

# META-LEARNING APPROACH FOR FEW-SHOT OBJECT RECOGNITION IN COMPUTER VISION

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**Abstract** — Few-shot learning (FSL) addresses one of the most fundamental challenges in modern machine learning: the ability to recognize novel object categories from only a small number of labeled training samples. Traditional deep learning models, while achieving remarkable results on standard benchmarks, are heavily dependent on large-scale annotated datasets, limiting their practical deployment in scenarios where data acquisition is expensive, time-consuming, or infeasible. This paper proposes a comprehensive meta-learning based framework for few-shot object recognition in computer vision, leveraging episodic training strategies and deep feature embedding networks to enable rapid adaptation to unseen classes. The proposed system integrates Model-Agnostic Meta-Learning (MAML) with ResNet-based convolutional backbones under a structured N-way K-shot classification protocol. Extensive experiments on benchmark datasets including Mini-ImageNet, Omniglot, and CIFAR-FS demonstrate that the proposed approach achieves 62.1% accuracy in the 1-shot setting and 75.6% in the 5-shot setting on Mini-ImageNet, outperforming CNN baselines by 17.1% and Siamese Network baselines by 6.8%. Ablation studies confirm the individual contributions of backbone depth, distance metric selection, and inner-loop adaptation steps. The results establish the effectiveness of meta-learning for low-data computer vision applications, with promising implications for medical imaging, industrial inspection, and wildlife monitoring.

**Key Words:** Few-Shot Learning, Meta-Learning, MAML, Episodic Training, Feature Embedding, Prototypical Networks, Object Recognition, Computer Vision, ResNet, EfficientNet.

## 1. INTRODUCTION

The past decade has witnessed unprecedented advances in deep learning for computer vision, driven by models such as VGGNet, ResNet, DenseNet, and EfficientNet trained on massive datasets like ImageNet (1.2 million images) and JFT-300M (300 million images). These models achieve super-human accuracy on standard classification benchmarks, yet their performance degrades catastrophically when data is scarce. In contrast, human visual cognition exhibits a remarkable ability: a child who has seen only a few examples of an unfamiliar animal can reliably identify new instances of that species across varied lighting, angles, and occlusions. Replicating this capacity in artificial systems remains a central open problem in computer vision research.

Few-Shot Learning (FSL) directly addresses this gap by designing systems capable of generalizing to new object categories from as few as one to five labeled examples per class. The learning paradigm is formally described as N-way K-shot classification, where N is the number of novel classes and K is the number of labeled support instances per class. While several families of approaches have been proposed—including memory-augmented networks, hallucination-based data augmentation, and graph neural networks—meta-learning has emerged as a particularly principled and powerful framework.

Meta-learning, often described as "learning to learn," shifts the optimization objective from task-specific performance to across-task generalization. Rather than learning a single mapping from inputs to outputs, a meta-learner acquires an initialization, optimization algorithm, or embedding space that facilitates rapid adaptation to novel tasks. The landmark Model-Agnostic Meta-Learning (MAML) algorithm demonstrated that a model trained with MAML could be fine-tuned to a new task with as few as one gradient step, achieving strong performance in both few-shot classification and reinforcement learning.

Despite significant progress, several challenges remain. First, the computational overhead of bi-level optimization in MAML can be prohibitive for large-scale backbones. Second, the sensitivity of meta-learned initializations to hyperparameter choices—particularly inner-loop learning rates and the number of adaptation steps—requires

careful tuning. Third, cross-domain generalization, where base and novel classes are drawn from different visual distributions, remains substantially unsolved. This paper addresses the first two challenges and provides a systematic empirical analysis of design choices within the MAML framework.

The principal contributions of this work are fourfold. First, we present a modular episodic training pipeline that decouples dataset preparation, backbone pre-training, and meta-optimization. Second, we integrate MAML with three backbone architectures—ResNet-18, ResNet-50, and EfficientNet-B0—and quantify the accuracy-efficiency trade-offs. Third, we evaluate Euclidean and cosine distance metrics for few-shot classification at inference time. Fourth, we conduct comprehensive experiments on three benchmark datasets and report results with 95% confidence intervals over 600 test episodes, ensuring statistical rigor.

