\sigma}_{\text{eff}}^2$ . Our method achieves this through multi-head regularization, which adaptively modulates the gradient contribution of noisy samples.

**Lemma 1** (Variance-Controlled Gradient Suppression). *For any noisy sample  $x_i$ , the per-sample gradient satisfies:*

$$\|\nabla_{\theta} \mathcal{L}_{\text{total}}(x_i)\|^2 \leq C \cdot \text{Var}_h[\phi_h(x_i)], \quad (14)$$

where  $C > 0$  is a constant and  $\text{Var}_h[\cdot]$  denotes inter-head variance. Consequently,

$$\bar{\sigma}_{\text{eff}}^2(\text{ours}) \ll \bar{\sigma}_{\text{eff}}^2(\text{vanilla}) = \mathcal{O}(1). \quad (15)$$

This behavior arises because the discrepancy loss is inactive for incorrectly assigned pseudo-OOD samples, yielding zero gradients [Li *et al.*, 2025], whereas the consensus loss is activated only when predictions exhibit sufficient disagreement. By contrast, conventional pseudo-labeling applies uniform updates to all samples irrespective of pseudo-label reliability, resulting in elevated gradient variance.

## 4 Experiments

### 4.1 Experimental Setup

**Benchmark Datasets.** Following prior work [Cao *et al.*, 2025], we utilize CIFAR-10/100 [Krizhevsky *et al.*, 2009], CUB-200-2011 [Wah *et al.*, 2011], Food-101 [Bossard *et al.*, 2014], Stanford-Cars [Krause *et al.*, 2013], ImageNet [Deng *et al.*, 2009] and its variants (ImageNet-V2 [Recht *et al.*, 2019], ImageNet-R [Hendrycks *et al.*, 2021], ImageNet-Sketch [Wang *et al.*, 2019]) as ID datasets. The OOD datasets include SVHN [Netzer *et al.*, 2011], LSUN [Yu *et al.*, 2015], iNaturalist [Van Horn *et al.*, 2018], SUN [Xiao *et al.*, 2010], Places [Zhou *et al.*, 2017], Texture [Cimpoi *et al.*, 2014].

