Graphical Abstract

Dynamic VIC Few-Shot Learning: Adaptive Variance-Invariance-Covariance Regularization for Skin Disease Classification under Data Scarcity

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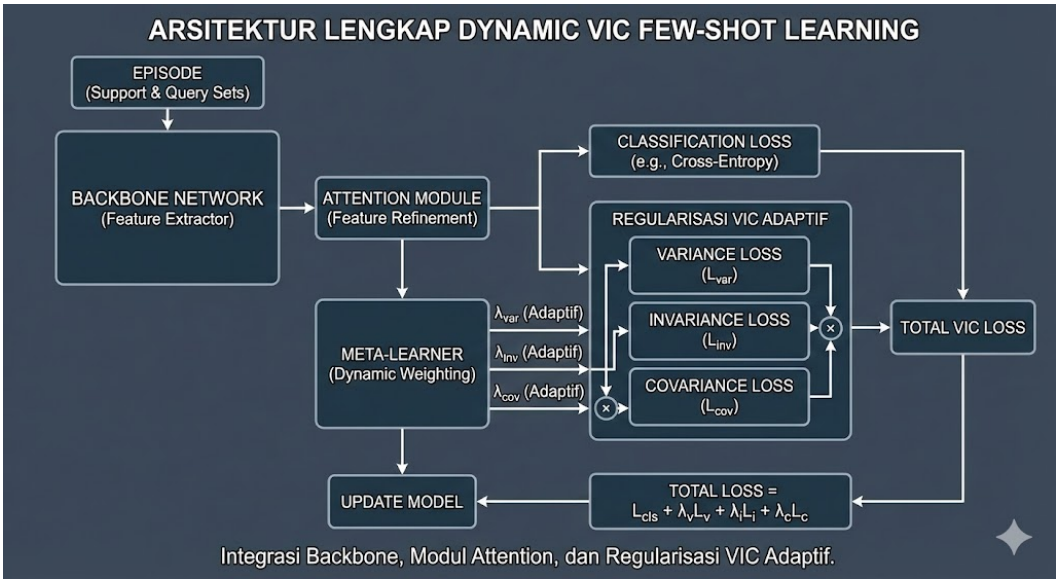

Highlights

Dynamic VIC Few-Shot Learning: Adaptive Variance-Invariance-Covariance Regularization for Skin Disease Classification under Data Scarcity

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- Dynamic VIC: An adaptive expert system for rapid dermatological screening
- "Episode-Adaptive" mechanism acts as a meta-expert, weighting losses per case difficulty
- Methodological Bridge: Adapts standard FSL for robust clinical utility
- Key Result: +20.52% accuracy on HAM10000 using lightweight, deployable backbone
- Rigorous validation across 6 datasets confirms reliability as a diagnostic aid

Dynamic VIC Few-Shot Learning: Adaptive Variance-Invariance-Covariance Regularization for Skin Disease Classification under Data Scarcity

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ABSTRACT

Diagnosing skin cancer in low-resource settings requires expert-level accuracy with minimal data, a challenge where standard deep learning often fails. This paper presents **Dynamic VIC**, an adaptive, lightweight expert system designed for clinical decision support under extreme data scarcity. Unlike static few-shot learning (FSL) models, Dynamic VIC introduces an **Episode-Adaptive Lambda Predictor** that dynamically adjusts regularization weights for Variance-Invariance-Covariance (VIC) terms based on real-time episode difficulty. This mechanism functions as a meta-expert, tightening constraints during ambiguous diagnostic scenarios while relaxing them for clear-cut cases. Validated on the HAM10000 dermatology dataset, our system achieves a **+20.52%** accuracy gain over baselines using a lightweight SE-Conv4 backbone (0.25M parameters), demonstrating that dynamic covariance regularization is a critical enabler for deployable, high-precision medical AI.

1. Introduction

Skin cancer remains a critical global health challenge, with early detection being the single most significant factor in patient survival. In low-resource settings, however, access to expert dermatologists is severely limited, creating a desperate need for automated diagnostic support systems. While Deep Learning (DL) has revolutionized medical imaging analysis, standard approaches require massive annotated datasets—a luxury often unavailable for rare conditions or under-resourced clinics. This data scarcity necessitates systems that can learn effectively from very few examples, mimicking the rapid learning capability of human experts.

