Computer Science (CO-SCIENCE)
Volume 6 Issue 2 July 2026
Accreditation **Sinta 3** No. SK : 295/C/C3/KPT/2026

Enhancing FOMAML with Domain-Specific Residual Pretraining for Few-Shot Chili Leaf Disease Classification

Rizal Amegia Saputra[1], Agus Buono[2], Karlisa Priandana[3*], Samsuzana Abd Aziz[4], Muhamad Syukur[5]

[1,2,3]Computer Science Study Program, School of Data Science, Mathematics and Informatics, IPB University, Bogor, 16680, Indonesia
[4]Department of Biological and Agricultural Engineering, Universiti Putra Malaysia, 43400, Serdang, Selangor, Malaysia.
[5]Department of Agronomy and Horticulture, IPB University, Bogor, 16680, Indonesia

e-mail: [1]rizal.rga@apps.ipb.ac.id, [2]agusbuono@apps.ipb.ac.id, [3]karlisa@apps.ipb.ac.id, [4]samsuzana@upm.edu.my, [5]muhsyukur@apps.ipb.ac.id

(*) Corresponding Author

Article Info: Received: 12-06-2026 | Revised : 22-06-2026 | Accepted : 24-06-2026

Abstract-Meta-learning is an approach designed to address data limitations in few-shot learning scenarios. The performance of meta-learning is influenced by the quality of the initial weights used during the meta-training process. Initial weights derived from a relevant domain have the potential to produce more informative feature representations, thereby enabling the adaptation process to new tasks to proceed more effectively. This study analyzes the impact of domain-specific pretrained initialization on classification performance, learning stability, convergence behavior, and computational trade-offs within the First-Order Model-Agnostic Meta-Learning (FOMAML) framework using an enhanced ResNet-50 backbone. Experiments were conducted on a 3-way classification scenario with 1-shot, 5-shot, and 10-shot configurations. Model evaluation was performed using accuracy, precision, recall, and F1-score, while learning stability was analyzed using standard deviation (Std) and coefficient of variation (CV). The experimental results show that a chili-domain pretrained initialization consistently yields better performance than random initialization. Accuracy reached 95.33%, 95.60%, and 95.94% in the 1-shot, 5-shot, and 10-shot scenarios, respectively an increase of 17.20, 12.61, and 17.49 percentage points compared to random initialization. In terms of stability, the CV values decreased to 1.00%, 0.59%, and 1.03%, compared to 1.10%, 3.66%, and 2.42% with random initialization. These performance improvements were achieved with relatively small differences in training time 0.056 minutes, 0.170 minutes, and 0.876 minutes for the 1-shot, 5-shot, and 10-shot scenarios, respectively. Domain-specific pretrained initialization produces more relevant initial feature representations, thereby improving the effectiveness and stability of FOMAML adaptation while maintaining computational requirements comparable to those of random initialization.

Keywords : Chili leaf disease classification; FOMAML; Meta-learning; Few-shot learning; Pretrained initialization.

INTRODUCTION

Chili leaf curl disease is one of the major problems in chili cultivation because it can reduce the quality and productivity of the harvest (Kleruk et al., 2024). Virus infections or pest infestations are the most common causes of leaf curl symptoms. These two types of infections often look the same (Syukur, 2018). The similarity of symptoms makes it difficult for farmers to identify early signs of infection. However, accurate disease identification is critical for identifying appropriate management strategies to minimize disease spread from the outset.

Advances in deep learning have yielded promising results in various image classification tasks, including plant disease identification (Trigka & Dritsas, 2025). However, deep learning models require large amounts of labeled data to achieve optimal performance (X. Chen & Lin, 2024). This poses a challenge for classifying diseases in chili peppers due to the relatively limited availability of datasets.

Meta-learning is an approach increasingly used in various few-shot classification tasks to address data limitations (Liu, 2026). One widely used method is FOMAML, an extension of MAML that features lower computational complexity since it does not involve second-order gradient calculations (Ramirez-alonso et al., 2025), making FOMAML lighter and more efficient for application in various few-shot learning scenarios (Zhang et al., 2019). The quality of the feature representation generated by the backbone (Ramirez-alonso et al., 2025) as

This work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.
Copyright (c) 2026 The Autour(s)

well as the initial weight initialization strategy model affect the performance of FOMAML (Bansal et al., 2022).

Several previous studies have explored various initialization strategies in meta-learning frameworks. The study by Sun et al. (Sun et al., 2019) proposed Meta-Transfer Learning (MTL), which utilizes pretrained DNN weights and a scaling-shifting mechanism to achieve a better starting point for learning. The results showed improved classification performance and accelerated convergence on miniimagenet datasets for few-shot learning. However, the evaluation focused solely on classification performance and convergence analysis without addressing learning stability or computational trade-offs. Furthermore, the study by Chen et al (Y. Chen et al., 2021) through Meta-Baseline, demonstrated that pretrained feature representations significantly contribute to improved few-shot classification performance. Nevertheless, that study placed greater emphasis on feature representation quality and classification accuracy, without evaluating learning stability or the resulting computational requirements. Research by Zhu et al (Zhu et al., 2022) proposed meta-learned initialization to improve the effectiveness of active learners under low-budget and cold-start learning conditions. The study demonstrates that the quality of initialization influences the model's adaptability during the early stages of learning; however, the analysis remains limited to classification performance and the effectiveness of active learning. Research by Huang et al (Huang et al., 2023) developed Meta-Learned Prompt Tuning (MetaPT), which leverages meta-learning to obtain better prompt initializations in few-shot learning scenarios. This research demonstrates improved performance and stability compared to conventional prompt tuning methods, but it is still limited to the natural language processing domain and has not yet evaluated computational requirements or its application to image classification.

