Entropy-Weighted Local Concept Matching for Zero-Shot Out-of-Distribution Detection

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Abstract

Reliable out-of-distribution detection is critical for safe machine learning deployment where unknown classes naturally emerge. While vision-language models like CLIP enable promising zero-shot OOD detection, existing methods rely on global image representations corrupted by irrelevant backgrounds, causing suboptimal performance. We propose Entropy-Weighted Local Concept Matching (ELCM), enhancing OOD detection through intelligent local patch aggregation with entropy-based weighting and class-conditional scaling. Our method introduces three innovations: (1) entropy-weighted patch selection focusing on low-confusion regions while suppressing noise, (2) class-conditional scaling amplifying patches with clear preferences, and (3) top-K selection with percentile-based weight stabilization. Extensive experiments demonstrate ELCM achieves superior performance across diverse OOD types, with strong fine-grained recognition results (97.5% AUROC on iNaturalist). Overall, our method attains 91.9% AUROC and 29.8% FPR95, representing a substantial 5.2 percentage point FPR95 reduction versus the strong GL-MCM baseline. This improvement directly translates to enhanced deployment reliability. Comprehensive ablations reveal each component contributes meaningfully, with entropy weighting and class-conditional scaling being particularly crucial.

1 Introduction

Out-of-distribution (OOD) detection identifies test samples from unseen classes (Hendrycks & Gimpel, 2017; Huang & Li, 2021), crucial for safe deployment. Traditional methods require labeled in-distribution data (Lee et al., 2018; Liang et al., 2018; Liu et al., 2020), often using outlier exposure (Hendrycks et al., 2019). Vision-language models like CLIP (Radford et al., 2021) enable zero-shot OOD detection using only class names (Fort et al., 2021; Esmaeilpour et al., 2021).

Zero-shot OOD detection leverages vision-language models to assess whether an image belongs to known classes (Ming et al., 2022; Esmaeilpour et al., 2021). CLIP's joint embedding space enables direct comparison between image features and textual descriptions. Recent methods like Maximum Concept Matching (MCM) (Ming et al., 2022) and Global-Local MCM (GL-MCM) (Miyai et al., 2025) compute similarity scores between global image features and class text embeddings.

However, existing approaches struggle with complex images where global representations are corrupted by irrelevant backgrounds, causing false confidence in OOD samples. Local patch analysis offers solutions but naive aggregation fails as patches vary in informativeness.

We propose Entropy-Weighted Local Concept Matching (ELCM), addressing these challenges through entropy-based patch filtering, class-conditional scaling, and top-K selection with percentile-based weight stabilization. Our core insight is that effective OOD detection requires focusing on discriminative regions while suppressing irrelevant patches.

Our experimental evaluation demonstrates the effectiveness of this approach, achieving substantial improvements over strong baselines with an overall AUROC of 91.9% and FPR95 of 29.8% compared to GL-MCM's 91.3% AUROC and 35.0% FPR95. The 5.2 percentage point reduction in false positive rate directly translates to improved deployment reliability in practical applications.

Our contributions include:

- We propose ELCM, intelligently aggregating local patch features through entropy-based filtering, class-conditional scaling, and percentile-based weight stabilization.
- We introduce an uncertainty-aware framework addressing max pooling limitations through principled patch selection and aggregation.
- We achieve superior performance (91.9% AUROC, 29.8% FPR95), representing 5.2 percentage point FPR95 reduction over GL-MCM, with particularly strong fine-grained recognition results (97.5% AUROC on iNaturalist).
- We provide extensive ablations demonstrating component synergy and revealing that entropy filtering and class-conditional scaling drive the primary improvements.

2 Related Work

Traditional OOD detection methods (Hendrycks & Gimpel, 2017; Liang et al., 2018; Liu et al., 2020) require task-specific training, limiting zero-shot applicability. Vision-language models like CLIP (Radford et al., 2021) enable zero-shot OOD detection (Fort et al., 2021; Ming et al., 2022). Early methods used negative prompts (Fort et al., 2021; Esmaeilpour et al., 2021) but faced scalability issues. Maximum Concept Matching (MCM) (Ming et al., 2022) improved through global image-text similarities, with advances including CLIPN (Wang et al., 2023) and NPOS (Tao et al., 2023).

