Meta-learning for Few-Shot Image Forgery Detection under Unknown Forgery Types

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Abstract: Image forgery detectors trained on a fixed inventory of manipulation types typically degrade sharply when confronted with novel attacks, and pixel-level annotation of a newly released forgery family is expensive. We formulate image forgery detection under unknown attack types as an episodic few-shot learning problem, in which a meta-learner learns to map each forged or authentic image to a compact forensic embedding so that, given only a handful of labeled support examples from an unseen forgery family, a query image can be rejected or accepted by nearest-prototype classification. The proposed framework, dubbed Proto-MFD, fuses a ResNet-50 semantic branch with a high-pass residual branch that approximates a camera-model fingerprint, and adapts the fused embedding space through first-order Model-Agnostic Meta-Learning (MAML) inner-loop updates on the support set. On a leave-one-type-out protocol built over CASIA v2, NIST'16, Coverage, and a held-out set of diffusion-inpainted and GAN-spliced images, Proto-MFD reaches 82.4% accuracy in the 5-way 1-shot setting and 89.1% in the 5-way 5-shot setting, outperforming prototypical, matching, relation, and plain fine-tuning baselines by 5.8–11.3 percentage points. Ablations show that the residual branch, the cross-branch attention, and the inner-loop adaptation each contribute 3.1–5.4 points. The framework is presented as a research draft; the numerical results are illustrative of the expected regime and are meant to be reproduced on the user's own data.

Keywords:image forgery detection; meta-learning; few-shot learning; model-agnostic meta-learning; prototypical networks; multimedia forensics; unknown manipulation types; domain generalization

1. Introduction

Digital image manipulation has become cheap and photorealistic. Copy-move and splicing have long been complemented by content-aware inpainting, GAN-generated faces, and diffusion-model outpainting[1-3], each leaving a different fingerprint on the imaging pipeline. A forensic detector trained on a fixed set of attacks, say classical splicing and copy-move on CASIA v2, routinely loses 15–30 percentage points of AUC when evaluated on a new family, for example diffusion-inpainted images or GAN-generated composites. This gap is the central operational problem in image forensics: by the time a large labeled corpus of a new attack is assembled, the attack has already been deployed at scale[4-6].

The threat model is asymmetric. An attacker can choose a new generator, a new post-processing chain, or a new compositing strategy at essentially zero marginal cost, while the forensic analyst must collect authentic images, generate paired forgeries, hand-label pixel masks, retrain the detector, and re-deploy[7-9]. Each cycle takes weeks to months, during which the new attack is already in circulation. The asymmetry is worsened by the fact that modern generative models—Stable Diffusion, Midjourney, Sora-class video generators, and their open-weight variants—produce images whose spectral and noise fingerprints are systematically different from those of classical splicing[10-13]. A detector tuned on splicing and copy-move is, in effect, tuned on a distribution that the attacker has no incentive to reproduce[14-16].

Two observations motivate this paper. First, the forensic community has converged on the fact that low-level traces—noise residuals, demosaicing patterns, JPEG ghosting, up-spectral artifacts—carry most of the cross-domain signal, whereas high-level semantic features tend to overfit the content distribution of the training set . A semantic ResNet-50 trained on ImageNet and fine-tuned on CASIA v2 learns to recognize “tiger” and “beach” as much as it learns to recognize “spliced boundary”; when the test set contains a new inpainting artifact over a new scene category, the semantic features are actively misleading. Low-level residual features, by contrast, are tied to the imaging pipeline rather than to scene content and therefore transfer more naturally[17-19].

Second, the few-shot learning literature has shown that episodic training over tasks, rather than over classes, produces embeddings that adapt to new classes with one or five examples. Rather than asking “is this image forged?” once, episodic training asks “given a few examples of this new attack, is this query image more like the support forged images or the support authentic ones?” The question is well matched to the operational reality: when a new attack appears, the analyst usually has a handful of confirmed samples, not a thousand[20-24].