| ID           | Method      | Avg          |              |              | iNaturalist  |              |              | SUN          |              |              | Texture      |              |              | Places       |              |              |
|--------------|-------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
|              |             | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      |
| ImageNet     | ZS-CLIP     | 83.07        | 57.97        | 63.11        | 86.71        | 50.39        | 64.58        | 84.05        | 57.43        | 63.58        | 79.50        | 64.20        | 61.53        | 82.00        | 59.84        | 62.76        |
|              | Tent        | 80.17        | 63.85        | 63.49        | 80.47        | 64.57        | 63.35        | 82.18        | 60.10        | 64.55        | 77.60        | 67.61        | 62.52        | 80.43        | 63.11        | 63.55        |
|              | SoTTA       | 79.06        | 65.73        | 62.24        | 77.67        | 67.19        | 61.39        | 80.46        | 63.48        | 62.82        | 78.45        | 67.30        | 62.17        | 79.64        | 64.93        | 62.57        |
|              | TPT         | 82.77        | 57.83        | 62.25        | 86.09        | 49.91        | 63.69        | 83.91        | 57.30        | 62.75        | 79.15        | 64.38        | 60.56        | 81.92        | 59.73        | 61.99        |
|              | TDA         | 83.02        | 57.89        | 63.20        | 86.72        | 50.35        | 64.68        | 84.06        | 57.39        | 63.67        | 79.30        | 63.90        | 61.60        | 82.00        | 59.91        | 62.84        |
|              | AdaND       | 94.09        | <u>24.42</u> | 70.31        | <b>98.51</b> | 7.21         | 75.91        | 94.47        | 26.79        | 70.13        | 91.44        | 31.49        | 67.06        | 91.94        | 32.20        | 68.13        |
|              | <b>NISP</b> | <b>95.58</b> | <b>12.52</b> | <b>73.71</b> | <b>98.11</b> | <b>2.47</b>  | <b>76.41</b> | <b>95.37</b> | <b>14.04</b> | <b>73.22</b> | <b>94.38</b> | <b>16.19</b> | <b>72.76</b> | <b>94.48</b> | <b>17.40</b> | <b>72.46</b> |
| ImageNet-R   | ZS-CLIP     | 85.98        | 58.89        | 71.18        | 91.05        | 49.66        | 73.95        | 87.94        | 56.55        | 72.27        | 79.62        | 69.95        | 67.65        | 85.30        | 59.39        | 70.83        |
|              | Tent        | 86.30        | 58.74        | 73.23        | 90.64        | 50.79        | 76.18        | 88.20        | 56.11        | 74.40        | 80.60        | 69.38        | 69.56        | 85.76        | 58.69        | 72.78        |
|              | SoTTA       | 86.67        | 56.61        | 73.73        | 90.91        | 50.14        | 76.59        | 88.54        | 53.50        | 74.82        | 81.21        | 65.92        | 70.17        | 86.02        | 56.88        | 73.34        |
|              | TPT         | 85.33        | 58.87        | 70.71        | 90.64        | 49.65        | 73.31        | 87.43        | 56.55        | 71.89        | 78.65        | 69.88        | 67.26        | 84.59        | 59.38        | 70.37        |
|              | TDA         | 85.98        | 58.80        | 71.20        | 91.05        | 49.50        | 74.02        | 87.94        | 56.43        | 72.29        | 79.62        | 69.89        | 67.65        | 85.30        | 59.37        | 70.82        |
|              | AdaND       | 96.33        | 16.02        | 78.95        | <b>99.58</b> | 1.42         | 82.23        | 97.93        | 10.44        | 80.49        | <b>91.81</b> | 34.06        | <b>74.40</b> | 96.00        | 18.17        | 78.67        |
|              | <b>NISP</b> | <b>96.39</b> | <b>9.59</b>  | <b>79.68</b> | <b>98.90</b> | <b>0.43</b>  | <b>83.24</b> | <b>97.94</b> | <b>5.09</b>  | <b>81.08</b> | <b>91.74</b> | <b>25.59</b> | <b>74.09</b> | <b>97.00</b> | <b>7.25</b>  | <b>80.31</b> |
| ImageNet-K   | ZS-CLIP     | 70.60        | 82.17        | 45.39        | 75.22        | 78.30        | 46.39        | 71.66        | 82.79        | 45.73        | 66.29        | 85.04        | 44.34        | 69.21        | 82.54        | 45.11        |
|              | Tent        | 70.30        | 80.73        | 47.96        | 70.85        | 80.83        | 48.24        | 72.90        | 79.21        | 48.54        | 66.97        | 83.07        | 46.92        | 70.47        | 79.79        | 48.15        |
|              | SoTTA       | 68.79        | 80.72        | 47.67        | 66.63        | 81.27        | 47.08        | 71.22        | 79.58        | 48.41        | 67.60        | 82.25        | 47.20        | 69.69        | 79.77        | 47.99        |
|              | TPT         | 70.35        | 81.94        | 43.84        | 74.80        | 78.19        | 44.81        | 71.54        | 82.32        | 44.15        | 65.85        | 85.00        | 42.77        | 69.20        | 82.23        | 43.64        |
|              | TDA         | 70.60        | 82.14        | 45.62        | 75.22        | 78.24        | 46.66        | 71.66        | 82.74        | 45.93        | 66.30        | 84.96        | 44.59        | 69.21        | 82.60        | 45.30        |
|              | AdaND       | 86.39        | 53.99        | 52.10        | 95.39        | <u>27.51</u> | 55.71        | 88.78        | 52.09        | 52.91        | 77.14        | 70.98        | 48.49        | 84.23        | 65.36        | 51.27        |
|              | <b>NISP</b> | <b>93.12</b> | <b>23.09</b> | <b>57.60</b> | <b>97.11</b> | <b>5.96</b>  | <b>60.45</b> | <b>95.58</b> | <b>11.37</b> | <b>59.01</b> | <b>84.92</b> | <b>60.35</b> | <b>52.55</b> | <b>94.88</b> | <b>14.67</b> | <b>58.39</b> |
| CUB-200-2011 | ZS-CLIP     | 78.61        | 62.92        | 52.28        | 80.82        | 59.52        | 53.12        | 80.37        | 61.15        | 53.05        | 73.38        | 68.33        | 50.12        | 79.88        | 62.69        | 52.81        |
|              | Tent        | 60.42        | 79.18        | 48.27        | 51.21        | 81.52        | 44.19        | 61.91        | 76.58        | 49.01        | 56.70        | 85.04        | 46.56        | 71.87        | 73.58        | 53.31        |
|              | SoTTA       | 79.96        | 62.02        | 55.75        | 80.23        | 61.82        | 56.15        | 82.21        | 59.26        | 56.76        | 75.72        | 66.88        | 53.57        | 81.69        | 60.11        | 56.51        |
|              | TPT         | 78.56        | 62.92        | 51.74        | 80.58        | 59.53        | 52.45        | 80.21        | 61.21        | 52.58        | 73.56        | 68.32        | 49.58        | 79.89        | 62.60        | 52.35        |
|              | TDA         | 78.61        | 62.92        | 52.45        | 80.82        | 59.54        | 53.32        | 80.37        | 61.24        | 53.22        | 73.38        | 68.33        | 50.27        | 79.88        | 62.57        | 52.97        |
|              | AdaND       | 94.93        | <u>20.62</u> | 63.90        | 96.64        | 14.63        | 65.30        | 96.70        | 14.75        | 65.27        | 90.36        | 36.77        | 60.40        | 96.01        | 16.32        | 64.63        |
|              | <b>NISP</b> | <b>96.87</b> | <b>7.93</b>  | <b>66.36</b> | <b>96.99</b> | <b>6.78</b>  | <b>66.09</b> | <b>97.69</b> | <b>4.35</b>  | <b>67.08</b> | <b>95.57</b> | <b>16.12</b> | <b>65.54</b> | <b>97.24</b> | <b>4.50</b>  | <b>66.71</b> |