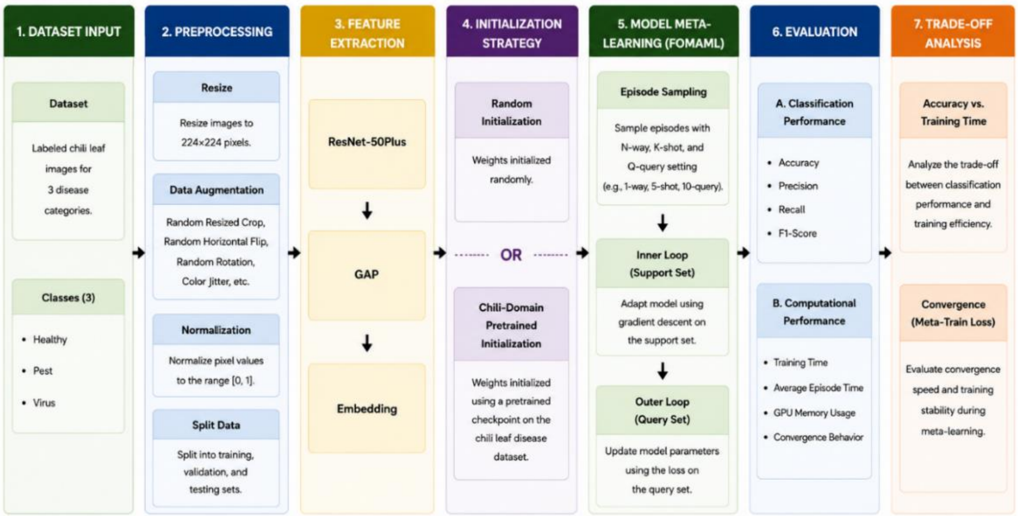
Based on the research gap discussed above, this study investigates the integration of chili-domain pretrained initialization and the ResNet-50Plus backbone within the FOMAML framework for few-shot classification of chili leaf curl disease. The ResNet-50Plus backbone is used as a slight modification of the ResNet-50 architecture by replacing the ReLU activation function with LeakyReLU to support gradient propagation (Xu et al., 2020), as well as adding dropout regularization to improve learning stability (Salehin & Kang, 2023). Unlike previous studies that focused on improving classification performance, the main contribution of this study lies in a comprehensive evaluation of the impact of domain-specific pretrained initialization, covering classification performance, convergence behavior, learning stability, and computational trade-offs in the few-shot chili leaf disease classification scenario.

Based on these issues, this study analyzes the performance and computational trade-offs in the FOMAML framework using the ResNet-50Plus backbone. The analysis focuses on a comparison between random initialization and domain-specific pretrained initialization. Evaluation is conducted not only based on classification performance but also includes convergence behavior, training time, average episode time, GPU memory usage, and stability analysis throughout the episodic meta-learning process.

RESEARCH METHOD

2.1 Proposed Framework

This section presents the overall framework of the proposed method. The developed framework integrates an enhanced ResNet-50Plus-based residual backbone with the LeakyReLU activation function across all layers and the addition of dropout before the final classification layer. In addition to serving as a feature extractor, the pretrained backbone is also utilized for parameter initialization in the meta-learning process. Subsequently, the backbone is integrated into the FOMAML framework. An overview of the proposed method is shown in Figure 1.



Source : Research results (2026).

Figure 1. Proposed framework of FOMAML with domain-specific residual pretrained initialization for few-shot chili leaf disease classification.

2.2 Dataset Acquisition and Preparation

The dataset for this study was collected from two different environments. A greenhouse was used to obtain images of healthy leaves and leaves exhibiting curling symptoms due to viral infection, while open farmland was used to obtain images of leaves exhibiting curling due to pest infestations. Virus-infected leaf samples were obtained through Begomovirus inoculation and subsequently verified through laboratory testing. Samples of healthy leaves were obtained from plants grown in a separate greenhouse without exposure to viral inoculation to minimize the risk of contamination. Samples of leaves infested by pests were identified through field observations by chili farmers and subsequently confirmed by a chili expert. Since the labeling process did not involve multiple independent raters, an inter-rater agreement analysis was not performed. All images were captured using a Samsung A55 smartphone camera with a resolution of 50 MP under various lighting conditions and against different backgrounds to represent real-world agricultural conditions. The dataset consists of 773 images, including 260 healthy leaves, 260 virus-infected leaves, and 253 pest-infested leaves. All original images had a resolution of 4080 × 3060 pixels and were subsequently resized to 224 × 224 pixels to meet the input requirements of the ResNet-50Plus backbone while maintaining consistency in feature dimensions across each training epoch.