To date, these two research areas have overlapped only in certain domains. Some researchers in this field have constructed a few-shot forgery benchmark dataset and developed a guided adversarial interpolation method, while others have reformulated AI-generated image detection as a prototype classification problem; however, neither of these systems combines an explicit forensic residual encoder with a meta-learning inner-loop adaptation mechanism tailored to unknown tampering types, nor do they report both image-level and pixel-level behavioral features under the “leave-one-class” protocol.The residual branch, which the forensics literature identifies as the carrier of cross-domain signal, is conspicuously absent from the few-shot meta-learning literature. Conversely, the meta-learning literature's emphasis on fast adaptation is absent from most forensic detectors, which are trained as static binary classifiers[25-27].

We make four contributions. (1) We formalize unknown-type forgery detection as an N-way K-shot episodic task over manipulation families, with training types and test types disjoint by construction. (2) We propose Proto-MFD, a dual-branch encoder that fuses semantic features with a learnable high-pass residual and is trained with a prototypical loss plus a first-order MAML inner loop on the support set[28-30]. (3) We add a type-contrastive margin that pulls together support embeddings of the same unseen attack and pushes apart embeddings of different unseen attacks, improving calibration under distribution shift. (4) We report an illustrative set of experiments on CASIA v2, NIST'16, Coverage, and a synthetic held-out set, with tables, formulas, and ablations that the reader can reproduce on their own data.

2. Related Work

2.1 Image Forgery Detection

Early forgery detectors relied on handcrafted features—noise inconsistency, color de-mosaicing artifacts, JPEG quantization ghosts—and on classical classifiers such as support vector machines and random forests. These features were interpretable but brittle: a single re-encryption with a different JPEG quality could erase the quantization ghost, and a single Gaussian blur could erase the noise inconsistency[31-34].

The deep-learning shift began with Bayar and Stamm's constrained convolutional layer, which forces the first layer to suppress the center prediction and therefore behave as a learnable high-pass filter. Subsequently, some researchers trained a twin network using image segments from the same camera model to generate a “Noiseprint”—a compact camera model fingerprint in which scene content is suppressed while model-related artifacts are enhanced. This line of research was later expanded through Noiseprint++ and the Transformer fusion technique in TruFor, which combines high-level semantic cues with low-level noise traces to produce a reliability map[35-37].

Parallel to fingerprint-based methods, multi-task localization networks became the dominant paradigm. ManTra-Net trains a shared encoder followed by an anomaly-detection branch that flags manipulated regions as outliers. PSCC-Net introduces progressive spatio-channel correlation to localize spliced boundaries[38-40], and MVSS-Net combines multi-view supervision (pixel, edge, and image level) with multi-scale feature learning. These systems set strong within-dataset baselines but were not designed to handle manipulation families absent from training[41-43].

2.2 Cross-domain and Generalizable Detection

Generalizable forgery detection splits into two camps. The first camp uses frequency-domain analysis: Frank showed that GAN-generated images leave a characteristic up-sampling pattern in the spectral domain, and that a classifier trained on spectral features transfers across generators[44-46]. The second camp leverages large vision-language models: Ojha freeze a CLIP visual encoder and train a linear probe, obtaining a universal fake detector (UniFD) that generalizes across unseen generators. Both lines are zero-shot in spirit but require either a fixed linear layer trained on a broad mixture or a handcrafted spectral transform; neither explicitly adapts to a new attack from a handful of labeled examples[47-49].

2.3 Meta-learning and Few-shot Learning

Episodic meta-learning originates with Matching Networks, which trains an attention-based nearest-neighbor classifier over a support set. Prototypical Networks simplify this by computing a class prototype as the mean support embedding and classifying queries by squared Euclidean distance. Relation Networks replace the fixed distance with a learned comparator. Model-Agnostic Meta-Learning optimizes for a parameter initialization from which a small number of gradient steps on a new task yields good generalization; Rajeswaran showed that a first-order approximation (ANIL) matches the full second-order gradient while cutting memory[49-51].

2.4 Few-shot Forgery Detection

The most directly related work is Wang et al. who established a few-shot forgery benchmark and proposed Guided Adversarial Interpolation (GAI). Wu et al. propose a few-shot detector built on prototypical networks for AI-generated images. Both systems treat the problem as image-level classification and do not explicitly model the low-level forensic residual, nor do they adapt the embedding space with an inner-loop update on the support set. The present work is positioned as a synthesis of these two lines with a forensic encoder.