Table 1: OSTTA results for the four benchmarks (ImageNet, ImageNet-R, ImageNet-K and CUB-200-2011) across four OOD datasets. **Bold** indicates best per column. Underline indicates second best.

| Method      | ImageNet-V2  |              |              | CIFAR-100    |              |              | Food-101     |             |              | CIFAR-10     |             |              | Stanford-Cars |             |              |
|-------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------|--------------|--------------|-------------|--------------|---------------|-------------|--------------|
|             | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95       | $ACC_H$      | AUC          | FPR95       | $ACC_H$      | AUC           | FPR95       | $ACC_H$      |
| ZS-CLIP     | 79.69        | 67.07        | 59.96        | 72.26        | 90.52        | 59.58        | 97.55        | 11.88       | 86.71        | 94.17        | 27.35       | 86.21        | 97.10         | 13.30       | 66.49        |
| Tent        | 74.14        | 72.70        | 57.57        | 66.29        | 80.61        | 57.27        | 90.27        | 24.23       | 81.18        | 91.86        | 30.00       | 82.47        | 95.85         | 16.10       | 66.95        |
| SoTTA       | 77.35        | 71.57        | 59.05        | 79.34        | 73.77        | 66.50        | 97.35        | 13.18       | 86.92        | 96.16        | 17.83       | 88.27        | 96.73         | 14.32       | 67.62        |
| TPT         | 79.22        | 66.93        | 59.24        | 70.77        | 90.52        | 57.81        | 97.27        | 12.01       | 86.28        | 93.39        | 27.60       | 85.46        | 97.00         | 13.28       | 65.47        |
| TDA         | 80.35        | 66.35        | 60.16        | 72.26        | 90.48        | 59.51        | 97.55        | 11.90       | 86.71        | 94.18        | 27.36       | 86.20        | 97.10         | 13.30       | 66.82        |
| AdaND       | <b>93.85</b> | 23.34        | 67.72        | 89.48        | 33.91        | 69.20        | <b>99.81</b> | 0.52        | <b>92.10</b> | <b>99.40</b> | 1.91        | 92.56        | <b>99.86</b>  | 0.32        | <b>77.27</b> |
| <b>NISP</b> | <u>93.72</u> | <b>22.03</b> | <b>67.80</b> | <b>91.08</b> | <b>33.38</b> | <b>71.99</b> | <u>99.54</u> | <b>0.37</b> | <u>91.35</u> | <u>98.19</u> | <b>1.58</b> | <b>92.69</b> | <u>99.44</u>  | <b>0.19</b> | <u>77.14</u> |