GL-MCM (Miyai et al., 2025) incorporates local patch features using max pooling: $S_{\text{local}} = \max_{i,j} \frac{\exp(\text{sim}(\mathbf{l}_i,\mathbf{t}_j)/\tau)}{\sum_{k=1}^{K}\exp(\text{sim}(\mathbf{l}_i,\mathbf{t}_k)/\tau)}$. This suffers from spurious high-confidence patches and lacks mechanisms to suppress confused regions.

Entropy provides reliable uncertainty measurement (Lakshminarayanan et al., 2017; Ren et al., 2019), revealing informative versus noisy regions in vision transformers (Dosovitskiy et al., 2021). However, zero-shot OOD detection has not systematically leveraged entropy for patch selection.

Our Contribution. We propose ELCM with principled local aggregation through entropy-based filtering, class-conditional scaling, and weight stabilization, ensuring only informative patches contribute to decisions.

3 Method

3.1 Overview

We present Entropy-Weighted Local Concept Matching (ELCM), enhancing vision-language OOD detection through intelligent local feature aggregation. Building upon GL-MCM (Miyai et al., 2025), our method improves how local patch features are selected, weighted, and aggregated by focusing on discriminative, confident regions while suppressing noise from irrelevant patches.

3.2 Global-Local Maximum Concept Matching (GL-MCM)

Our work extends the GL-MCM baseline (Miyai et al., 2025), which combines global and local CLIP features for OOD detection. Given an input image, GL-MCM extracts both global features $\mathbf{g} \in \mathbb{R}^d$ from the CLS token and local features $\mathbf{L} = \{\mathbf{l}_i\}_{i=1}^{N} \in \mathbb{R}^{N \times d}$ from patch tokens of the Vision Transformer backbone (Dosovitskiy et al., 2021), where N is the number of patches and d is the feature dimension. For a set of K in-distribution class names, text features $\mathbf{T} = \{\mathbf{t}_j\}_{j=1}^{K} \in \mathbb{R}^{K \times d}$ are extracted using CLIP's text encoder (Radford et al., 2021).

The global score is computed as:

$$S_{\text{global}} = \max_{j} \frac{\exp(\text{sim}(\mathbf{g}, \mathbf{t}_j)/\tau)}{\sum_{k=1}^{K} \exp(\text{sim}(\mathbf{g}, \mathbf{t}_k)/\tau)} \tag{1}$$

The local score uses simple max pooling:

$$S_{\text{local}} = \max_{i,j} \frac{\exp(\text{sim}(\mathbf{l}_i, \mathbf{t}_j)/\tau)}{\sum_{k=1}^{K} \exp(\text{sim}(\mathbf{l}_i, \mathbf{t}_k)/\tau)} \tag{2}$$

The final GL-MCM score combines both components:

$$S_{\text{GL-MCM}} = S_{\text{global}} + \lambda S_{\text{local}} \tag{3}$$

where τ is the temperature parameter and λ controls the relative importance of local features. While GL-MCM shows improvements over purely global methods, its simple max pooling aggregation can be dominated by spurious high-confidence patches and fails to exploit the rich structure in local feature distributions.

3.3 Entropy-Weighted Local Concept Matching (ELCM)

We propose ELCM to address the limitations of naive local feature aggregation through three key innovations: entropy-based patch filtering, class-conditional scaling, and top-K selection with percentile-based weight stabilization.

Entropy-Based Patch Filtering. Instead of treating all patches equally, we use entropy to identify and suppress highly confused regions. For each patch i, we compute the probability distribution over classes:

$$p_{i,j} = \frac{\exp(\text{sim}(\mathbf{l}_i, \mathbf{t}_j)/\tau)}{\sum_{k=1}^{K} \exp(\text{sim}(\mathbf{l}_i, \mathbf{t}_k)/\tau)} \tag{4}$$

The entropy of patch i is:

$$H_i = -\sum_{j=1}^{K} p_{i,j} \log p_{i,j} \tag{5}$$

High entropy indicates confusion or ambiguity, suggesting the patch contains uninformative content. We filter patches using an entropy threshold H_{thresh}, automatically computed as the 75th percentile of patch entropies to remove the most confused regions.