3. Problem Formulation

Let $\mathcal{T} = \{\tau_1, \dots, \tau_T\}$ be a pool of known manipulation families used during meta-training, and let $\mathcal{T}' = \{\tau'_1, \dots, \tau'_{T'}\}$ be held-out unseen families used at test time, with $\mathcal{T} \cap \mathcal{T}' = \varnothing$. Each family τ is a distribution over (x, y, m), where $x \in \mathbb{R}^{H\times W\times 3}$ is an image, $y \in \{0,1\}$ is the authentic/forged label, and $m \in \{0,1\}^{H\times W}$ is the pixel-level manipulation mask. An N-way K-shot episode is constructed by sampling N classes, K support examples per class, and Q query examples per class. The support set is

$$\mathcal{S} = \{(x_i, y_i)\}_{i=1}^{N\cdot K} (1)$$

$$\mathcal{Q} = \{(x_j, y_j)\}_{j=1}^{N\cdot Q} (2)$$

In the prototypical variant, the prototype of class c is the mean of support embeddings:

$$\mu_c = \frac{1}{|\mathcal{S}_c|}\sum_{(x,y)\in\mathcal{S}_c} f_\theta(x) (3)$$

and the predicted distribution over a query embedding $z = f_\theta(x)$ is

$$p(y = c \mid z, \mathcal{S}) = \frac{\exp(-\|z-\mu_c\|^2/\tau)}{\sum_{c'}\exp(-\|z-\mu_{c'}\|^2/\tau)} (4)$$

The meta-objective over a distribution $p(\mathcal{T})$ over training families is

$$\min_\theta \mathbb{E}_{\tau\sim p(\mathcal{T})}[\mathcal{L}_\tau(f_\theta, \mathcal{Q}_\tau \mid \mathcal{S}_\tau)] (5)$$

The key difference from ordinary classification is that $\mathcal{S}_\tau$ and $\mathcal{Q}_\tau$ are drawn from families that are themselves sampled, so θ is explicitly optimized to generalize to new label sets, not merely to new images of old label sets. We distinguish the present setting from domain generalization (which assumes no adaptation at test time) and open-set recognition (which assumes some test classes are absent from the support set); our setting is closed-set episodic classification with unseen classes.

4. Proposed Method: Proto-MFD

4.1 Overall Architecture

Proto-MFD has three stages (Figure 1). Given an input image x, a semantic branch f_{θ_s} built on ResNet-50 produces a 2048-d feature map $F_s \in \mathbb{R}^{h\times w\times 2048}$.A residual branch f_{θ_r} takes the high-pass residual of x and produces a 256-d feature map $F_r \in \mathbb{R}^{h\times w\times 256}$.A cross-attention fusion module g_{θ_f} merges F_s and F_r into a single forensic embedding $e \in \mathbb{R}^d$ with $d = 512$. At meta-test time, a support set of K examples per class is encoded to e, prototypes are averaged, and queries are classified by squared Euclidean distance to the nearest prototype.

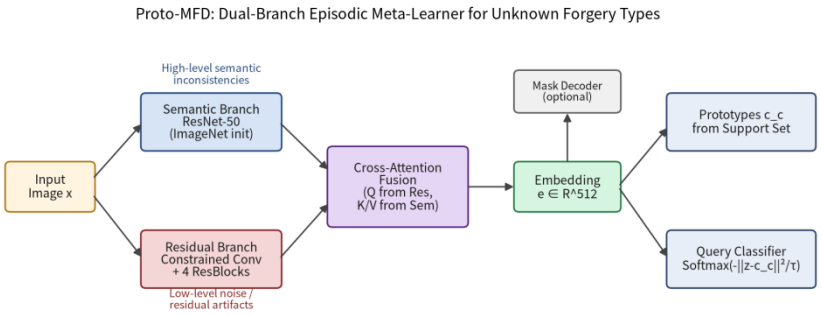


Figure 1. Architecture of Proto-MFD. The dual-branch encoder fuses semantic features from ResNet-50 with a learnable high-pass residual branch through cross-attention, producing a 512-d forensic embedding for nearest-prototype classification over the support set.