Table 2: OSTTA results for per-benchmark average performance over all OOD datasets in ImageNet-V2, CIFAR-100, Food-101, CIFAR-10 and Stanford-Cars. **Bold** indicates best per column. Underline indicates second best.

**Evaluation Metric.** We adopt the harmonic mean accuracy ( $ACC_H$ ) as the metric for OSTTA evaluation in VLMs, which is computed over the classification accuracies of ID and OOD samples. For OOD detection performance, we employ FPR95 and AUC for evaluation [Cao *et al.*, 2025; Ming *et al.*, 2022]. FPR95 refers to the false positive rate of OOD samples when the true positive rate of ID samples is fixed at 95%, and AUC is a widely used metric that quantifies the overall separability between ID and OOD samples, based on the receiver operating characteristic (ROC) curve.

**Compared Methods and Setups.** We evaluate ZS-CLIP [Radford *et al.*, 2021], Tent [Wang *et al.*, 2021], SoTTA [Gong *et al.*, 2023], TDA [Karmanov *et al.*, 2024], TPT [Shu *et al.*, 2022] and AdaND [Cao *et al.*, 2025] in the benchmarks. In our main experiments, we utilize CLIP [Radford *et al.*, 2021] with a ViT-B/16 [Dosovitskiy, 2020] backbone. Moreover, we report our method’s performance across

multiple pretrained VLM backbones in Section 4.3. The batch size is fixed at 128, ensuring each sample is processed exactly once (one-pass adaptation). For the initial 10 steps, we retain predictions from the frozen VLM and derive OOD scores via the MCM detector [Ming *et al.*, 2022]. The model is updated using the Adam [Kingma, 2014] optimizer with a learning rate of 0.005 and no weight decay. While the loss weight  $\lambda$  is tuned via grid search, other hyperparameters remain consistent for datasets with over 50 classes: the truncation bound  $M = 6$ , adapter heads  $H = 5$ , and a hidden dimension of 128.

## 4.2 Main Results

Tables 1 and 2 present a comparative analysis of OSTTA performance across diverse benchmarks, yielding four pivotal insights: (1) Both standard (e.g., Tent) and VLM-specific TTA methods (e.g., TPT, TDA) struggle to consistently surpass the frozen baseline (ZS-CLIP). Notably, under severe distribution

| Thresholding | Noise-Resilient | Avg          |              |              | iNaturalist  |             |              | SUN          |              |              | Texture      |              |              | Places       |              |              |
|--------------|-----------------|--------------|--------------|--------------|--------------|-------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
|              |                 | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95       | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      |
| ✓            | ✗               | 94.06        | 24.55        | 70.28        | <b>98.48</b> | 7.28        | 75.87        | 94.44        | 27.07        | 70.12        | 91.43        | 31.52        | 67.05        | 91.90        | 32.34        | 68.07        |
| ✗            | ✓               | 93.97        | 17.21        | 72.87        | 97.07        | 7.03        | 75.34        | 93.48        | 23.41        | 72.84        | 92.34        | 20.53        | 71.39        | 92.97        | 17.88        | 71.92        |
| ✓            | ✓               | <b>95.58</b> | <b>12.52</b> | <b>73.71</b> | <b>98.11</b> | <b>2.47</b> | <b>76.41</b> | <b>95.37</b> | <b>14.04</b> | <b>73.22</b> | <b>94.38</b> | <b>16.19</b> | <b>72.76</b> | <b>94.48</b> | <b>17.40</b> | <b>72.46</b> |

Table 3: Ablation of OOD thresholding and noise-resilient adaptation. Results for the ImageNet benchmark show that each component improves performance, with their combination achieving the best overall performance.