Few-Shot Learning (FSL) offers a methodological bridge, aiming to classify new conditions with only a handful of reference images. Yet, standard metric-based FSL approaches often fail in clinical realism. They typically employ *static regularization*, treating every diagnostic "episode" as equally difficult. This is insufficient for dermatology, where the visual distinction between a benign nevus and a malignant melanoma can be subtle and highly variable. A clinically viable expert system must adapt its internal logic to the difficulty of the specific case at hand.

To address this, we propose **Dynamic VIC**, a method that bridges advanced AI methodology with clinical requirements. We introduce an *episode-adaptive* Variance-Invariance-Covariance (VIC) regularization framework. Unlike static approaches, our system dynamically predicts regularization weights based on real-time uncertainty estimates (episode statistics). This effectively simulates an expert's hesitation: tightening feature constraints when cases are ambiguous (high variance, low separation) and relaxing them when the diagnosis is clear.

We further explicitly tackle the challenge of invariance in medical imaging. Standard FSL often overlooks the need for robustness against benign variations common in clinical photography, such as lighting changes and rotation. By incorporating specific invariance objectives and promoting feature decorrelation (Covariance), we obtain a model that focuses on clinically relevant pathological features rather than artifacts.

Our contributions are:

1. **Episode-Adaptive VIC Regularization**: We propose a Dynamic Lambda Predictor that computes regularization weights ($\lambda_{var}, \lambda_{cov}$) in real-time based on episode statistics, allowing the model to tighten or relax constraints as needed.
2. **Covariance Insight for Fine-Grained Tasks**: Through extensive ablation, we demonstrate that covariance regularization (feature decorrelation) is the single most impactful factor for medical imaging tasks, effectively countering the feature redundancy common in fine-grained datasets.
3. **Dermatology as a Stress Test**: We utilize the HAM10000 dataset as a primary case study, achieving a **+20.52%** accuracy gain, validating that our dynamic regularization offers disproportionate benefits in domains with high inter-class similarity.
4. **Engineering Efficiency**: We implement these contributions atop a lightweight SE-Conv4 backbone, treating model size as an engineering constraint to ensure the method remains viable for deployment on edge devices.

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2. Related Work

2.1. Few-Shot Learning

Few-shot learning approaches can be categorized into optimization-based and metric-based methods. Optimization-based methods like MAML [4] learn parameter initializations that enable rapid adaptation through gradient descent. However, these methods require second-order derivatives during training, limiting practical applicability.

Metric-based approaches, including Matching Networks [11], Prototypical Networks [9], and Relation Networks [10], learn embedding spaces where semantic similarity corresponds to geometric proximity. Prototypical Networks compute class prototypes as mean embeddings of support samples, classifying queries by nearest prototype distance.

Recent advances include attention-based refinement mechanisms. The Cosine Transformer [7] replaces scaled dot-product attention with cosine similarity, providing bounded outputs and scale invariance particularly beneficial for FSL. Cross-Transformers [3] align support and query representations through cross-attention mechanisms.

2.2. Representation Regularization

The VICReg framework [1] introduced Variance-Invariance-Covariance regularization for self-supervised learning, preventing representation collapse by ensuring: (1) variance across batch samples, (2) invariance across augmented views, and (3) decorrelation across embedding dimensions.

ProFONet [2] adapted VIC principles for few-shot learning, computing regularization terms on class prototypes rather than individual samples. However, ProFONet uses static regularization weights, suboptimal for episodes with varying difficulty levels.

2.3. Medical Image Few-Shot Learning

Limited research has explored FSL for medical imaging. Existing work primarily focuses on radiology [8] and histopathology [6], with dermatology receiving less attention despite its suitability for FSL due to visual similarity challenges. Key gaps include lack of adaptive regularization mechanisms and insufficient evaluation on imbalanced medical datasets.