## 2. RELATED WORK

The literature on few-shot learning spans three major paradigms: optimization-based, metric-based, and hallucination-based methods.

### A. Optimization-Based Methods

MAML is the seminal work in optimization-based FSL, proposing a bi-level objective that meta-trains an initialization that can be rapidly fine-tuned. Ravi and Larochelle proposed a LSTM-based meta-learner that replaces the inner gradient descent with a learned update rule, improving adaptation efficiency. Meta-SGD extends MAML by learning per-parameter learning rates alongside the initialization, yielding faster convergence. ANIL (Almost No Inner Loop) demonstrates that effective meta-learning can occur with adaptation applied only to the classification head, reducing computational cost substantially. Reptile, a first-order approximation to MAML, avoids second-order gradient computation by performing multiple inner SGD steps, matching MAML performance at lower cost.

### B. Metric-Based Methods

Siamese Networks were among the first to apply metric learning to one-shot recognition, training a twin-network with contrastive loss to distinguish same-class from different-class pairs. Matching Networks introduced an attention mechanism that computes a weighted sum of support labels based on embedding similarity. Prototypical Networks simplify this approach by representing each class as the mean of its support embeddings and assigning queries to the nearest class prototype. Relation Networks replace fixed distance functions with a learned relation module, enabling more flexible comparisons. Recently, FEAT employs a Transformer-based set-to-set function to contextualize support embeddings with respect to one another.

### C. Transformer-Based Few-Shot Learning

Vision Transformers (ViT) have recently been adopted as feature extractors for FSL. FEAT and other Transformer-based approaches demonstrate that self-attention mechanisms capture long-range dependencies in images that convolutional networks miss, improving few-shot generalization particularly in cross-domain settings. Our work focuses on CNN backbones for computational tractability on standard hardware, but we discuss Transformer integration as a direction for future work.

## 3. PROBLEM STATEMENT

Let  $D_{\text{base}}$  denote a base dataset with abundant labeled data across  $C_{\text{base}}$  classes, and  $D_{\text{novel}}$  a disjoint novel dataset containing only  $K$  labeled samples per class across  $C_{\text{novel}}$  classes, where  $C_{\text{base}} \cap C_{\text{novel}} = \emptyset$ . The  $N$ -way  $K$ -shot classification task requires a model to correctly assign a query image to one of  $N$  classes randomly sampled from  $C_{\text{novel}}$ , given a support set of  $N \times K$  labeled examples.

Traditional empirical risk minimization (ERM) fails under this constraint because gradient-based optimization requires sufficient data to estimate loss gradients reliably. For  $K = 1$  or  $K = 5$ , ERM overfits severely to the few support examples, producing classifiers that fail to generalize to new queries. This is particularly problematic in three real-world domains: Medical Imaging (rare disease classification), Industrial Quality Control (novel defect detection), and Wildlife and Ecological Monitoring (rare species classification). The meta-learning formulation addresses these limitations by training across a distribution of simulated few-shot tasks during the base-class phase.

## 4. PROPOSED METHODOLOGY

The proposed framework consists of five sequential, modular components: dataset preparation, feature extraction, meta-learning optimization, episodic training, and inference-time classification.

### A. Dataset Preparation

The complete dataset is partitioned into disjoint class splits with no overlap: base classes  $C_{base}$  used for meta-training and novel classes  $C_{novel}$  reserved for meta-testing. For the Mini-ImageNet benchmark, the standard split assigns 64 classes to  $C_{base}$ , 16 to a validation set, and 20 to  $C_{novel}$ . All images undergo standard preprocessing: resizing to  $84 \times 84$  pixels, normalization by ImageNet channel statistics (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]), and random augmentation during meta-training (horizontal flip, color jitter, random crop with padding). Augmentation is disabled at meta-test time to ensure reproducibility.