| Method              | Avg          |              |              | iNaturalist  |              |              | SUN          |              |              | Texture      |              |              | Places       |              |              |
|---------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
|                     | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      | AUC          | FPR95        | $ACC_H$      |
| BLIP                | 83.55        | 55.42        | 56.96        | 83.44        | 75.36        | 57.26        | 80.76        | 54.45        | 56.27        | 81.90        | 53.83        | 54.96        | 88.10        | 38.04        | 59.35        |
| BLIP+NISP           | 89.48        | 33.66        | 66.51        | 93.41        | <b>17.66</b> | 70.55        | 84.90        | 41.55        | 62.87        | 88.52        | <b>32.71</b> | 65.42        | 91.11        | 42.70        | 67.20        |
| ALIGN               | 73.36        | 75.75        | 58.18        | 77.39        | 73.36        | 60.95        | 73.97        | 76.88        | 58.58        | 70.83        | 73.69        | 56.89        | 71.26        | 79.05        | 56.30        |
| ALIGN+NISP          | 80.86        | 65.08        | 61.10        | 84.29        | 78.40        | 62.30        | 82.93        | 48.66        | 63.52        | 80.27        | 57.73        | 60.88        | 75.93        | 75.55        | 57.69        |
| EVACLIP             | 88.32        | 45.99        | 75.94        | 92.96        | 34.48        | 79.30        | 89.26        | 45.24        | 76.48        | 84.27        | 52.06        | 73.00        | 86.80        | 52.18        | 74.96        |
| <b>EVACLIP+NISP</b> | <b>93.50</b> | <b>31.80</b> | <b>84.18</b> | <b>95.67</b> | <b>22.13</b> | <b>86.02</b> | <b>93.98</b> | <b>30.14</b> | <b>83.94</b> | <b>90.62</b> | <b>40.11</b> | <b>82.42</b> | <b>93.72</b> | <b>34.81</b> | <b>84.33</b> |

Table 4: OSTTA results in different VLMs for ImageNet benchmark.

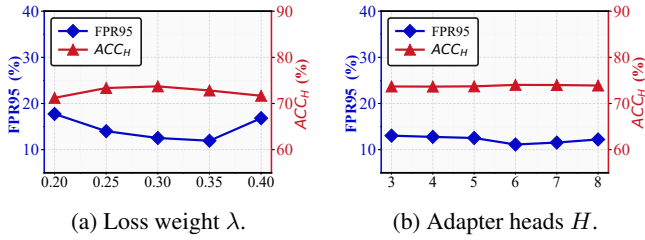


Figure 4: Sensitivity analysis of key hyperparameters on ImageNet.

shifts, these approaches often succumb to negative adaptation, yielding lower performance than the non-adapted model. Even specialized OSTTA methods like SoTTA demonstrate only marginal or inconsistent gains across benchmarks. (2) AdaND substantially improves VLMs’ performance through decoupling ID classification and OOD detection, establishing a strong baseline in the OSTTA setting. (3) NISP achieves the highest  $ACC_H$  and lowest FPR95 across the majority of benchmarks. Specifically on ImageNet, NISP delivers a remarkable  $ACC_H$  improvement of 3.40% and a FPR95 reduction of 11.90% relative to AdaND. (4) NISP’s advantage is most pronounced in challenging, low-accuracy regimes (e.g., ImageNet-K and CUB-200-2011). Conversely, on saturated benchmarks (e.g., Food-101) where AdaND already performs well, NISP maintains competitive parity. This dichotomy underscores NISP’s critical strength in mitigating noise accumulation, a claim further substantiated in Section 4.4.