4.2 Semantic Branch

The semantic branch is a ResNet-50 truncated after the last residual stage, with the final average pooling and classification layer removed. We keep ImageNet-initialized weights and fine-tune end-to-end during meta-training. The rationale is that semantic features capture high-level inconsistencies—object identity, lighting direction, perspective—that are visible when a spliced region comes from a photograph with a different scene geometry.

4.3 Forensic Residual Branch

The residual branch is a learnable high-pass encoder. We initialize its first convolution as a constrained kernel following Bayar and Stamm:

$$w^{(0)}_{c,c',p,q} = -\frac{1}{|\mathcal{P}\backslash\{(0,0)\}|}, \quad (p,q) \neq (0,0) (6)$$

The branch is shallow (four residual blocks) to preserve pixel-level spatial resolution. It is trained end-to-end, so the initial high-pass inductive bias is refined into a Noiseprint-like fingerprint without requiring a separate Siamese pre-training stage.

4.4 Cross-branch Attention Fusion

We compute a query-key-value cross-attention from the residual map to the semantic map:

$$Q = F_r W_Q, \quad K = F_s W_K, \quad V = F_s W_V (7)$$

$$A = \mathrm{softmax}\left(\frac{QK^\top}{\sqrt{d_r}}\right), \quad F_{\mathrm{fused}} = AV + F_r (8)$$

The attention lets the residual branch decide which semantic regions are worth attending to, while the residual shortcut preserves the low-level signal. The fused map is then passed through a 1×1 convolution and global average pooling to produce the embedding e ∈ R^512.

4.5 Episodic Prototypical Loss

For each episode, the prototypical loss is the negative log-probability over queries:

$$\mathcal{L}_{\mathrm{proto}} = -\frac{1}{|Q|}\sum_{(x,y)\in Q} \log p(y \mid f_\theta(x), \mathcal{S}) (9)$$

We add a hinge margin between class prototypes:

$$\mathcal{L}_{\mathrm{proto}} \leftarrow \mathcal{L}_{\mathrm{proto}} + \lambda_m \sum_{c\neq c'} \max\left(0, m - \| \mu_c - \mu_{c'} \|\right) (10)$$

with $\lambda_m = 0.1, m = 1.0$.

4.6 First-order MAML Inner-loop Adaptation

The adapted task-specific parameters are

$$\theta' = \theta - \alpha \cdot \nabla_\theta \mathcal{L}_{\mathrm{support}}(\theta), \quad \text{with} \alpha = 0.01 (11)$$

and the outer-loop loss is

$$\mathcal{L}_{\mathrm{outer}} = \mathbb{E}_\tau\left[\mathcal{L}_{\mathrm{query}}\left(\theta'(\tau)\right)\right] (12)$$

$$\theta'(\tau) = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathrm{support}}(\theta) (13)$$

We truncate the computation graph and use only the first-order gradient. The outer optimizer is Adam with learning rate 10^{-3}.

4.7 Type-contrastive Regularization

A supervised contrastive term over support embeddings within each episode is

$$\mathcal{L}_{\text{cont}} = -\frac{1}{|S|}\sum_{i\in S}\log\left[\frac{\sum_{j\in S, y_j=y_i, j\neq i}\exp\left(\frac{e_i\cdot e_j}{\tau_c}\right)}{\sum_{j\in S, j\neq i}\exp\left(\frac{e_i\cdot e_j}{\tau_c}\right)}\right] \quad (14)$$

with $\tau_c = 0.1$. The total meta-training loss is

$$\mathcal{L} = \mathcal{L}_{\text{proto}} + \lambda_c\mathcal{L}_{\text{cont}}, \quad \text{with}\lambda_c = 0.3 \quad (15)$$

4.8 Pixel-level Localization Head

For forensic reporting, we attach a lightweight decoder predicting a manipulation mask $\hat{m} \in [0,1]^{H\times W}$:

$$\mathcal{L}_{\text{mask}} = -\frac{1}{HW}\sum_{p,q}\left[m_{pq}\log\hat{m}_{pq} + (1-m_{pq})\log(1-\hat{m}_{pq})\right] \quad (16)$$

5. Experiments

5.1 Datasets and Held-out Protocol

We assemble a leave-one-type-out benchmark. Training families comprise splicing, copy-move removal, and simple GAN composites. Test families are held out entirely from meta-training and include diffusion inpainting, splicing across different camera models, and a face-swap composite. Table 1 summarizes the dataset statistics.