2.3 ResNet-50Plus Backbone

Modifications to the ResNet-50 architecture focused on changing the activation functions and network regularization mechanisms without altering the main structure of the residual network. In this study, all ReLU activation functions in the convolutional layers were replaced with Leaky ReLU. Unlike ReLU, which produces a value of zero for all negative inputs, Leaky ReLU retains a small portion of information in the negative range by multiplying the input value by a constant α. Thus, neurons can still generate gradients even when receiving negative input values. The formula for the Leaky ReLU function is shown in Equation (1)(Padshetty & Ambika, 2023):

$$f(x) = \begin{cases} \alpha x, \ if \ x < 0 \\ x, if \ x \geq \ 0 \end{cases}, \qquad (1)$$

where x represents the neuron's input value, $f(x)$ is the output of the activation function, and α is a small constant in the negative region.

2.4 Meta-Learning Framework

The adaptation process in FOMAML consists of two main stages: inner-loop adaptation and outer-loop meta-update (Nichol et al., n.d.). In the inner-loop adaptation phase, the model parameters are updated using the support set through several gradient descent steps to obtain the temporary parameters θ_i'. The parameter update process in this phase is expressed as:

$$\theta_i' = \theta - \alpha \nabla_\theta \mathcal{L}_{S_i}(\theta), \qquad (2)$$

where θ denotes the initial model parameters, α denotes the inner-loop learning rate, and $\mathcal{L}_{S_i}$ denotes the loss on the support set of the i-th episode.

Once the adaptation process is complete, the model is evaluated using a query set during the outer-loop meta-update phase. The loss generated from the query set is used to update the model's global parameters so that it can adapt more effectively in subsequent episodes. The meta-update process is defined as:

$$\theta \leftarrow \theta - \beta \textstyle\sum_i \nabla_\theta \, \mathcal{L}_{Q_i}(\theta_i'), \qquad (3)$$

where β denotes the outer-loop learning rate and $\mathcal{L}_{Q_i}$ represents the loss on the query set.

This study evaluates two strategies for initializing model parameters: random initialization and chili-domain pre-trained initialization. In random initialization, the ResNet-50Plus backbone parameters are initialized randomly before the episodic meta-learning process begins. Meanwhile, chili-domain pretrained initialization uses the weights obtained from supervised pretraining on the chili leaf curl disease dataset as the initial weights before the FOMAML process begins.

2.5 Experimental Setup

All experiments were conducted using a Kaggle Notebook in a Linux (Ubuntu) environment with an NVIDIA Tesla P100 GPU featuring 16 GB of VRAM. The model was implemented using Python 3.10 with the assistance of PyTorch, TorchVision, and Scikit-learn libraries. All images in the dataset were first resized to 224×224 pixels before being processed by the model. The embedding dimension in the meta-learning framework was set to 128 for all test scenarios. To maintain consistency in experimental results and improve reproducibility, the training and evaluation processes were performed using several random seed settings in the range of 42 to 46. The complete episodic meta-learning configuration used in this study is presented in Table 1.

Table 1. Meta-Learning Experimental Setup

Parameter	Configuration
Few-Shot Setting	3-way
Shot Variations	1-shot, 5-shot, 10-shot
Query Samples	5 per class
Epoch	10
Training Episodes	100

Meta-Test Episodes	50
Learning Rate	1×10^{-4}
Inner Learning Rate	1×10^{-2}

Source : Research results (2026)

2.6 Evaluation Metrics

The evaluation metrics used in this study are accuracy, precision, recall, and F1-score, which are calculated based on the values in the confusion matrix (Rachmad et al., 2023), defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$Precision = \frac{TP}{TP + FP} \quad (5)$$

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

$$F1\text{-}Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

where TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative.

In addition to evaluating classification performance, this study also analyses computational aspects to assess the computational trade-offs in the meta-learning framework. The computational evaluation was conducted using metrics such as training time, average episode time, GPU memory usage, and model convergence behaviour during the episodic training process.