### 4.3 Ablation Study

**Effectiveness of Each Module.** Table 3 presents an ablation study on ImageNet, evaluating the individual contributions of the thresholding strategy and the noise-resilient adaptation module. Excluding the thresholding strategy leads to a noticeable decline in pseudo-label quality, resulting in overall performance degradation. More significantly, ablating the noise-resilient module triggers a 12.03% surge in FPR95 and a 3.43% drop in  $ACC_H$ , primarily due to overfitting on noisy pseudo-labels. These findings highlight the critical role of each component in maintaining adaptation robustness. The

| Method      | Avg          | iNaturalist  | SUN          | Texture      | Places       |
|-------------|--------------|--------------|--------------|--------------|--------------|
| MEAN        | 63.16        | 64.38        | 63.53        | 61.89        | 62.82        |
| AdaND       | 64.11        | 65.17        | 64.26        | 63.39        | 63.63        |
| <b>NISP</b> | <b>67.66</b> | <b>68.74</b> | <b>67.69</b> | <b>67.51</b> | <b>66.70</b> |

Table 5: Pseudo-label accuracy for ImageNet benchmark.

| Resource       | ZS-CLIP | Tent    | AdaND  | NISP   |
|----------------|---------|---------|--------|--------|
| Time (s) ↓     | 0.0023  | 0.0059  | 0.0024 | 0.0038 |
| Memory (GiB) ↓ | 4.5889  | 11.5107 | 4.6241 | 4.6494 |

Table 6: Resource consumption under 128 batchsize.

full model achieves optimal average performance by jointly leveraging both mechanisms in a complementary manner.

**Sensitivity Analysis of Key Hyperparameters.** Figure 4 visualizes a sensitivity analysis of key hyperparameters on ImageNet. The loss weight  $\lambda$  demonstrates robust adaptation efficacy, striking an optimal trade-off between pseudo-ID consistency and pseudo-OOO discrepancy at approximately 0.3. Furthermore, the model exhibits remarkable insensitivity to the number of adapter heads  $H$ . The performance fluctuations are negligible across varying configurations, where our approach consistently outperforms baselines, validating the structural stability of the proposed framework.

**Impact of Different VLMs.** Table 4 scrutinizes the architectural scalability of NISP across diverse VLM backbones. While EVACLIP establishes a superior baseline due to advanced alignment, incorporating NISP yields universal performance gains regardless of the backbone’s capacity. Notably, NISP empowers EVACLIP to achieve peak performance (93.50% Avg AUC and 84.18% Avg  $ACC_H$ ), significantly surpassing its unadapted counterpart. This confirms that the performance gains are independent of specific architectural inductive biases. These results attest that our framework is architecturally agnostic: it effectively revitalizes weaker models (e.g., BLIP) while further amplifying the capabilities of advanced foundations.

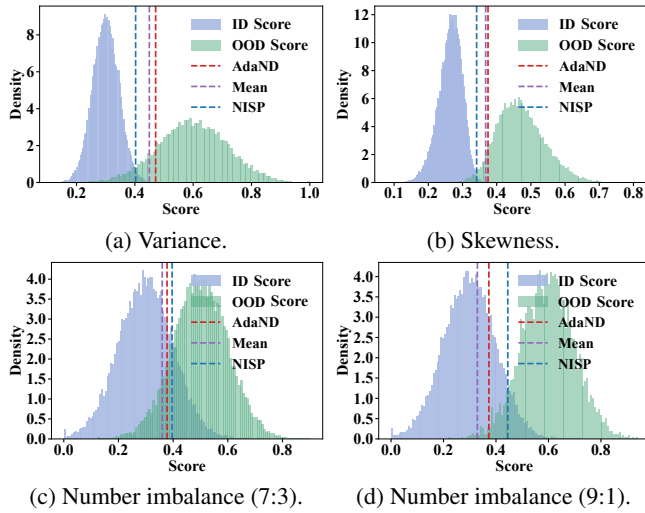


Figure 5: Visualization of threshold placement under different data distributions. The optimal threshold ideally aligns with the intersection of posterior densities.

#### 4.4 Further Analysis

**Thresholding under Distribution Shift.** Table 5 presents a comparative analysis of pseudo-label accuracy achieved by different thresholding strategies on the ImageNet. MEAN adopts the per-batch average OOD score as the threshold, while AdaND selects the threshold by minimizing intra-cluster score variance. In contrast, NISP achieves the highest pseudo-label accuracy across all datasets. Figure 5 illustrates threshold placement under various data distributions, including settings with variance imbalance, skewness, and number imbalance. NISP consistently locates thresholds near the posterior density intersections to minimize classification risk, demonstrating superior adaptability and reliable pseudo-labeling under complex conditions.