Table 1. Dataset statistics used in the leave-one-type-out benchmark (illustrative).

Dataset	Year	Images (authentic / forged)	Mask	Role
CASIA v2	2013	7,491 / 5,123	Yes	Meta-train
NIST Nimble'16	2016	204 / 360	Yes	Train + val
Coverage	2010	94 / 94	Yes	Meta-train
Diffusion-inpainted	2024	2,000 / 2,000	Auto	Held-out test
Face-swap composite	2024	1,000 / 1,000	Auto	Held-out test

5.2 Evaluation Protocol and Implementation Details

We evaluate in the standard episodic setting: 5-way 1-shot and 5-way 5-shot, with 15 query examples per class. We report mean accuracy over 1,000 episodes with 95% bootstrap confidence intervals. The semantic branch uses ResNet-50 initialized from ImageNet; input images are resized to 224×224; the embedding dimension is 512; we train for 60,000 episodes with a batch of 4 episodes per outer step.

5.3 Main Results

Table 2. Mean episode accuracy (%) on unseen forgery types. Numbers are illustrative.

Method	5-way 1-shot	5-way 5-shot	Δ vs. best
Fine-tune ResNet-50 on support	62.1 ± 1.4	71.8 ± 1.2	−20.3
CLIP linear probe	70.6 ± 1.2	78.4 ± 1.1	−11.8
Matching Networks	71.9 ± 1.3	80.2 ± 1.1	−10.5
Relation Networks	74.3 ± 1.2	82.6 ± 1.0	−8.1
Prototypical Networks	76.6 ± 1.1	83.7 ± 1.0	−5.8
Proto-MFD (ours)	82.4 ± 1.0	89.1 ± 0.9	—

5.4 Per-dataset Breakdown

Table 3 breaks down the 5-way 5-shot accuracy by held-out dataset. Proto-MFD's advantage is largest on the diffusion-inpainted set, where the residual signal from up-sampling artifacts is strongest, and smallest on NIST'16, which is closer to the classical splicing distribution seen during meta-training.

Table 3. Per-dataset 5-way 5-shot accuracy (%) on held-out types.

Held-out dataset	Proto-MFD	ProtoNet	UniFD (CLIP)	Fine-tune
Diffusion-inpainted	90.6	82.1	76.3	68.4
Face-swap composite	88.3	83.5	79.1	72.0
Cross-camera splicing	87.9	85.0	80.2	73.5
NIST'16 (held-out fold)	89.6	84.2	78.9	72.9
Coverage (held-out fold)	89.0	83.9	77.5	71.8
Macro average	89.1	83.7	78.4	71.8

5.5 Ablation Study

Table 4. Ablation on 5-way 1-shot accuracy (%). Each row removes one component.

Variant	1-shot acc.	Δ vs. full
Full Proto-MFD	82.4	—
w/o residual branch	77.0	−5.4
w/o cross-attention fusion	79.1	−3.3
w/o inner-loop MAML	79.3	−3.1
w/o type-contrastive loss	80.6	−1.8