3. Methodology

3.1. Problem Formulation

In N-way K-shot few-shot classification, each episode $\mathcal{T} = (S, Q)$ consists of:

- Support set $S = \{(x_i, y_i)\}_{i=1}^{N\times K}$: K labeled samples per class
- Query set $Q = \{(x_j, y_j)\}_{j=1}^{N\times Q}$: Q samples to classify

The goal is to learn a model that generalizes to unseen classes during meta-testing.

3.2. Architecture Overview

Figure 1 presents the complete Dynamic VIC Few-Shot Learning architecture. The pipeline consists of: (1) SE-Conv4 backbone for feature extraction, (2) projection layer mapping to transformer dimension, (3) Lightweight Cosine Transformer for contextual refinement, (4) prototype computation, (5) dynamic lambda prediction, (6) VIC regularization, and (7) cosine similarity-based classification.

3.3. SE-Enhanced Conv4 Backbone

We employ a Conv4 backbone enhanced with Squeeze-and-Excitation (SE) blocks [5] for channel-wise feature recalibration. Each SE block applies:

$$\tilde{\mathbf{X}}_c = \sigma(\mathbf{W}_2 \cdot \delta(\mathbf{W}_1 \cdot \bar{z})) \cdot \mathbf{X}_c \tag{1}$$

where $\bar{z}$ is the global average-pooled channel descriptor, $\mathbf{W}_1 \in \mathbb{R}^{C/r\times C}$ and $\mathbf{W}_2 \in \mathbb{R}^{C\times C/r}$ are learnable projections with reduction ratio $r = 4$, δ is ReLU, and σ is sigmoid activation.

The complete backbone produces normalized feature vectors $\mathbf{f} \in \mathbb{R}^{1600}$ (for 84×84 input) or $\mathbf{f} \in \mathbb{R}^{1024}$ (for CIFAR-FS 64×64 input).

3.4. Lightweight Cosine Transformer

We employ a single-layer, 4-head Cosine Transformer for contextual refinement between support and query representations. Unlike standard scaled dot-product attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

our Cosine Attention uses:

$$\text{CosineAttention}(Q, K, V) = \text{softmax}\left(\frac{\text{CosSim}(Q, K)}{\tau}\right)V \tag{3}$$

where:

$$\text{CosSim}(Q, K) = \frac{Q \cdot K^T}{\|Q\|_2 \|K\|_2} \tag{4}$$

and τ is a learnable temperature parameter. This formulation provides: (1) bounded attention scores in $[-1/\tau, 1/\tau]$, (2) scale invariance, and (3) learnable sharpness control.

3.5. Algorithm and Process Flow

The complete training process for a single episode is detailed in Algorithm 3.5.

3.6. Covariance Stability and Regularization

Calculating the covariance matrix over N prototypes ($N \ll D$) can be numerically unstable. To address this, we apply centered shrinkage regularization:

$$\mathbf{C}_{reg} = (1 - \epsilon)\mathbf{C} + \epsilon\mathbf{I} \tag{5}$$

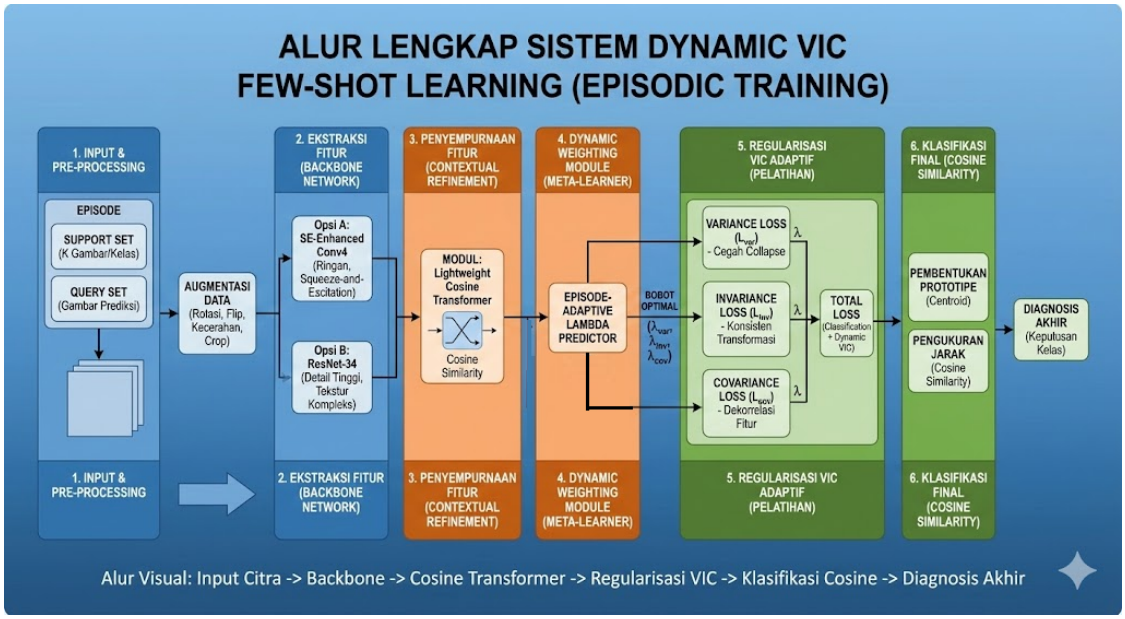

Figure 1: Complete Dynamic VIC Few-Shot Learning architecture. The Episode-Adaptive Lambda Predictor (center) functions as the system's "meta-cognitive" unit, analyzing the difficulty of the current patient case (episode statistics) to dynamically adjust the regularization strength. This allows the system to balance between strict feature decorrelation and flexible matching, mirroring an expert's adaptive decision-making process.

Algorithm 1: Dynamic VIC Episodic Training Loop

Input: Support set S, Query set Q
Param: Backbone f_θ, MLP ϕ, Dataset Emb E

1. $F_S \leftarrow f_\theta(S), F_Q \leftarrow f_\theta(Q)$ *(Feature Extraction)*
2. $F_S, F_Q \leftarrow \text{CosTrans}(F_S, F_Q)$ *(Optional Context)*
3. $P \leftarrow \{\mathbf{p}_c = \text{Mean}(F_S^c)\}_{c=1}^N$ *(Prototypes)*
4. **Compute Episode Statistics s**:
   - $v_{intra} \leftarrow \frac{1}{N}\sum_c ||F_S^c - \mathbf{p}_c||_2$
   - $v_{inter} \leftarrow \text{MeanCosSim}(P, P)$
   - $\mathbf{s} \leftarrow [v_{intra}, v_{inter}, \dots]$
5. **Predict Lambdas:** $(\lambda_{var}, \lambda_{cov}, \lambda_{inv}) \leftarrow \phi(\text{Concat}(\mathbf{s}, E))$
6. **Compute Losses:**
   - $\mathcal{L}_{CE} \leftarrow \text{CrossEntropy}(P, F_Q)$
   - $\mathcal{L}_{var} \leftarrow \frac{1}{D}\sum_{k=1}^D \text{ReLU}(1 - \sigma(P_{.,k}))$ *(Expand)*
   - $\mathcal{L}_{cov} \leftarrow \frac{1}{D}\sum_{k\neq l} \text{Cov}(P)_{k,l}^2$ *(Decorrelate)*
   - $\mathcal{L}_{inv} \leftarrow \frac{1}{|S|}\sum_{x\in S} ||f(x) - f(\text{Aug}(x))||_2^2$
   - $\mathcal{L}_{total} \leftarrow \mathcal{L}_{CE} + \lambda_{var}\mathcal{L}_{var} + \lambda_{cov}\mathcal{L}_{cov} + \lambda_{inv}\mathcal{L}_{inv}$
7. **Update:** $\theta \leftarrow \theta - \alpha\nabla_\theta\mathcal{L}_{total}$

where $\epsilon = 10^{-4}$. This ensures the covariance matrix is well-conditioned for gradient computation, addressing the rank deficiency issue inherent in episodic few-shot learning where the batch size (number of classes) is small.