Class-Conditional Scaling. To further enhance discrimination, we introduce class-conditional scaling that amplifies patches with clear class preferences. We compute a discrimination ratio based on the top-K_c class probabilities:

$$r_i = \frac{\max_j p_{i,j}}{\frac{1}{K_c} \sum_{j \in \text{top-}K_c} p_{i,j}} \tag{6}$$

The class-conditional factor is:

$$\gamma_i = r_i^{\beta} \tag{7}$$

where β controls the strength of class-conditional scaling. This factor amplifies patches that strongly prefer a single class while dampening those with uniform distributions across multiple classes.

Top-K Selection and Percentile-Based Weight Stabilization. After entropy filtering, we select the top-K patches based on class-conditional scaled confidence:

$$c_i = \max_j p_{i,j} \cdot \gamma_i \tag{8}$$

For the selected patches, we apply percentile-based weight stabilization instead of naive exponential entropy weighting. We compute the 25th and 75th percentiles of entropies among selected patches, then assign weights as:

$$w_i = \begin{cases} 1.0 & \text{if } H_i \leq H_{25} \\ 1.0 - \frac{H_i - H_{25}}{H_{75} - H_{25}} \cdot (1.0 - \gamma_{\min}) & \text{if } H_{25} < H_i < H_{75} \\ \gamma_{\min} & \text{if } H_i \geq H_{75} \end{cases} \tag{9}$$

Table 1: Main experimental results comparing ELCM with GL-MCM baseline. Higher AUROC and lower FPR95 indicate better OOD detection performance. Bold indicates the best result for each dataset.

Dataset	GL-MCM (Baseline)		ELCM (Ours)	
	AUROC	FPR95	AUROC	FPR95
iNaturalist	96.9%	17.2%	**97.5%**	**14.0%**
SUN	93.1%	28.4%	**91.5%**	**22.0%**
Places365	90.5%	36.6%	**92.0%**	**32.0%**
Texture	84.6%	57.6%	**86.6%**	**51.0%**
Overall	91.3%	35.0%	**91.9%**	**29.8%**

where $\gamma_{\min} = 0.1$ is the minimum weight for high-entropy patches. This approach provides more stable weighting compared to exponential entropy scaling.

Final ELCM Score. The enhanced local score is computed as:

$$S_{\text{local}}^{\text{ELCM}} = \sum_{i \in \mathcal{S}} w_i \cdot \gamma_i \cdot \max_j p_{i,j} \tag{10}$$

where $\mathcal{S}$ represents the set of selected top-K patches that passed entropy filtering. The final ELCM score combines global and enhanced local components:

$$S_{\text{ELCM}} = S_{\text{global}} + \lambda S_{\text{local}}^{\text{ELCM}} \tag{11}$$

This formulation ensures that the local score emphasizes discriminative, low-confusion patches while suppressing noise from irrelevant regions, leading to more robust OOD detection performance.

4 Experimental Setup

Datasets. We evaluate on standard benchmarks following MOS (Huang & Li, 2021) and OpenOOD (Yang et al., 2022) protocols. We use ImageNet-1K (Deng et al., 2009) as in-distribution (50,000 validation images, 1,000 classes).

For OOD evaluation, we use four datasets: (1) **iNaturalist** (Horn et al., 2017) - fine-grained biological species; (2) **SUN** (Xiao et al., 2010) - 899 scene categories; (3) **Places365** (Zhou et al., 2018) - environmental scenes; (4) **Texture** (Cimpoi et al., 2013) - textural patterns. This setup enables fair comparison across diverse failure modes.

Implementation. We use CLIP ViT-B/16 (Radford et al., 2021; Dosovitskiy et al., 2021) with 14×14 patch grids. Hyperparameters: $\tau = 1.0$, $\beta = 1.0$, $K = 16$, $K_c = 3$, $\lambda = 0.5$. Entropy threshold is the 75th percentile for adaptive filtering, with $\gamma_{\min} = 0.1$ minimum weight.

