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TRAINING-FREE MULTI-MODAL ALIGNMENT FOR FINE-GRAINED COUNTERFEIT FRUIT DETECTION

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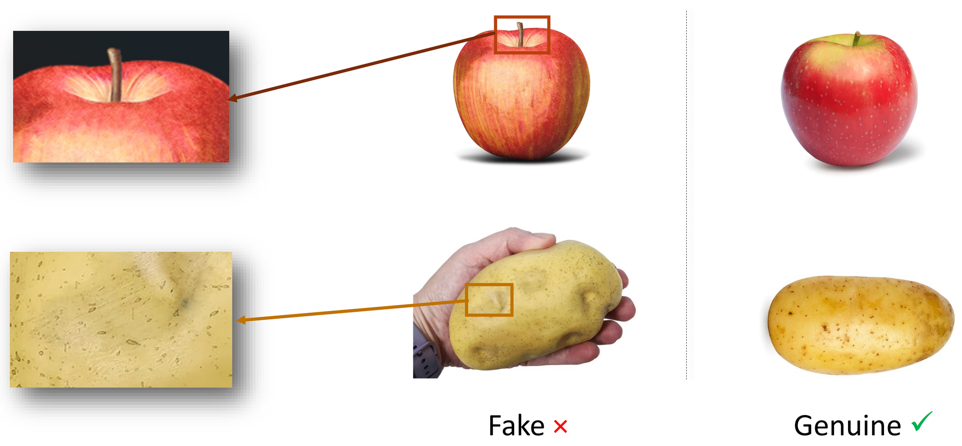
PROBLEM DEFINITION AND CONTRIBUTION

Goal:

Detect fine-grained counterfeit fruits in a training-free and incrementally expandable manner.



Fine-grained differences between authentic and fake fruits (texture, gloss, micro-patterns).

Contributions: AMAF-Net (Adaptive Multi-modal Alignment Framework):

- A training-free framework for fine-grained counterfeit fruit detection.
- Enriched semantic representations to capture subtle visual differences.
- Stabilized few-shot visual features using base knowledge.