RESULTS AND DISCUSSION

4.1 Classification Performance Analysis

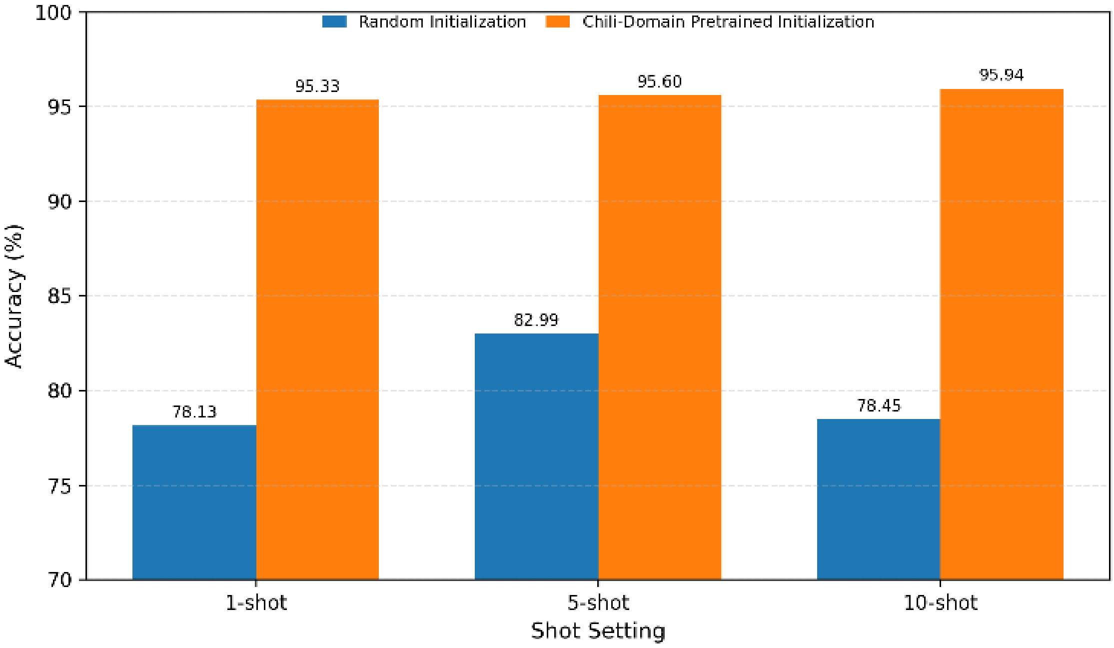
The results of the classification tests in the few-shot learning scenario are shown in Table 2. The evaluation was conducted using the accuracy, precision, recall, and F1-score metrics to compare the performance of random initialization and chili-domain pre-trained initialization in the FOMAML framework.

Table 2. Classification Performance under Different Initialization Strategies

Initialization	Shot	Accuracy	Precision	Recall	F1-Score
Random Initialization	1-shot	78.13 ± 0.86	0.79 ± 0.01	0.78 ± 0.01	0.78 ± 0.01
	5-shot	82.99 ± 3.04	0.83 ± 0.03	0.83 ± 0.03	0.83 ± 0.03
	10-shot	78.45 ± 1.90	0.78 ± 0.02	0.78 ± 0.02	0.78 ± 0.02
Chili domain pretrained initialization	1-shot	95.33 ± 0.95	0.95 ± 0.01	0.95 ± 0.01	0.95 ± 0.01
	5-shot	95.60 ± 0.56	0.96 ± 0.01	0.96 ± 0.01	0.96 ± 0.01
	10-shot	**95.94** ± 0.99	0.96 ± 0.01	0.96 ± 0.01	0.96 ± 0.01

Source : Research results (2026)

Based on Table 2, chili-domain pretrained initialization yields higher classification performance than random initialization across all testing scenarios. In the 1-shot scenario, the achieved accuracy reached 95.33%, whereas random initialization only reached 78.13%. The same pattern is also observed in the 5-shot and 10-shot scenarios, with accuracies of 95.60% and 95.94%, respectively, while random initialization achieved 82.99% and 78.45%. Performance differences are not only evident in accuracy but also in the precision, recall, and F1-score metrics. Chili-domain pretrained initialization maintains Precision, Recall, and F1-Score values within the range of 0.95–0.96 across all testing configurations, whereas random initialization remains within the range of 0.78–0.83. These results indicate that using initial weights derived from the chili leaf disease domain helps the model build better feature representations, enabling more effective adaptation to new tasks. To clarify the performance differences between the two initialization strategies, a visualization of accuracy for each shot configuration is shown in Figure 2.