### B. Feature Extraction Backbone

A convolutional neural network backbone maps each input image to a  $d$ -dimensional embedding vector, where  $d = 512$  for ResNet-18,  $d = 2048$  for ResNet-50, and  $d = 1280$  for EfficientNet-B0. The backbone is pre-trained on  $C_{base}$  classes using standard cross-entropy loss for 90 epochs with an initial learning rate of 0.1, decayed by a factor of 10 at epochs 45 and 67, with batch size 128 and weight decay  $5 \times 10^{-4}$ . ResNet-18 provides a lightweight baseline with strong inductive bias from residual connections, while ResNet-50 captures richer semantic representations and EfficientNet-B0 employs compound scaling for high parameter efficiency.

### C. Meta-Learning Framework (MAML)

We adopt Model-Agnostic Meta-Learning (MAML) as the core optimization strategy. MAML learns an initial parameter vector  $\theta$  such that a small number of gradient descent steps computed on a new task's support set yields parameters that generalize well to that task's query set. The bi-level meta-objective is:  $\min_{\theta} \sum_{T_i \sim p(T)} L_{T_i}(f_{\theta} - \alpha \nabla_{\theta} L_{T_i}(f_{\theta}))$ , where  $T_i$  is a sampled task (episode),  $\alpha$  is the inner-loop learning rate, and the outer summation is taken over a batch of tasks. The inner-loop adaptation uses standard gradient descent, and the outer-loop optimization uses Adam with  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ , and outer learning rate  $\eta = 10^{-3}$ . We use five inner adaptation steps during meta-training and ten steps at meta-test time.

### D. Episodic Training Protocol

Each training episode simulates an  $N$ -way  $K$ -shot scenario by randomly sampling  $N$  classes from  $C_{base}$  and  $K$  support images plus 15 query images per class. The model performs  $K$  inner-loop gradient steps on the support set and is evaluated on the query set to compute the episode loss. This process repeats over 60,000 meta-training episodes (organized into epochs of 100 episodes), with validation performed every epoch on the validation split. The episodic training regime is critical to the meta-learning framework's effectiveness: by constructing each episode to mirror the  $N$ -way  $K$ -shot test conditions, the model is forced to develop an initialization that supports rapid, reliable adaptation from minimal data.

### E. Inference-Time Classification

At meta-test time, the model is presented with a novel-class support set containing  $K$  labeled images per class from  $C_{novel}$ . The adapted parameters  $\theta'$  are obtained by performing the inner-loop gradient updates on this support set. Query images are then classified by computing their embedding and comparing it to the mean support embeddings for each class using Euclidean or cosine distance. The query is assigned to the class whose mean support embedding minimizes the chosen distance metric.

## 5. EXPERIMENTAL SETUP

### A. Datasets

Mini-ImageNet contains 100 classes, each with 600 color images resized to  $84 \times 84$  pixels. The standard split adopts 64 base classes, 16 validation classes, and 20 novel classes. Omniglot contains 1,623 handwritten characters from 50 alphabets, with 20 samples per character, augmented with  $90^\circ$ ,  $180^\circ$ , and  $270^\circ$  rotations yielding 6,492 classes. CIFAR-FS consists of 100 classes derived from CIFAR-100, using the same split as Mini-ImageNet with images resized to  $84 \times 84$  pixels for consistency.

## B. Implementation Details

All experiments are implemented in PyTorch 2.0 and run on a single NVIDIA RTX 3090 GPU (24 GB VRAM). The meta-training batch size is 4 episodes per outer update. Backbone pre-training uses SGD with momentum 0.9 and cosine annealing. During meta-training, both the backbone parameters and a linear classification head are subject to inner-loop adaptation. The classification head is initialized from scratch for each episode. Hyperparameters are selected by maximizing 5-way 1-shot accuracy on the validation split. All reported accuracy values are computed over 600 randomly sampled test episodes with 95% confidence intervals.

## C. Baselines

We compare against three baselines: (1) CNN Baseline — ResNet-18 fine-tuned per episode with standard cross-entropy loss, no meta-training; (2) Siamese Networks, trained with contrastive loss on same/different class pairs; and (3) Prototypical Networks, which classify queries by nearest class prototype in a learned embedding space. These baselines span the major few-shot learning paradigms and provide a comprehensive picture of where MAML-based meta-learning stands relative to alternative approaches.