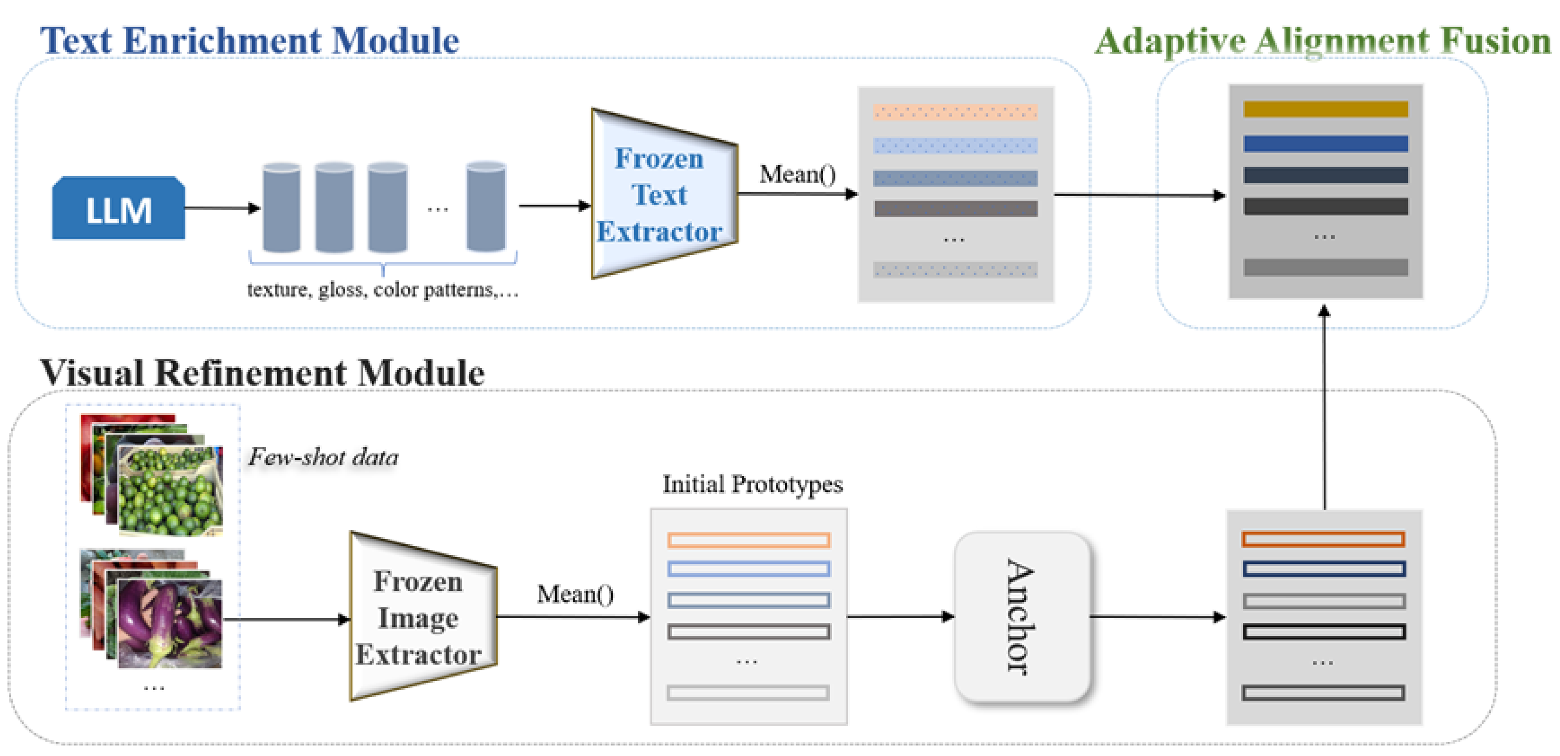
METHODOLOGY

Assumption: Access to a frozen Vision–Language Models and a small number of support images per new class. No fine-tuning or retraining is allowed in any session.

Process:

Encode → Refine → Fuse → Predict

Model Architecture: Images and enriched texts are encoded with frozen backbones, refined using base knowledge, and fused adaptively to produce stable, training-free fine-grained predictions.



EXPERIMENTATION

Dataset: Evaluate on four FSCIL benchmarks: MiniImageNet, CUB-200 (fine-grained bird species), EuroSAT (remote sensing), and FG-Fruit (authentic vs. counterfeit fruits). This setup covers both generic and highly fine-grained scenarios.

MiniImageNet. 100 classes — *CUB-200. 200 classes* — *FG-Fruit. 50 classes*

Visual Backbones:

- ResNet-50/101.
- ViT-B/16, ViT-B/32, ViT-L/14.

LLMs for Semantic Prompts:

- Attribute-based descriptions.
- Capture subtle cues (texture, gloss, micro-patterns).

QUANTITATIVE RESULTS

Method	MiniImageNet		CUB-200		EuroSAT		FG-Fruit	
	Acc_{avg} (%)	Drop (%)	Acc_{avg} (%)	Drop (%)	Acc_{avg} (%)	Drop (%)	Acc_{avg} (%)	Drop (%)
CLIP-Zero	84.4	**-0.24**	87.0	-0.30	86.7	**-0.41**	87.0	**-0.29**
CoOp	86.8	-0.11	89.3	-0.13	88.6	0.14	89.3	0.22
CoCoOP	87.4	0.021	89.5	**-0.41**	88.8	0.21	88.9	-0.16
FSIL-VL	86.1	-0.15	89.0	0.12	89.1	-0.18	88.4	0.26
Ours	**87.9**	-0.11	**90.6**	0.20	**89.6**	-0.12	**90.2**	0.13

Performance comparison across four FSCIL datasets in the 5-shot setting

Overall Performance:

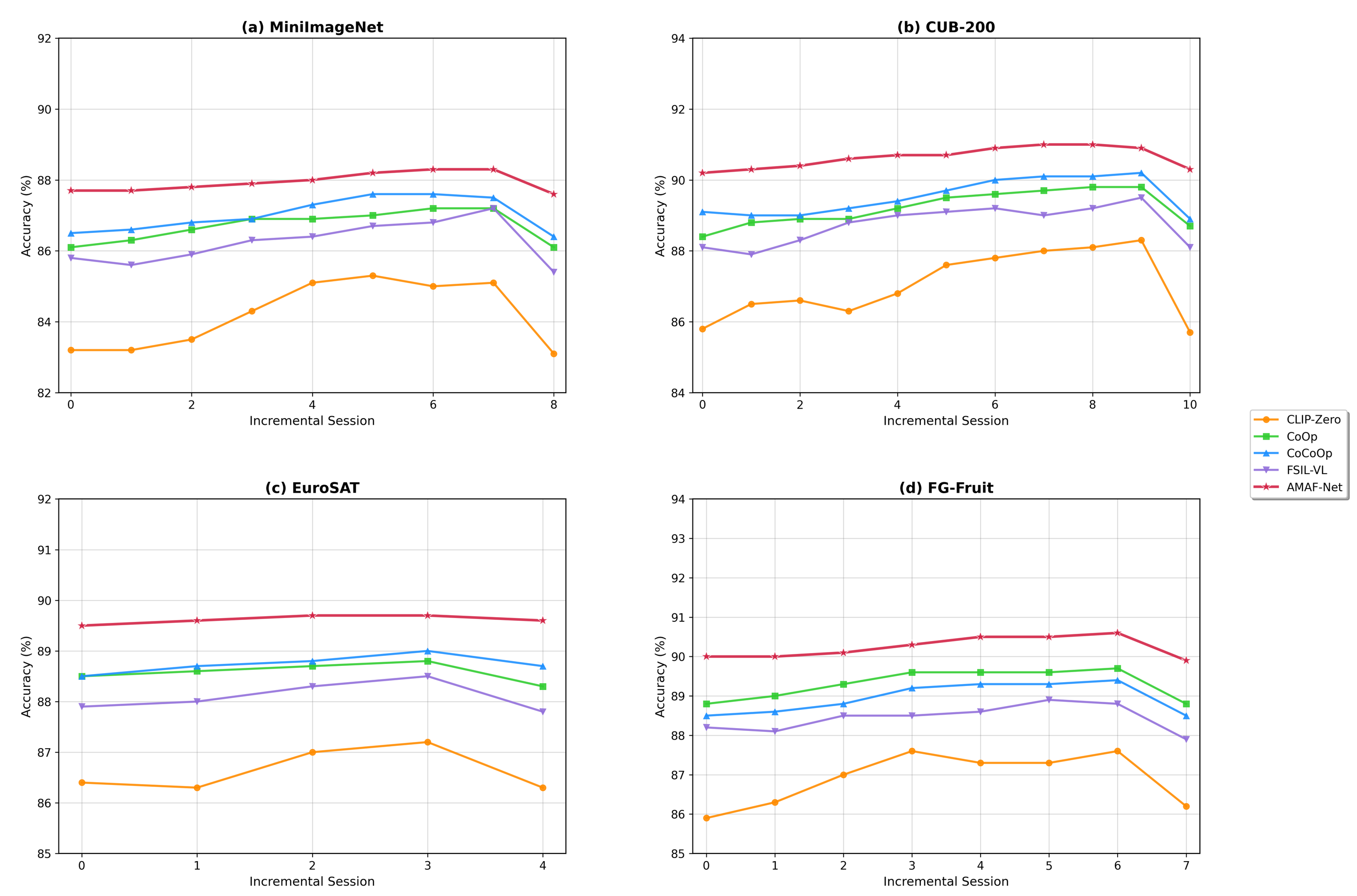
- Highest accuracy across all four FSCIL benchmarks.
- Stable performance under the training-free condition.

Fine-Grained Ability:

- 90.2% accuracy on FG-Fruit.
- 90.6% accuracy on CUB-200.
- Strong at capturing subtle visual differences.

ANALYSIS & DISCUSSION

Analysis of quantitative results: Achieves the highest average accuracy across all four benchmarks, outperforming all training-free and VLM-based baselines.



Consistent Across All Sessions:

- AMAF-Net consistently outperforms baselines.
- Prototype refinement slows accuracy degradation.
- Stable across all incremental sessions.

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