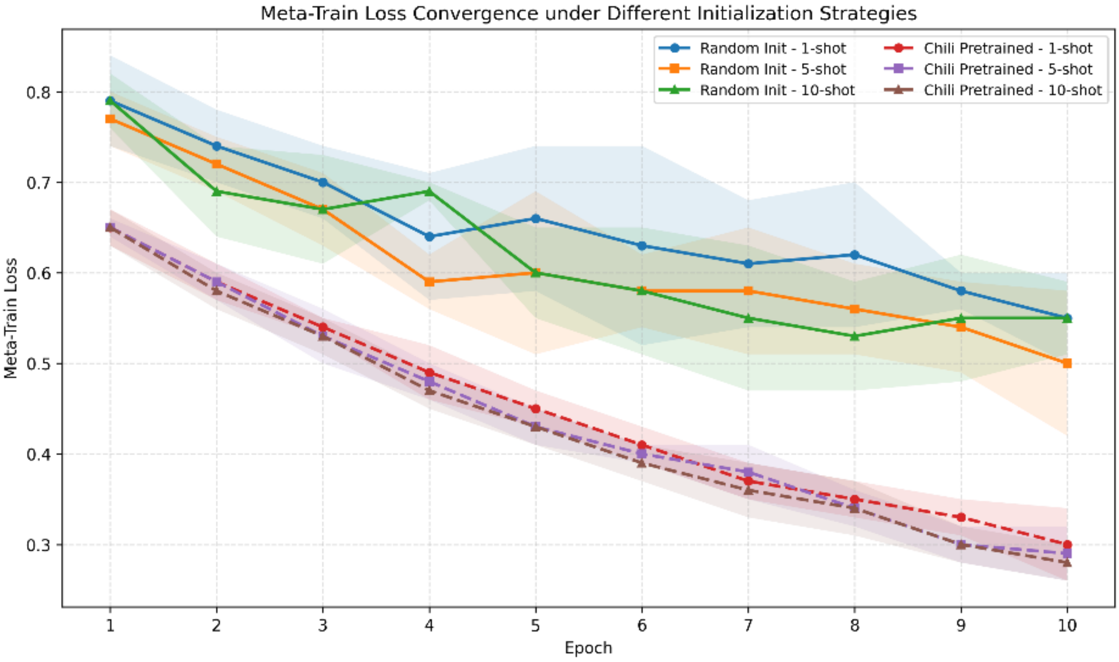


Source : Research results (2026)
Figure 2. Classification accuracy under different initialization strategies.

In Figure 2, the chili-domain pretrained initialization strategy consistently yields higher accuracy than random initialization across all shot configurations. The greatest accuracy improvement is observed in the 10-shot scenario, with a difference of 17.49%, followed by the 1-shot scenario at 17.20% and the 5-shot scenario at 12.61%. Meanwhile, with random initialization, an increase in the number of samples is not accompanied by an improvement in performance, as evidenced by the decrease in accuracy in the 10-shot scenario. In contrast, the chili-domain pretrained initialization shows a relatively consistent increase in accuracy from 1-shot to 10-shot.

4.2 Convergence Behavior Analysis

To observe the convergence behavior during the meta-training process, the average meta-training loss for each epoch is shown in Figure 3. Each data point represents the average loss calculated from 100 training episodes within a single epoch. Both initialization strategies exhibit a decrease in loss during the early stages of training, but differences in the optimization patterns begin to emerge after the first few epochs. With random initialization, the loss reduction is accompanied by greater fluctuations, particularly in the 1-shot and 10-shot scenarios, so the loss values do not always decrease consistently until the end of training. In contrast, a chili-domain pretrained initialization produces a more stable loss reduction pattern across all shot configurations. By the 10th epoch, the meta-train loss for chili-domain pretrained initialization was in the range of 0.28–0.30, while that for random initialization remained in the range of 0.50–0.55. Quantitatively, the average meta-train loss for chili-domain pretrained initialization reached 0.45, 0.44, and 0.43 in the 1-shot, 5-shot, and 10-shot scenarios, respectively—lower than that of random initialization, which reached 0.65, 0.61, and 0.62. Loss variability during training was also lower, with a standard deviation of 0.02 across all shot configurations, whereas random initialization ranged from 0.05 to 0.06. These results indicate that the chili-domain pretrained initialization model produces a more stable optimization process, as evidenced by lower average loss and lower loss variability compared to random initialization.



Source : Research results (2026)
Figure 3. Convergence behavior based on epoch-averaged meta-train loss under different initialization strategies.

4.3 Computational Trade-Off Analysis

In addition to evaluating classification performance, this study also analyzes computational aspects to examine the impact of initialization strategies on the efficiency of the meta-learning process. The analysis was conducted using several computational metrics, namely training time, average episode time, and GPU memory usage. This evaluation was conducted to determine whether the improvement in classification performance achieved through chili-domain pretrained initialization is accompanied by a significant increase in computational cost or not.

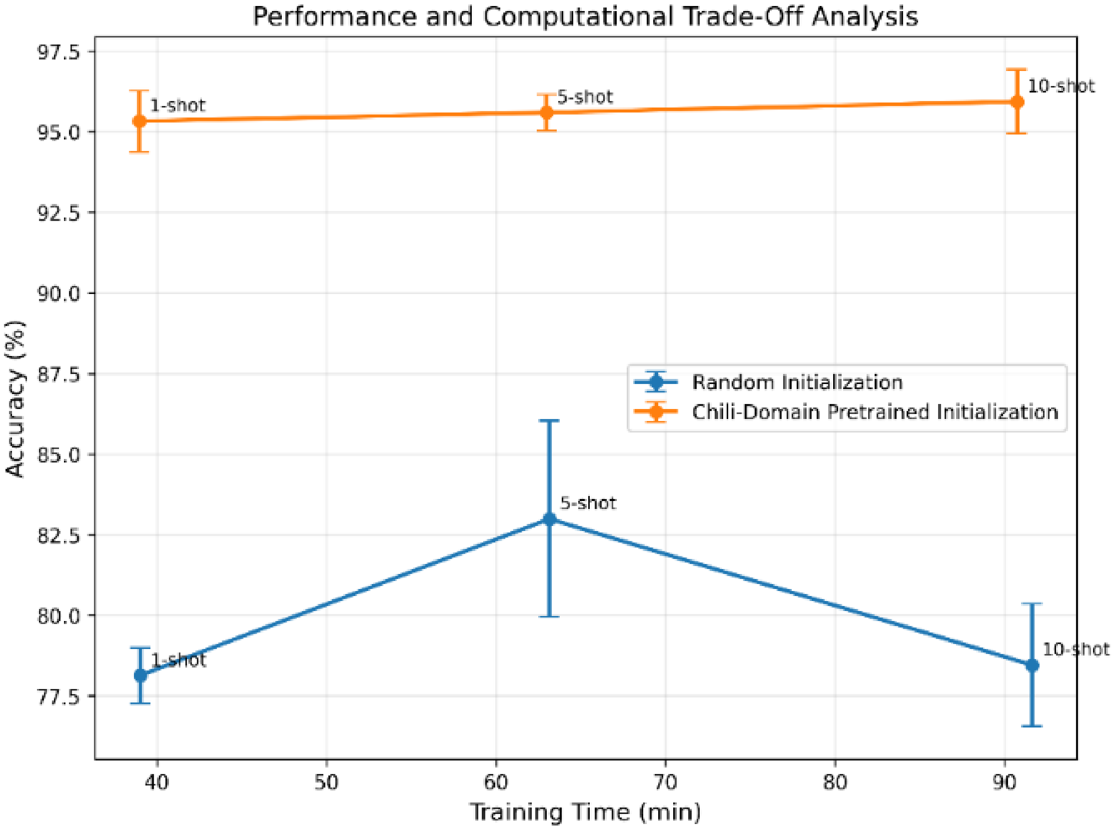
Table 3 shows the results of the computational performance evaluation across all few-shot learning scenarios based on the average of experiments using random seeds 42-46. In general, chili-domain pretrained initialization yields slightly lower training time, average episode time, and GPU memory usage compared to random initialization in nearly all test scenarios. Although the resulting difference in computational cost is not very large, chili-domain pretrained initialization has previously demonstrated a much higher improvement in classification performance compared to random initialization.