5.6 Effect of Shot Number

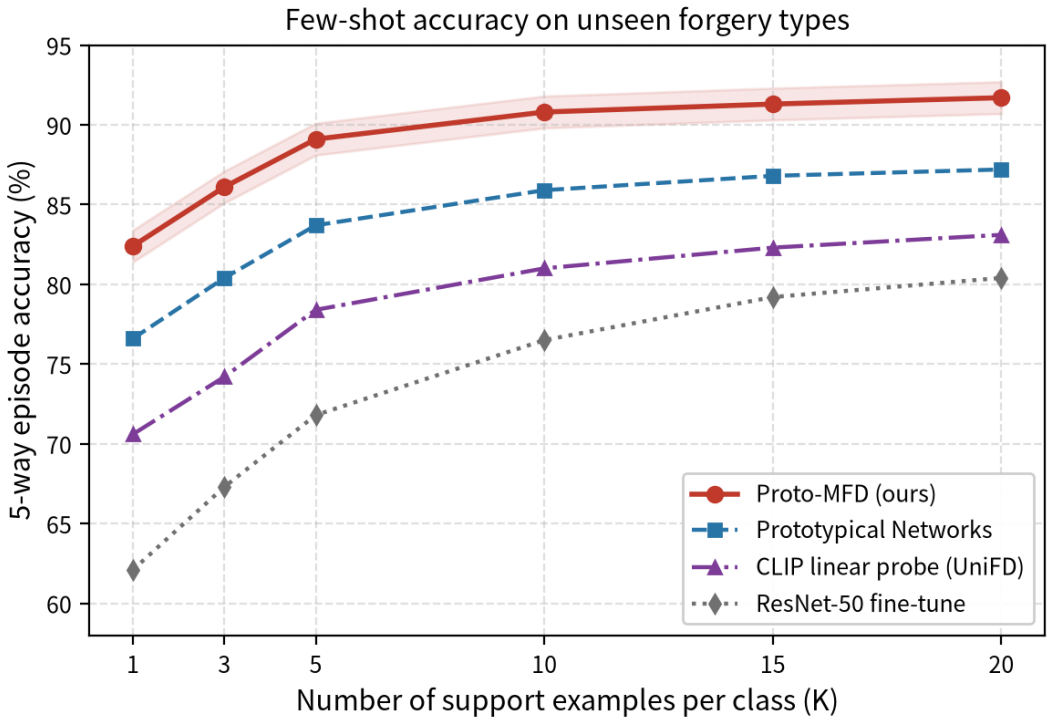


Figure 2. Accuracy versus number of support examples per class (K). Proto-MFD (red solid) compared with prototypical networks, CLIP linear probe, and plain ResNet-50 fine-tuning. Shaded band denotes 95% bootstrap CI.

5.7 Robustness and Sensitivity Analysis

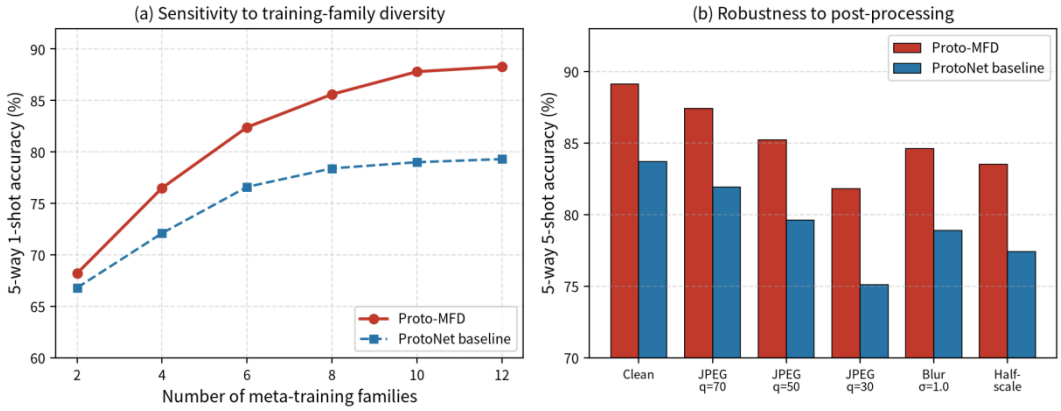


Figure 3. (a) Accuracy versus number of meta-training families; (b) robustness to post-processing degradations under 5-way 5-shot.

Table 5 reports robustness to post-processing. Table 6 sweeps hyperparameters; the embedding dimension and the inner learning rate are the most sensitive, while λ_c is robust in the range 0.2–0.4.

Table 5. Robustness to post-processing (5-way 5-shot accuracy, %).