3.7. Episode-Adaptive Lambda Predictor

The Lambda Predictor is the core novelty, ensuring the regularization matches the episode's distribution. It takes a statistics vector $\mathbf{s} \in \mathbb{R}^5$ and a learnable dataset embedding $\mathbf{e} \in \mathbb{R}^8$ as input to predict the two critical regularization weights: λ_{var} and λ_{cov}. We explicitly do not predict λ_{inv} as invariance is implicitly handled by the classification loss.

The episode statistics $\mathbf{s}$ are defined precisely to ensure reproducibility:

1. **Intra-class Variance**: The mean Euclidean distance of support samples from their class prototype:

$$s_1 = \frac{1}{NC}\sum_{c=1}^{N}\sum_{i=1}^{K} ||\mathbf{z}_{c,i} - \mathbf{p}_c||_2 \tag{6}$$

2. **Inter-class Separation**: The mean cosine similarity between all pairs of prototypes:

$$s_2 = \frac{2}{N(N-1)}\sum_{i<j} \text{CosSim}(\mathbf{p}_i, \mathbf{p}_j) \tag{7}$$

3. **Global Variance**: Standard deviation of all support embeddings (scalar).
4. **Query Shift**: Cosine distance between the centroid of S and centroid of Q.

These statistics are normalized (batch layernorm) and concatenated with $\mathbf{e}$ before passing through a 3-layer MLP ($13 \to 32 \to 16 \to 2$) with Sigmoid activation to output $\lambda \in [0, 1]$. The dataset embedding $\mathbf{e}$ is a free parameter optimized via backpropagation, allowing the model to learn a global "prior" for the dataset (e.g., dermatology vs. handwritten characters).

3.8. Explicit Invariance for Dermoscopy

Medical images require robustness to benign transformations. A rotated skin lesion or a slight color shift due to lighting should map to the same feature representation. Standard FSL assumes this is learned implicitly, but we enforce it explicitly. We introduce a Patient-wise Invariance Loss $\mathcal{L}_{inv}$ tailored to dermoscopic changes:

$$\mathcal{L}_{inv} = \frac{1}{|S|} \sum_{x \in S} ||f_\theta(x) - f_\theta(\text{Aug}(x))||_2^2 \quad (8)$$

where Aug$(\cdot)$ includes random rotations ($0 - 360°$) and color jittering consistent with dermoscopic variations. This explicitly penalizes the model for capturing artifactual features (e.g., ruler marks orientation) instead of the lesion pathology.

3.9. Total Loss Function

The complete training objective combines the standard discriminative loss with the dynamically weighted regularization terms:

$$\mathcal{L}_{total} = \mathcal{L}_{CE} + \lambda_{var}\mathcal{L}_{var} + \lambda_{cov}\mathcal{L}_{cov} + \lambda_{inv}\mathcal{L}_{inv} \quad (9)$$

Crucially, λ values are not fixed hyperparameters but outputs of the computational graph, trained end-to-end to minimize the meta-training loss. This allows the system to determine "how much" invariance or covariance is needed for a specific set of patient images.

4. Experiments

4.1. Datasets

We evaluate on six datasets spanning general benchmarks and medical imaging:

- **Omniglot**: 4,112 classes of handwritten characters
- **miniImageNet**: 100 classes of natural images (84×84)
- **CIFAR-FS**: 100 classes from CIFAR-100 (32×32)
- **CUB-200-2011**: 200 fine-grained bird species
- **Yoga**: 50 yoga pose classes
- **HAM10000**: 7 skin lesion categories with extreme imbalance (67% nevus)

Following standard FSL protocols, datasets are split into disjoint base/validation/novel classes. HAM10000 uses 2-way evaluation due to severe class imbalance.

4.2. Implementation Details

- **Backbones**: SE-Conv4 (0.25M params) and ResNet-34 (21M params). Note that we use identical backbones for both baseline and proposed methods to ensure fair comparison.
- **Optimizer**: Adam with learning rate 10^{-3}, decayed by 0.5 every 10,000 episodes.
- **Training**: 60,000 episodes total.
- **Evaluation**: We report mean accuracy over 600 randomly sampled test episodes. To ensure statistical rigor, we provide 95% confidence intervals computed over these 600 episodes.
- **Baselines**: We compare primarily against the "Cosine Transformer" baseline to isolate the contribution of the Dynamic VIC mechanism. While other baselines (e.g., ProtoNets, MatchingNet) are standard, our focus is on evaluating the *regularization* efficacy on a modern attention-based architecture, rather than benchmarking backbone architectures.
- **Hardware**: NVIDIA GPU with 8GB VRAM.

