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Revolutionizing Plant Phenotyping With AI & Harnessing AI For Digital Phenomics From Data Collection To Actionable Insights

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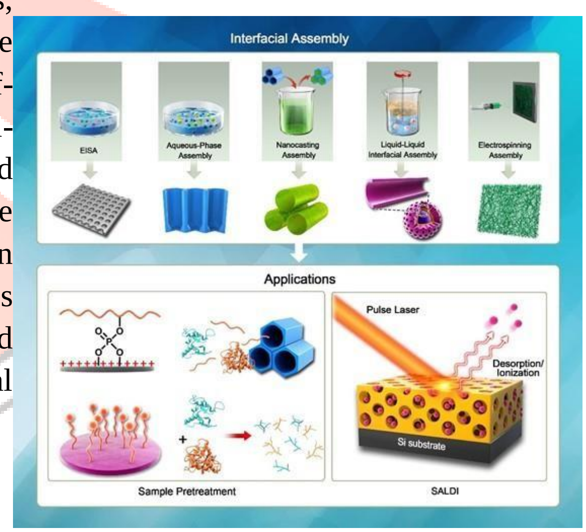
Abstract: Artificial Intelligence (AI) is transforming many fields, and plant digital phenomics is no exception. The intersection of AI and plant phenomics— the study of plant traits and their variation— is paving the way for significant advancements in agriculture, ecology, and plant sciences. Here's a primer on how AI is shaping this field, focusing on the journey from data to insights: Plant digital phenomics involves the collection and analysis of detailed, quantitative data on plant traits using digital tools. These traits can include growth rates, leaf shape, flower color, and stress responses. The goal is to understand the genetic, environmental, and physiological factors that influence plant development and performance. Efficient image recognition is important in crop and forest management. However, it faces many challenges, such as the large number of plant species and diseases, the variability of plant appearance, and the scarcity of labeled data for training. To address this issue, we modified a SOTA Cross-Domain Few-shot Learning (CDFSL) method based on prototypical networks and attention mechanisms. We employed attention mechanisms to perform feature extraction and prototype generation by focusing on the most relevant parts of the images, then used prototypical networks to learn the prototype of each category and classify new instances. Finally, we demonstrated the effectiveness of the modified CDFSL method on several plant and disease recognition datasets. The results showed that the modified pipeline was able to recognize several cross-domain datasets using generic representations, and achieved up to 97.85% and 95.06% classification accuracy on datasets with the same and different domains, respectively. In addition, we visualized the experimental results, demonstrating the model's stable transfer capability between datasets and the model's high visual correlation with plant and disease biological characteristics. Moreover, by extending the classes ofdifferent semantics within the training dataset, our model can be generalized to other domains, which implies broad applicability.

Keywords: AI**,** image characteristics ;ML, CDFL; learning transformation; bark images database.

1. **Introduction** Image recognition technology based on artificial intelligence can provide scientific decision-making basis and optimization solutions by analyzing and processing images. This technology is of great importance to crop and forest management. However, its application faces many challenges, such as difficulties in data collection, the large number of classes, the variability of plant appearance, the difficulty of lesion detection, the in invasion of new pathogens, and the impact of climate change [1]. Machine learning has been widely used in various agriculture and plant science domains [2], such as plant breeding [3], in vitro culture [4], stress phenotyping [5], stress physiology [6], plant system biology [7], plant identification [8] plant genetic engineering [9], and pathogen identification [10]. However, traditional machine learning methods have