## 6. RESULTS AND ANALYSIS

### A. Main Results on Mini-ImageNet

Table 1 presents 5-way classification accuracy on Mini-ImageNet for 1-shot and 5-shot settings. The proposed MAML + ResNet-50 model achieves  $62.1 \pm 0.7\%$  in the 1-shot setting and  $75.6 \pm 0.5\%$  in the 5-shot setting, outperforming all baselines. The improvement over the CNN baseline is particularly large in the 1-shot setting (+17.1%), underscoring the importance of meta-trained initialization when only one support example is available.

**Table – 1: 5-Way Classification Accuracy on Mini-ImageNet (%)**

| Method                        | 1-Shot (%)     | 5-Shot (%)     |
|-------------------------------|----------------|----------------|
| CNN Baseline (ResNet-18)      | $45.0 \pm 0.8$ | $60.2 \pm 0.7$ |
| Siamese Network               | $55.3 \pm 0.9$ | $68.4 \pm 0.6$ |
| Prototypical Networks         | $58.6 \pm 0.8$ | $72.1 \pm 0.6$ |
| MAML + ResNet-18 (Ours)       | $59.4 \pm 0.7$ | $73.2 \pm 0.5$ |
| MAML + EfficientNet-B0 (Ours) | $60.7 \pm 0.7$ | $74.5 \pm 0.5$ |
| MAML + ResNet-50 (Ours)       | $62.1 \pm 0.7$ | $75.6 \pm 0.5$ |

### B. Results on Omniglot and CIFAR-FS

Table 2 extends the evaluation to Omniglot and CIFAR-FS. On Omniglot, all models achieve higher accuracy due to the simpler visual structure of handwritten characters. The proposed MAML + ResNet-50 achieves 97.4% 5-way 1-shot and 99.1% 5-way 5-shot accuracy on Omniglot, and 64.8% 1-shot and 78.3% 5-shot accuracy on CIFAR-FS, demonstrating consistent gains across diverse benchmarks.

**Table – 2: Accuracy on Omniglot and CIFAR-FS (5-way, %)**

| Method                  | Omniglot 1-Shot | Omniglot 5-Shot | CIFAR-FS 1-Shot | CIFAR-FS 5-Shot |
|-------------------------|-----------------|-----------------|-----------------|-----------------|
| CNN Baseline            | $89.2 \pm 0.5$  | $95.6 \pm 0.3$  | $57.1 \pm 0.8$  | $71.4 \pm 0.7$  |
| Siamese Network         | $92.0 \pm 0.4$  | $97.1 \pm 0.3$  | $61.2 \pm 0.7$  | $74.3 \pm 0.6$  |
| Prototypical Nets       | $95.1 \pm 0.4$  | $98.4 \pm 0.2$  | $63.0 \pm 0.7$  | $76.5 \pm 0.5$  |
| MAML + ResNet-50 (Ours) | $97.4 \pm 0.3$  | $99.1 \pm 0.2$  | $64.8 \pm 0.7$  | $78.3 \pm 0.5$  |

### C. Ablation Study

To isolate the contribution of each design choice, we conduct a systematic ablation study on Mini-ImageNet 5-way 1-shot accuracy. The results show that episodic training alone accounts for +9.1% over the CNN baseline, confirming that the training regime is at least as important as the optimization algorithm. Adding MAML yields a further +6.3% gain, validating the meta-learning objective. Upgrading from ResNet-18 to ResNet-50 adds +2.7%, and switching from Euclidean to cosine distance adds +0.6%. These incremental gains are consistent across five random seeds (standard deviation < 0.3%).

### D. Effect of Inner-Loop Adaptation Steps

We examine the sensitivity of the proposed model to the number of inner-loop gradient steps (1, 3, 5, 10) during meta-testing. Performance increases monotonically from 58.2% at 1 step to 62.1% at 5 steps, with marginal improvement (62.3%) at 10 steps. This plateau behavior suggests that 5 inner steps provide a good balance between adaptation quality and computational overhead.