**Noisy Overfitting Analysis.** To elucidate the performance degradation observed in AdaND during late-stage adaptation, we analyze the dynamics of pseudo-label optimization. As depicted in Figure 6, AdaND initially benefits from clean samples, it progressively succumbs to noise memorization, overfitting incorrect pseudo-labels. This leads to a distinct inverse correlation: rising accuracy on noisy samples at the expense of clean accuracy. In contrast, our method maintains a sustained focus on clean samples throughout adaptation, resulting in stable improvements in clean accuracy while suppressing the influence of noise-induced supervision.

**Resource Analysis.** Table 6 reports computational efficiency analysis on ImageNet. Even with a multi-head configuration comprising  $H = 5$  heads and a hidden dimension of 128, our method maintains inference runtime and memory usage comparable to frozen VLM baseline (ZS-CLIP) and AdaND. This is attributed to the lightweight nature of our adapter architecture (a simple two-layer MLP). Unlike Tent, which requires memory-intensive full-graph backpropagation, NISP isolates gradients within the terminal adapter to prevent storing massive intermediate activations. Con-

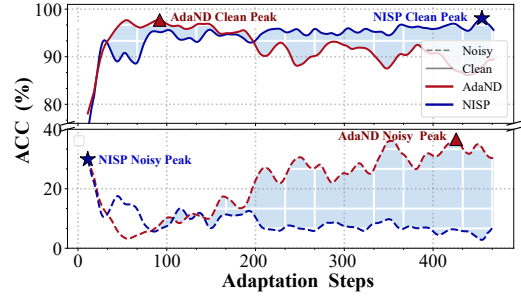


Figure 6: Adaptation dynamics of pseudo-labels. AdaND gradually overfits to noisy samples, degrading clean accuracy, whereas NISP sustains clean supervision and avoids noise-induced collapse.

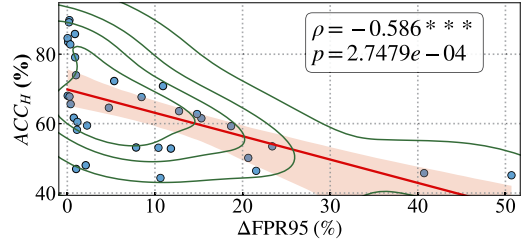


Figure 7: FPR95 gain vs. base pseudo-label accuracy. NISP shows greater improvement on harder benchmarks, with a significant negative correlation.

sequently, our method allows for efficient online adaptation with significantly lower resource demands than Tent.

**Gain Analysis.** Experiments reveal heterogeneous performance gains across benchmarks: while reducing FPR95 by 11.90% on ImageNet, our method achieves marginal improvements on other datasets with already high pseudo-label fidelity like Food-101. Figure 7 demonstrates a moderate negative correlation ( $\rho = -0.586$ ,  $p < 0.001$ ) between FPR95 reduction gains and base VLM pseudo-label accuracy across ID/OOD pairs. This stems from AdaND’s limited noisy overfitting at high pseudo-label accuracy regimes (e.g., 87.34% on Food-101/SUN), reducing our method’s relative advantage. Whereas at low accuracy (e.g., 63.58% on ImageNet/SUN), our method delivers 12.75% FPR95 reduction, validating its noise robustness.

## 5 Conclusion

In this paper, we propose a novel OSTTA approach named NISP that achieves unsupervised OOD self-purification via a coarse-to-fine noise-resilient adaptation paradigm. Technically, NISP introduces (1) a dual-cluster BGMM posterior-risk thresholding to generate high-fidelity pseudo-labels based on VLM-derived OOD scores, and (2) a fine-grained noise-resilient adapter updates under consensus-discrepancy constraints to refine pseudo-labels and suppress error propagation. Rigorous theoretical analysis demonstrates that NISP upper-bounds the Bayes risk in noisy environments, while extensive experiments across multiple OSTTA benchmarks confirm that NISP outperforms SOTA methods, demonstrating both theoretical soundness and practical efficacy.

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