Table 3. Computational Performance under Different Initialization Strategies

Initialization	Shot	Training Time (min)	Avg Episode Time (s)	GPU Memory (GB)
Random Initialization	1-shot	39.024	1.17066	6.9706
	5-shot	63.158	1.88202	3.9832
	10-shot	91.628	2.74888	6.3258
Chili domain pretrained initialization	1-shot	38.968	1.169	2.7518
	5-shot	62.988	1.88968	3.946
	10-shot	90.752	2.73864	6.3796

Source : Research results (2026)

Figure 4 illustrates the relationship between classification performance and computational cost for the two initialization strategies. Domain-specific pretrained initialization consistently yields higher accuracy than random initialization across all few-shot learning scenarios with relatively similar training times. In contrast, the performance of random initialization is more variable, particularly in the 10-shot scenario, even as training time increases. These results indicate that domain-specific pretrained initialization can enhance the effectiveness of the FOMAML adaptation process without adding significant computational overhead.



Source : Research results (2026)

Figure 4. Accuracy versus training time under different initialization strategies

4.4 Stability Analysis

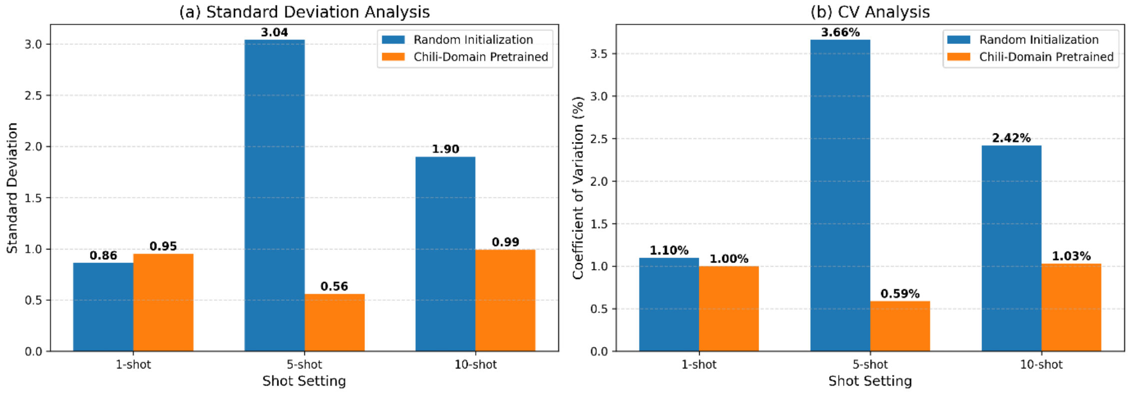
Based on the results in Table 4, chili-domain pretrained initialization yields better performance stability than random initialization across all few-shot learning scenarios. Stability analysis was conducted using the mean accuracy, Std, and CV values obtained from the average of experiments using random seeds 42–46. With random initialization, an increase in the number of shots was not accompanied by a consistent performance pattern. Accuracy increased in the 5-shot scenario but declined again in the 10-shot scenario, with relatively high Std and CV values. In contrast, chili-domain pretrained initialization maintained high accuracy with lower Std and CV values across all test configurations. The CV values decreased from 1.10% to 1% in the 1-shot scenario, from 3.66% to 0.59% in the 5-shot scenario, and from 2.42% to 1.03% in the 10-shot scenario. These reductions are equivalent to 9.09%, 83.88%, and 57.44%, respectively, indicating that performance variation across seeds has decreased.