### E. Distance Metric Analysis

Cosine distance consistently outperforms Euclidean distance for ResNet-50 embeddings (62.1% vs. 61.5% in 1-shot), while the gap is smaller for ResNet-18 (59.4% vs. 59.1%). We hypothesize that deeper networks produce embeddings with more consistent magnitude across classes, reducing the advantage of cosine normalization. For EfficientNet-B0, cosine distance yields a larger advantage (+0.8%), likely due to compound scaling introducing magnitude variations across feature channels.

## 7. APPLICATIONS

### A. Medical Imaging

Rare disease classification represents a canonical few-shot learning challenge. In ophthalmology, uncommon retinal conditions such as macular telangiectasia or central serous chorioretinopathy affect small patient populations, making large-scale dataset construction prohibitively slow. The proposed framework can be pre-trained on common retinal conditions and rapidly adapted to rare conditions from a handful of expert-annotated examples. Similar opportunities exist in dermatology for rare skin conditions, in pathology for infrequent tumor subtypes, and in radiology for emerging imaging findings.

### B. Industrial Quality Inspection

Manufacturing quality control systems must detect novel defect types as product designs and production processes evolve. Traditional supervised detectors require hundreds or thousands of defect images per class—a requirement that cannot be satisfied for defects encountered for the first time. A meta-learned feature extractor pre-trained on a diverse base set of known defect categories can adapt to a new defect type from as few as five reference images, enabling rapid deployment of updated inspection systems with minimal annotation burden.

### C. Wildlife and Ecological Monitoring

Camera trap networks deployed across biodiversity hotspots generate millions of images annually, yet species from rare or recently described taxa appear only infrequently. A meta-learning system pre-trained on common species can classify rare species from the handful of photographs available in initial discovery records. This capability is particularly valuable for conservation monitoring of critically endangered species, where population sizes may be too small to support large labeled datasets.

### D. Robotics and Autonomous Systems

Robotic manipulation systems operating in open-world environments regularly encounter novel object categories not present during training. Few-shot recognition enables a robot to learn a new object category from a brief demonstration and immediately incorporate it into its manipulation pipeline. This capability is critical for flexible manufacturing, service robotics, and assistive technology applications.

## 8. FUTURE WORK

Several directions offer promising extensions of the proposed framework. First, replacing CNN backbones with Vision Transformers (ViT) may yield more expressive embeddings through global self-attention, potentially improving cross-domain few-shot accuracy. Second, self-supervised pre-training methods such as SimCLR, MoCo, and DINO can generate powerful visual representations from unlabeled data, reducing reliance on annotated base classes. Third, cross-domain few-shot learning—where base and novel classes are drawn from different visual distributions—remains substantially unsolved; domain adaptation techniques including adversarial alignment and style transfer may improve generalization. Fourth, edge deployment of meta-learned models requires quantization, pruning, and knowledge distillation to meet embedded system constraints. Post-training quantization to INT8 precision degrades accuracy by only 0.4% in preliminary experiments, suggesting feasibility of efficient deployment. Fifth, extending the framework to few-shot object detection and instance segmentation opens applications in robotics and autonomous driving where spatial localization is essential.

## 9. CONCLUSION

This paper presented a comprehensive meta-learning framework for few-shot object recognition in computer vision, systematically integrating MAML-based bi-level optimization with deep convolutional feature extractors under an episodic training protocol. Through extensive experiments on Mini-ImageNet, Omniglot, and CIFAR-FS, we demonstrated that the proposed approach consistently outperforms CNN baselines, Siamese Networks, and Prototypical Networks across 1-shot and 5-shot settings. The best-performing configuration—MAML with a ResNet-50 backbone and cosine distance classification—achieves 62.1% 5-way 1-shot accuracy and 75.6% 5-way 5-shot accuracy on Mini-ImageNet, representing improvements of 17.1% and 15.4% over the CNN baseline.

Ablation studies revealed that episodic training contributes the largest accuracy gain, followed by the meta-learning objective, backbone depth, and distance metric selection. These findings provide actionable design guidance for practitioners deploying few-shot recognition systems. The framework's modularity enables independent substitution of backbones, distance metrics, and meta-optimization algorithms, making it a flexible foundation for continued research and real-world deployment in data-scarce domains.

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