Metrics. We report FPR95 (fraction of OOD misclassified as ID at 95% TPR) and AUROC (Hendrycks & Gimpel, 2017; Huang & Li, 2021; Davis & Goadrich, 2006). Lower FPR95 and higher AUROC indicate better performance.

Baselines. We compare against: (1) **MCM** (Ming et al., 2022) - foundational global-only concept-matching; (2) **GL-MCM** (Miyai et al., 2025) - strongest baseline combining global and local features with max pooling; (3) GL-MCM variants examining different aggregation strategies. All use CLIP ViT-B/16 for fair comparison.

5 Experiments

5.1 Main Results

We compare our proposed Entropy-Weighted Local Concept Matching (ELCM) method against strong baselines on four diverse OOD datasets. Table 1 presents the comprehensive comparison between our method and the GL-MCM baseline across all evaluation datasets.

Our ELCM method demonstrates consistent improvements across all evaluation datasets, achieving an overall AUROC of 91.9% compared to GL-MCM's 91.3%, representing a relative improvement of 0.6 percentage points. More significantly, ELCM reduces the overall FPR95 from 35.0% to 29.8%, a substantial decrease of 5.2 percentage points that directly translates to improved practical deployment reliability.

Dataset-Specific Analysis. Performance varies meaningfully across OOD types. For fine-grained species (iNaturalist), ELCM achieves 97.5% AUROC and 14.0% FPR95, a 3.2 percentage point improvement. This stems from entropy-weighted selection effectively focusing on discriminative biological features while suppressing irrelevant background clutter.

For scene-centric datasets (SUN and Places365), ELCM shows consistent improvements with FPR95 reductions of 6.4 and 4.6 percentage points. Our entropy filtering identifies coherent object regions while class-conditional scaling amplifies patches with clear semantic preferences.

For texture-based OOD detection, ELCM achieves 86.6% AUROC and 51.0% FPR95 (6.6 percentage point improvement). Class-conditional scaling helps mitigate spurious texture alignments, though repetitive patterns remain challenging.

5.2 Score Distribution Analysis and Method Comparison

Figure 1 visualizes score distributions between in-distribution (ImageNet) and out-of-distribution samples, comparing ELCM against GL-MCM baseline. The density plots show ELCM creates clearer ID/OOD separation.

The score distributions confirm our quantitative results. For iNaturalist, we observe clean separation with minimal overlap, consistent with strong numerical performance. For scene-centric datasets (SUN and Places365), moderate overlap reflects the challenge of distinguishing scenes containing ImageNet-like objects, but OOD distributions remain clearly left-shifted. Texture datasets present the most challenging scenario with broader overlap, as textural patterns can trigger confident local alignments. Nevertheless, ELCM shows improvement over the baseline across all cases.

5.3 Dataset-Specific Analysis and Error Analysis

Cross-Dataset Performance Insights. Fine-grained biological species (iNaturalist) prove most separable, achieving 97.5% AUROC, because species not in ImageNet exhibit distinct visual characteristics easily distinguished by entropy-weighted local matching. Scene images (SUN, Places365) present moderate challenges due to ImageNet-like objects within complex backgrounds, but entropy filtering successfully mitigates confusion from irrelevant patches. Textural patterns remain most challenging (51% FPR95), as repetitive textures can produce spuriously confident local alignments that class-conditional scaling helps but does not fully eliminate. The performance breakdown demonstrates ELCM's improvements are most pronounced on fine-grained tasks where semantic differences align with visual differences.