Table 4. Performance stability analysis under different initialization strategies

Initialization	Shot	Mean+Std	CV
Random Initialization	1-shot	78.13 ± 0.86	1.10%
	5-shot	82.99 ± 3.04	3.66%
	10-shot	78.45 ± 1.90	2.42%
Chili domain pretrained initialization	1-shot	95.33 ± 0.95	1.00%
	5-shot	95.60 ± 0.56	0.59%
	10-shot	95.94 ± 0.99	1.03%

Source : Research results (2026)

The trend in performance stability shown in Table 4 is further visualized in Figure 5. In Figure 5(a), the differences in standard deviation values among the initialization strategies become increasingly apparent in the 5-shot and 10-shot scenarios. Meanwhile, Figure 5(b) shows that chili-domain-pretrained initialization maintains a low CV value across all testing scenarios.



Source : Research results (2026)

Figure 5. Stability analysis based on standard deviation and coefficient of variation across different shot settings

4.5 Comparison with Previous Studies

As shown in Table 5, several previous studies have explored initialization strategies in meta-learning and highlight differences in the methods, testing scenarios, and initialization approaches used. This comparison aims to qualitatively overview the studies' characteristics rather than directly compare their performance.

Tabel 5. Comparison with Previous Studies

Author	Method	Initialization Strategy	Setting	Accuracy (%)
(Sun et al., 2019)	MTL	Pretrained DNN Weights	5-way 5-shot	75.50
(Sun et al., 2019)	AVIATOR	Task-Adaptive Initialization	5-way 5-shot	68.37
(Chijiwa et al., 2022)	Meta-ticket	Learned Subnetwork Initialization	5-way 5-shot	74.23
(Y. Chen et al., 2021)	Meta-Baseline	Whole-Classification Pretraining	5-way 5-shot	80.02
This Study	FOMAML	Chili-Domain Pretrained Initialization	3-way 10-shot	95.94

Source : Research results (2026)

Overall, the results in Tables 2-4 show that the quality of the initialization affects the performance of few-shot learning. Based on Table 2, chili-domain pretrained initialization achieved accuracies of 95.33%, 95.60%, and 95.94% in the 1-shot, 5-shot, and 10-shot scenarios, representing increases of 17.20, 12.61, and 17.49 percentage points, respectively, compared to random initialization. In terms of stability, as shown in Table 4, chili-domain pretrained initialization yields CV values of 1.00%, 0.59%, and 1.03%, which are lower than those of random initialization, which reach 1.10%, 3.66%, and 2.42%. The reduction in CV reached 83.88% in the 5-shot scenario and 57.44% in the 10-shot scenario, indicating that performance across seeds became more consistent.

Also, as seen in Figure 3, the final meta-train loss for chili-domain pretrained initialization was between 0.28 and 0.30, while the final meta-train loss for random initialization was between 0.50 and 0.55. This shows that the convergence process for chili-domain pretrained initialization is more effective. Based on Table 3, the training time for chili-domain pretrained initialization ranged from 38.968 to 90.752 minutes, slightly lower than that of random initialization, which ranged from 39.024 to 91.628 minutes, with a maximum difference of 0.876 minutes. The average episode time is also relatively identical across all test configurations, ranging from approximately 1.17 to 2.74 seconds per episode.

In terms of GPU memory usage, chili-domain pretrained initialization requires less computational resources in the 1-shot and 5-shot scenarios compared to random initialization. In the 1-shot scenario, GPU memory usage decreased from 6.9706 GB to 2.7518 GB, a reduction of 60.52%. In the 5-shot scenario, memory usage was also slightly lower, dropping from 3.9832 GB to 3.9460 GB—a decrease of 0.93%. Meanwhile, in the 10-shot scenario, there was a minimal increase in memory usage, from 6.3258 GB to 6.3796 GB—just 0.85%. This increase is relatively insignificant and is likely influenced by variations in GPU memory allocation during the training process, given that the model architecture, number of parameters, and training configuration used in both initialization strategies remained the same. These results indicate that improvements in classification performance and learning stability can be achieved with computational requirements that remain comparable to those of random initialization.

CONCLUSION

This study evaluates the impact of initial weight initialization strategies on the performance, learning stability, convergence behavior, and computational requirements of FOMAML in the few-shot classification of chili leaf curl disease. The results show that using a chili-domain pretrained initialization consistently improves accuracy by 12.61–17.49 percentage points compared to random initialization. In terms of stability, chili-domain pretrained initialization yields lower CV values across all test configurations, with the largest reduction reaching 83.88% in the 5-shot scenario. Furthermore, the final meta-train loss for chili-domain pretrained initialization ranged from 0.28 to 0.30, which is lower than that of random initialization, which ranged from 0.50 to 0.55. These improvements in performance and stability were achieved with computational requirements comparable to those of random initialization. These results indicate that initial feature representations relevant to the target domain play a crucial role in enhancing the adaptability of FOMAML under data-scarce conditions. This study still has several limitations; the evaluation was conducted solely on a 3-way classification of chili leaf curl disease using the ResNet-50Plus backbone and the FOMAML framework. Furthermore, the impact of domain-specific pretrained initialization has not yet been evaluated on different backbone architectures. Therefore, future research could examine the effectiveness of this approach on other backbones and feature enhancement mechanisms to assess its generalization capabilities across various few-shot learning scenarios.