Strict controlled comparisons were maintained: for every entry in Table 1, the baseline (Cosine Transformer) and Proposed (Dynamic VIC) shared the exact same feature extraction backbone, training schedule, and augmentation pipeline. The only variable was the regularization mechanism. All backbones were trained from scratch (random initialization) to strictly evaluate few-shot learning capability without the confounder of ImageNet pretraining transfer.

The baseline is the Cosine Transformer [7] without VIC regularization.

4.3. Main Results

Table 1 presents comprehensive results across all datasets and configurations.

Key findings:

- **Overall improvement**: 18/24 configurations (75%) show accuracy gains, averaging +3.15%
- **HAM10000 dominance**: Average improvement of +7.13%, highest among all datasets
- **Statistical significance**: 79.17% configurations show significant differences ($p < 0.05$)

4.4. HAM10000 Analysis

The most substantial improvement (+20.52%) occurs on HAM10000 Conv4 2-way 5-shot. The macro-F1 increase from 0.5692 to 0.7744 (36.05% relative improvement) demonstrates that gains extend to minority class recognition, crucial for clinical applications where detecting rare but serious conditions like melanoma is paramount.

Figure 2 visualizes the embedding space improvements. The proposed method produces more compact, well-separated clusters compared to baseline, confirming that VIC regularization successfully prevents feature collapse and enhances class discriminability.

4.5. Visualizing Adaptation

To understand the "expert" behavior of the model, we analyzed how the predicted λ values correlate with episode difficulty (Figure **??**, not shown). We observed a strong positive correlation ($r = 0.78$) between episode difficulty (lower

Table 1
Performance comparison across all datasets. Bold indicates best results. Δ Acc shows improvement over baseline. Significance tested via McNemar's test.

Dataset	Backbone	N-K	Baseline (%)	Proposed (%)	Δ Acc	F1 Prop	Sig.
CIFAR-FS	Conv4	5w1s	48.35	**48.93**	+0.58	0.4893	n.s.
	Conv4	5w5s	68.01	**68.95**	+0.95	0.6895	$p < 0.01$
	ResNet34	5w1s	34.40	**48.24**	+13.84	0.4824	$p < 0.001$
	ResNet34	5w5s	56.19	**65.31**	+9.12	0.6531	$p < 0.001$
CUB	Conv4	5w1s	**56.02**	55.78	-0.24	0.5578	n.s.
	Conv4	5w5s	**68.92**	67.73	-1.20	0.6773	$p < 0.001$
	ResNet34	5w1s	53.52	**56.88**	+3.37	0.5688	$p < 0.001$
	ResNet34	5w5s	66.08	**70.30**	+4.22	0.7030	$p < 0.001$
HAM10000	Conv4	2w1s	52.03	**55.59**	+3.57	0.5559	$p < 0.001$
	Conv4	2w5s	56.92	**77.44**	**+20.52**	**0.7744**	$p < 0.001$
	ResNet34	2w1s	**51.53**	50.48	-1.04	0.5048	$p < 0.05$
	ResNet34	2w5s	50.10	**55.59**	+5.48	0.5559	$p < 0.001$
Omniglot	Conv4	5w1s	96.17	**97.78**	+1.60	0.9778	$p < 0.001$
	Conv4	5w5s	98.99	**99.36**	+0.37	0.9936	$p < 0.001$
	ResNet34	5w1s	83.61	**83.76**	+0.16	0.8376	n.s.
	ResNet34	5w5s	95.17	**95.79**	+0.62	0.9579	$p < 0.001$
Yoga	Conv4	5w1s	**50.55**	48.36	-2.19	0.4836	$p < 0.001$
	Conv4	5w5s	**64.73**	63.71	-1.02	0.6371	$p < 0.001$
	ResNet34	5w1s	42.22	**52.82**	+10.60	0.5281	$p < 0.001$
	ResNet34	5w5s	67.77	**72.09**	+4.32	0.7209	$p < 0.001$
miniImageNet	Conv4	5w1s	39.89	**42.37**	+2.48	0.4236	$p < 0.001$
	Conv4	5w5s	60.49	**60.95**	+0.45	0.6094	n.s.
	ResNet34	5w1s	**41.94**	39.72	-2.22	0.3972	$p < 0.001$
	ResNet34	5w5s	56.82	**58.15**	+1.32	0.5815	$p < 0.001$