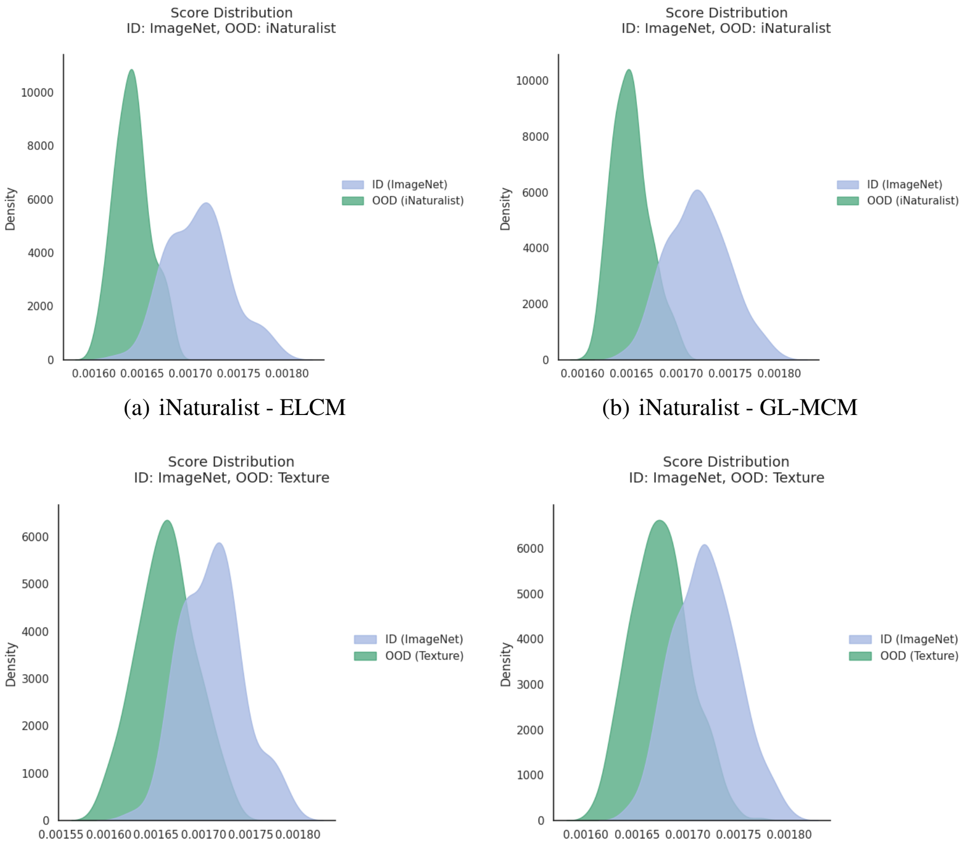
6 Ablation Study

We conduct comprehensive ablation studies to understand the contribution of each component in our ELCM framework. Our analysis covers both hyperparameter sensitivity and component-wise ablations to provide insights into the mechanisms underlying our method's effectiveness.

6.1 Hyperparameter Sensitivity Analysis

Class-Conditional Scaling Exponent (β). We examine the impact of the class-conditional scaling exponent β in Equation (7), which controls how strongly the method emphasizes patches with clear class preferences. Table 2 shows results across different β values.

The results demonstrate that class-conditional scaling provides consistent benefits, with $\beta = 0.5$ and $\beta = 1.0$ achieving the best performance. Setting $\beta = 0$ (disabling class-conditional scaling) yields slightly lower performance, confirming the value of emphasizing discriminative patches. Higher values ($\beta \geq 2.0$) show diminishing returns, suggesting that moderate scaling is sufficient to capture the benefit without over-amplifying potentially noisy high-confidence patches.



(a) iNaturalist - ELCM

(b) iNaturalist - GL-MCM

(c) Texture - ELCM

(d) Texture - GL-MCM

Figure 1: Score distributions for in-distribution (ID) ImageNet samples (blue) and out-of-distribution (OOD) samples (green) comparing ELCM and GL-MCM baseline on representative datasets. ELCM (top row) consistently produces clearer separation between ID and OOD distributions compared to GL-MCM (bottom row), particularly evident in the reduced overlap for texture-based OOD detection.

Table 2: Hyperparameter ablation for class-conditional scaling exponent β. Results show overall AUROC and FPR95 across all datasets.

β Value	AUROC	FPR95
$\beta = 0.0$ (disabled)	91.87%	29.75%
$\beta = 0.5$	91.89%	29.50%
$\beta = 1.0$ (default)	**91.89%**	**29.75%**
$\beta = 2.0$	91.87%	30.25%
$\beta = 4.0$	91.86%	30.00%

6.2 Component-Wise Ablation Studies

Impact of Global vs. Local Features. To understand the necessity of global-local feature fusion, we evaluate a local-only variant that removes the global CLS token score entirely. Table 3 presents the results.