ACKNOWLEDGEMENTS

The author acknowledge the use of AI tool solely for language editing and manuscript preparation, including grammar correction and improvement of writing clarity. The AI tool was not used for data collection, data analysis, result interpretation, or scientific decision-making. All datasets, experiments, analyses, and conclusions reported in this study were conducted and validated by the author, who assume full responsibility for the content of this manuscript.

REFERENCES

Bansal, T., Alzubi, S., Wang, T., & Andrew, J. L. (2022). Meta-Adapters : Parameter Efficient Few-shot Fine-tuning through Meta-Learning. *Proceedings of the First International Conference on Automated Machine Learning*, 1–18.

Chen, X., & Lin, P. (2024). Few-Shot Image Classification Based on Multimodal Information Fusion. *2024 International Conference on Image Processing, Computer Vision and Machine Learning (ICICML)*, *Icicml*, 657–660. https://doi.org/10.1109/ICICML63543.2024.10957775

Chen, Y., Liu, Z., Xu, H., Darrell, T., & Wang, X. (2021). Meta-Baseline : Exploring Simple Meta-Learning for Few-Shot Learning. *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 9062–9071.

Chijiwa, D., Amaguchi, S., Kumagai, A., & Ida, Y. (2022). Meta-ticket : Finding optimal subnetworks for few-shot learning within randomly initialized neural networks. *Conference on Neural Information Processing Systems*, *NeurIPS*, 1–14.

Huang, Y., Qian, K., & Yu, Z. (2023). Learning a Better Initialization for Soft Prompts via Meta-Learning. *Proceedings of the 13th International Joint Conference on Natural Language Processing and the 3rd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics*, *2*, 67–75.

Kleruk, Y. A., Beja, H. D., & Wahyuni, Y. (2024). Identifikasi Hama Dan Penyakit Serta Pengendalian Pada Tanaman Cabai (Capsicum Annuum L .) Di Kelompok Tani Sinar Bahagia Desa Nitakloang Kabupaten Sikka. *PUCUK : Jurnal Ilmu Tanaman*, *4*(2).

Liu, X. (2026). Meta-Learning Enhanced Few-Shot Image Classification : A Hybrid Framework Combining Prototypical Networks And Contrastive Learning. *Journal OfApplied Science and Engineering*, *31*.

Nichol, A., Achiam, J., & Schulman, J. (n.d.). *On First-Order Meta-Learning Algorithms*. 1–15.

Padshetty, S., & Ambika. (2023). Leaky ReLU-ResNet for Plant Leaf Disease Detection: A Deep Learning Approach. *RAiSE-2023*, 39. https://doi.org/10.3390/engproc2023059039

Rachmad, A., Fuad, M., & Rochman, E. M. S. (2023). Convolutional Neural Network-Based Classification Model of Corn Leaf Disease. *Mathematical Modelling of Engineering Problems*, *10*(2), 530–536. https://doi.org/10.18280/mmep.100220

Ramirez-alonso, G., Gaxiola, F., Manzo-martinez, A., Cornejo, R., & Lopez-flores, D. R. (2025). A Comparative Evaluation of Meta-Learning Models for Few-Shot Chest X-Ray Disease Classification. *Diagnostics*, *15*(18), 1–22. https://doi.org/https://www.mdpi.com/2075-4418/15/18/2404

Salehin, I., & Kang, D. K. (2023). A Review on Dropout Regularization Approaches for Deep Neural Networks within the Scholarly Domain. *Electronics (Switzerland)*, *12*(14). https://doi.org/10.3390/electronics12143106

Sun, Q., Liu, Y., Chua, T.-S., & Schiele, B. (2019). Meta-Transfer Learning for Few-Shot Learning. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 403–412.

Syukur, M. (2018). *8 Kiat Sukses Panen Cabai Sepanjang Musim "Penghujan dan Kemarau."* PT AgroMedia Pustaka.

Trigka, M., & Dritsas, E. (2025). A Comprehensive Survey of Deep Learning Approaches in Image Processing. *Sensors*, *25*(2). https://doi.org/https://doi.org/10.3390/s25020531

Xu, J., Li, Z., Du, B., Zhang, M., & Liu, J. (2020). Reluplex made more practical: Leaky ReLU. *Proceedings -*

IEEE Symposium on Computers and Communications, *2020-July*. https://doi.org/10.1109/ISCC50000.2020.9219587

Zhang, J., Yu, W., Yang, X., & Deng, F. (2019). Few-shot learning for ear recognition. *Proceedings of the 2019 International Conference on Image, Video and Signal Processing*, 50–54.

Zhu, Z. L., Yadav, V., Afzal, Z., & Tsatsaronis, G. (2022). Few-shot initializing of Active Learner via Meta-Learning. *Findings of the Association for Computational Linguistics: EMNLP*, 1117–1133.