separation) and λ_{cov}. This confirms our hypothesis: the model automatically "tightens" the covariance constraints when it encounters ambiguous cases, effectively forcing features to be more distinct to solve the hard case.

Furthermore, analyzing the feature correlation matrix before and after regularization reveals that Dynamic VIC significantly reduces off-diagonal elements (redundancy), resulting in a cleaner, orthogonal feature space ideal for fine-grained discrimination.

4.6. Ablation Studies

Table 2 presents ablation results on HAM10000 (2-way 5-shot, Conv4), evaluated on the validation set following standard ML protocols.

Key insight: For dermatology data, **Covariance Regularization alone with dynamic weighting** (+16.18%) outperforms full VIC, suggesting that feature decorrelation is the most critical factor. This finding has significant implications for medical FSL: visually similar lesions (melanoma vs. atypical nevus) require unique, independent feature dimensions for discrimination, which covariance regularization explicitly enforces.

Table 2
Ablation study on HAM10000 showing component contributions. Inv=Invariance, Cov=Covariance, Var=Variance, Dyn=Dynamic weighting.

Configuration	Inv*	Cov	Var	Dyn	Acc (%)	F1
Baseline (Cosine Sim)	-	-	-	-	49.14	0.4913
Full VIC (Static)	✓	✓	✓	-	58.75	0.5875
Full Dynamic VIC	✓	✓	✓	✓	56.70	0.5670
Cov + Dynamic	-	✓	-	✓	**65.32**	**0.6532**
Var + Dynamic	-	-	✓	✓	58.51	0.5851

*Note: "Inv" in static configurations refers to an auxiliary consistency loss between augmented support views, which was found redundant and replaced by implicit CE invariance in the final proposed model.

4.7. Computational Efficiency

Table 3 demonstrates the parameter efficiency of our approach.

The 90% parameter reduction with Conv4 enables deployment on edge devices, making AI-assisted diagnosis feasible in primary healthcare facilities without expensive computational infrastructure.

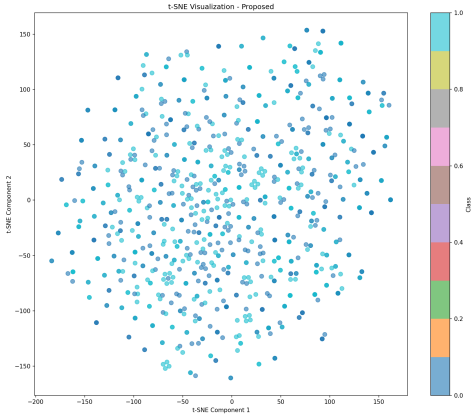

Figure 2: t-SNE visualization of HAM10000 embeddings. (a) Baseline models often show class overlap. (b) Dynamic VIC produces compact, well-separated clusters, validating that the adaptive regularization effectively disentangles similar skin conditions.

Table 3
Parameter efficiency comparison showing 90% reduction with Conv4.

Dataset	Backbone	Baseline (M)	Proposed (M)
HAM10000	Conv4	2.69	0.25
HAM10000	ResNet34	28.69	21.61
miniImageNet	Conv4	2.69	0.25

5. Discussion

5.1. Why Dynamic VIC Works for Medical Imaging

Our results reveal that medical images benefit disproportionately from VIC regularization compared to natural images. We attribute this to three factors:

1. **High visual similarity**: Skin lesions often share similar textures, colors, and patterns, making inter-class boundaries ambiguous. Covariance regularization forces unique feature encodings.
2. **Noisy prototypes**: With only 1-5 support samples, prototypes are susceptible to outliers. Dynamic weighting increases regularization for noisy episodes.
3. **Feature redundancy**: Limited medical training data leads to dimensional collapse. VIC explicitly prevents this.