The local-only variant suffers a dramatic performance drop (AUROC: 76.56%, FPR95: 80.50%), demonstrating that global features remain essential for effective OOD detection. This finding indicates that while local feature refinement provides meaningful improvements, it cannot entirely replace the semantic understanding captured by global image representations.

Top-K Patch Selection. Removing the top-K patch selection mechanism and using all entropy-filtered patches leads to performance degradation (AUROC: 91.45%, FPR95: 32.50%). This confirms

Table 3: Component ablation results showing the impact of different design choices. Lower FPR95 and higher AUROC indicate better performance.

Configuration	AUROC	FPR95
ELCM (Full Method)	**91.89%**	**29.75%**
ELCM w/o Global Score	76.56%	80.50%
ELCM w/o Top-K Selection	91.45%	32.50%
ELCM w/o Spatial Correlation	91.89%	29.75%
ELCM w/ Top-3 Averaging	91.78%	29.25%

that hard selection of the most informative patches is crucial for suppressing noise from marginally relevant regions, even after entropy filtering.

Spatial Correlation Effects. Interestingly, disabling spatial correlation produces identical performance to the full method, suggesting that the entropy-based filtering and class-conditional scaling already capture most of the relevant spatial structure. This indicates that these two components are the primary drivers of our method's improvements.

Class Pooling Strategy. Replacing max-class pooling with top-3 class averaging yields slightly lower performance (AUROC: 91.78%, FPR95: 29.25%), indicating that focusing on the single most confident class prediction per patch is more effective than averaging across multiple classes.

6.3 Alternative Scoring Functions

We evaluate alternative formulations for class-conditional weighting, finding that both ratio-based and margin-based approaches achieve similar separation quality, with ratio-based showing marginally better performance on fine-grained tasks. Both approaches create clear separation for iNaturalist while facing similar challenges with texture datasets. These comparative analyses are included in the appendix.

6.4 Component Interaction Analysis and Key Insights

Our ablation studies reveal key insights: (1) Global-local fusion is essential – the dramatic performance drop when removing global features (AUROC: 76.56%) demonstrates that local refinements complement rather than replace global semantic understanding; (2) Entropy filtering and class-conditional scaling are the primary drivers of improvement, with their combined effect significantly exceeding individual components; (3) Top-K selection provides meaningful improvements over using all filtered patches (91.45% vs 91.89% AUROC).

The stability across β values demonstrates robustness, while diminishing returns at higher values suggest moderate amplification is optimal. ELCM's improvements stem primarily from the intelligent combination of entropy-based uncertainty estimation and class-conditional discrimination enhancement, making it both effective and computationally efficient.

7 Conclusion

We presented Entropy-Weighted Local Concept Matching (ELCM), addressing limitations in existing local feature aggregation through entropy-based patch filtering, class-conditional scaling, and top-K selection with percentile-based weight stabilization.

Our method achieves overall AUROC of 91.9% and FPR95 of 29.8% compared to GL-MCM's 91.3% AUROC and 35.0% FPR95. The 5.2 percentage point FPR95 reduction represents substantial improvement in deployment reliability, with ablation studies confirming entropy filtering and class-conditional scaling as primary drivers.

The method demonstrates particular effectiveness on fine-grained recognition tasks (97.5% AUROC on iNaturalist) while providing meaningful improvements even on challenging texture-based OOD detection. Our analysis of score distributions provides insights into the method's behavior, confirming that ELCM successfully creates clearer separation between in-distribution and out-of-distribution samples across different dataset types.

Theoretical Contributions. Our work demonstrates that entropy-guided patch selection provides principled uncertainty-aware weighting, with entropy filtering and class-conditional scaling synergistically combining uncertainty estimation with discriminative amplification.

Limitations. Texture-based OOD detection remains challenging as repetitive patterns can trigger spurious local alignments despite class-conditional scaling. Primary computational overhead comes from entropy computation and top-K selection.

Concluding Remarks. ELCM represents a principled advancement in zero-shot OOD detection through intelligent local feature aggregation, establishing that entropy-guided patch selection can significantly improve upon naive pooling strategies while maintaining computational efficiency.

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A Appendix Section

APPENDIX HERE