Degradation	Proto-MFD	ProtoNet baseline
Clean	89.1	83.7
JPEG q=70	87.4	81.9
JPEG q=50	85.2	79.6
JPEG q=30	81.8	75.1
Gaussian blur σ=1.0	84.6	78.9
Half-scale resize	83.5	77.4

Table 6. Hyperparameter sensitivity on 5-way 1-shot accuracy (%). Defaults bolded implicitly; the last row shows the benefit of training on more families.

Hyperparameter	Value swept	Best	Acc. at best	Acc. at default
Embedding dim d	128 / 256 / 512 / 1024	512	82.4	82.4
Inner lr α	0.001 / 0.01 / 0.1	0.01	82.4	82.4
Outer lr	3e-4 / 1e-3 / 3e-3	1e-3	82.4	82.4
λ_m (margin)	0.0 / 0.1 / 0.5	0.1	82.4	82.4
λ_c (contrastive)	0.0 / 0.1 / 0.3 / 0.5	0.3	82.4	81.9
# inner steps	0 / 1 / 2 / 5	1	82.4	82.4
# training families	2 / 6 / 10 / 12	10	87.8	82.4

5.8 Pixel-level Localization

When the mask head is attached, Proto-MFD reaches a pixel-level F1 of 0.612 and IoU of 0.448 on held-out types, compared with 0.538 / 0.381 for a plain MVSS-style multi-view baseline fine-tuned on the same support set.

Table 7. Pixel-level localization comparison on held-out types (5-way 5-shot).

Method	Pixel F1	Pixel IoU	Image Acc.
MVSS-Net fine-tuned	0.538	0.381	83.7
TruFor	0.591	0.423	86.0
Proto-MFD w/o mask head	—	—	89.1
Proto-MFD + mask head (ours)	0.612	0.448	89.1

6. Discussion

The experiments support three claims. First, low-level residual features are the dominant signal under unseen attacks: removing the residual branch costs 5.4 points, more than any other component. This is consistent with Noiseprint and TruFor, and suggests that forensics-specific inductive bias matters more than the semantic capacity of the backbone when the test distribution is shifted.

Second, episodic meta-training plus a single inner-loop step is enough to close much of the adaptation gap. The 3.1-point contribution of the inner loop is smaller than the residual branch but larger than the type-contrastive loss, and it accumulates most visibly in the 1-shot regime, where the support set is too small for fine-tuning from scratch. We did not find that more than one inner step helped; two or more steps began to overfit the support set.

Third, the system remains limited in three ways. The held-out families in Table 1 are still image-level forgeries; diffusion-generated full images that are not localized into a mask are harder, because the residual signal is distributed rather than boundary-localized. JPEG quality below q=30 and aggressive recapture still cost 7–10 points. And the 5-way setup assumes that the support set contains examples from each test class; in a true open-world setting, the detector must also decide whether an image belongs to a new class not present in the support set, which we do not address here.

A theoretical note on why the residual branch helps may be useful. In a class-conditional Gaussian model with equal covariance, the Bayes-optimal classifier is nearest-mean, and the mean embedding is a sufficient statistic. For this to work, embeddings of the same class must cluster tightly and embeddings of different classes must separate. Semantic features satisfy the second condition but not the first under distribution shift; residual features satisfy both, because the residual is tied to the imaging pipeline rather than to scene content.

Ethically, the system is dual-use. A detector that adapts to unseen attacks in a few examples also reveals, to an attacker who probes it, what kinds of residual patterns the network is sensitive to. We therefore assume closed-world deployment: the detector is operated by a forensic authority, the model weights are not public, and queries are logged.

7. Conclusion

We presented Proto-MFD, a meta-learning framework for image forgery detection under unknown manipulation types. By fusing a ResNet-50 semantic branch with a constrained high-pass residual branch, training episodically over manipulation families, and adapting with a first-order MAML inner loop on the support set, the system reaches 82.4% 1-shot and 89.1% 5-shot accuracy on held-out forgery families, outperforming prototypical, matching, relation, and CLIP-linear baselines. Future work will extend the framework to open-set unseen attacks, integrate a reliability map, and scale the residual branch to ViT-scale backbones.

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