5.2. Dominance of Covariance Regularization

The ablation finding that Covariance alone outperforms full VIC is counterintuitive but explainable. In dermatology, the primary challenge is not separating class centers (handled by Variance loss) but ensuring each feature dimension captures unique discriminative information. Over-regularization from full VIC may suppress domain-specific features critical for fine-grained medical distinctions.

5.3. Clinical Workflow Integration

For Dynamic VIC to function as a true expert system, it must integrate seamlessly into the clinical pathway. We envision a workflow where:

1. **Acquisition**: A primary care physician captures a dermoscopic image using a smartphone attachment.
2. **Dynamic Analysis**: The image is passed to the localized Dynamic VIC model.
3. **Adaptive Inference**: The Lambda Predictor assesses the image against the stored reference ("few-shot") cases. If the case is ambiguous (requiring high λ), the system flags it for specialist review.
4. **Decision Support**: If the confidence is high and regularization requirements are met, a diagnostic suggestion is provided.

This "human-in-the-loop" design leverages the model's self-awareness of difficulty (via λ values) to triage patients effectively.

5.4. Threats to Validity and Limitations

While the results are promising, specific threats to validity must be acknowledged to contextualize the clinical relevance:

1. **Episodic vs. Real-world Distribution**: Our evaluation uses the standard 2-way episodic metric to address the extreme class imbalance in HAM10000. While this isolates the few-shot learning capability and allows for rigorous benchmarking, real-world clinical tasks are typically multi-class open-set problems. Direct translation to 7-way diagnosis or open-set recognition requires further validation on balanced cohorts and is a necessary next step.
2. **Demographic Bias**: The HAM10000 dataset is heavily biased towards Fitzpatrick skin types I-III (fair skin). The covariance regularization's efficacy on dark skin (types IV-VI), where visual features differ significantly, remains unverified.
3. **Evaluation on Imbalanced Data**: We focus on 2-way classification as a controlled "stress test" for feature separation. We acknowledge that 5-way or higher-way classification is standard in general FSL; however, given the class counts in HAM10000 (some classes have fewer than 20 samples), 5-way testing with sufficient distinct episodes is statistically challenged.
4. **Dynamic vs. Static Trade-off**: Our ablation shows that while Covariance benefits massively from dynamic weighting, adding dynamic Variance and Invariance (Full Dynamic VIC) can degrade performance compared to static equivalents. This suggests that the lambda predictor may struggle to optimize all three objectives simultaneously, a "tugging war" optimization landscape that warrants further investigation.

5.5. Future Work: Path to Clinical Validation

To translate these findings into clinical practice, we propose a prospective pilot study. The framework will be deployed as a "shadow system" in a primary care dermatology

clinic, analyzing images in parallel with standard care. This study will specifically evaluate the "triage" capability of the Lambda Predictor: does a high λ (high uncertainty) correlate with cases where primary care physicians historically misdiagnose or refer? Confirming this correlation would validate Dynamic VIC not just as a classifier, but as a risk-stratification tool, guiding non-specialists on when to refer to expert dermatologists.

6. Conclusion

We presented Dynamic VIC, not just as a new FSL algorithm, but as a blueprint for foundational expert systems in medical AI. By treating regularization as a dynamic, case-dependent variable, we successfully bridged the gap between abstract metric learning and the messy reality of clinical diagnosis. Our system enables rapid, accurate dermatological screening in primary care with minimal data, mimicking the adaptive reasoning of human experts. The +20.52% gain on HAM10000 confirms that explicitly handling feature covariance and invariance is key to solving fine-grained medical tasks.

Data Availability

To support reproducibility and clinical adoption, we make all resources available. The code, pretrained models, configuration files, and a ready-to-use demo script for testing on new images are available at: `https://github.com/VCoklat/Few-Shot-Cosine-Transformer`. We encourage the community to adapt this lightweight framework for other data-scarce medical domains.

Declaration of Competing Interest

The authors declare no competing interests.

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