shortcomings in feature extraction, model selection, and data processing, which make it difficult to learn high-dimensional, non-linear, and unstructured data [11]. With the rapid development of computer science, deep learning began to appear. Deep learning refers to the use of deep neural networks to perform operations, such as automatic feature extraction and data classification, to achieve a high-level understanding and representation of features [12–14]. In agriculture and forestry, deep learning also provides effective technical methods to solve various computer visual tasks, such as plant pest and disease detection,forest inventory, plant classification and segmentation, and real-time monitoring of crop and forest resources, etc. On the other hand, the applications of FSL in forestry are fewer, and most of the studies are based on remote sensing images for classification, such as hyperspectral image classification of tree species . These studies demonstrate the effectiveness and the potential of FSL methods for plant and disease recognition. However, most previous research has focused on image recognition of species within a single domain. While these studies have contributed significantly to our understanding of specific agricultural or forestry applications, there is a noticeable gap in research that extends beyond these single domains. In real-world scenarios, plant and disease recognition often requires cross-domain adaptation, where the source domain (the labeled training set) and the target domain (the unlabeled test set) have different distributions. This poses a great challenge for traditional FSL methods, which may suffer from domain shift and over-fitting problems. Therefore, we plan to implement a Cross-Domain Few-shot Learning (CDFSL) image classification model for tree species classification and recognition of common plant and crop diseases (e.g., phytophthora, anthracnose, etc.). By extending our research across domains, we can obtain a more comprehensive understanding of the capabilities and limitations of FSL in these domains, ultimately providing agricultural and forestry operators with more functional and effective solutions. PMF pipeline achieved state-of-the-art results on various CDFSL benchmarks, such as mini-ImageNet and Meta-Dataset .In our study, we adapted and optimized the PMFeline to make it more suitable for plant and disease recognition. To test the performance of the tuned pipeline in different domains, we meta-trained and fine-tuned several models using BarkNetV3 and BarkVN50 datasets, respectively, and evaluated and visualized the effectiveness of the models on several datasets in the same and different domains.



2. Materials and Methods:- AI, particularly machine learning (ML) and computer vision, is revolutionizing plant phenomics by enhancing data collection, analysis, and interpretation. Here's how AI fits into the process:

Figure1

A. Data Collection

1. **High-Throughput Phenotyping**: AI-powered systems can automate the collection of large volumes of plant data. Drones, robots, and imaging technologies capture detailed images and sensor data from crops and plant specimens.
2. **Image Analysis**: Computer vision algorithms process images to extract features such as leaf area, color, and texture. This high-resolution data helps in assessing plant health, growth, and other traits.

B. Data Analysis

1. **Pattern Recognition**: Machine learning models identify patterns and correlations in large datasets. For example, AI can detect subtle differences between healthy and stressed plants or predict growth outcomes based on environmental conditions.
2. **Predictive Modeling**: AI algorithms can predict future plant behaviors or traits based on historical data. This helps in forecasting crop yields, assessing plant responses to various stressors, and optimizing breeding programs.

3. **Trait Mapping**: AI helps in associating specific traits with genetic markers. This trait-genotype mapping accelerates the identification of beneficial traits for breeding programs.

C. Data Interpretation

1. **Insights Extraction**: Advanced analytics and AI-driven tools provide actionable insights from complex datasets. These insights can guide decisions on plant management, breeding strategies, and resource allocation.
2. **Visualization**: AI-powered visualization tools help in interpreting and communicating data effectively. Interactive charts, heatmaps, and 3D models make it easier to understand complex relationships and trends.

3. Key Technologies and Techniques

1. **Deep Learning**: Neural networks, especially convolutional neural networks (CNNs), are used for analyzing plant images and extracting detailed features.
2. **Natural Language Processing (NLP)**: NLP tools can mine literature and databases for relevant information, aiding in the synthesis of knowledge across studies.
3. **Robotics and Automation**: Robots equipped with AI can perform tasks like planting, monitoring, and harvesting, increasing efficiency and precision.
4. **Big Data Analytics**: AI techniques handle and analyze massive datasets generated from phenotyping platforms, providing insights that are not apparent from smaller datasets.

Database The dataset for FSL is somewhat different from the common image classification task in deep learning. Traditional deep learning methods usually require a large amount of labeled data to train the model, while FSL aims to learn new categories from a few examples (usually no more than 10). Therefore, the datasets for FSL typically have the following characteristics: (1) the datasets contain multiple different data sources; (2) to simulate encountering a new classification situation in real work scenarios, there is no overlapping category in each subset; (3) the dataset provides test tasks of different difficulties. We show an example of an FSL image classification dataset, as shown in Figure 1. To test the performance of the tuned pipeline in different domains, we meta-trained and fine-tuned several models using BarkNetV3 and BarkVN50 datasets, respectively, and evaluated and visualized the effectiveness of the models on several datasets in the same and different domains. The research objectives include: (1) compare the performance of PMF of various frameworks on several novel datasets; (2) visualize the visual attractiveness of networks and analyze the inner workings of the mechanism; (3) analyze the generalization ability of PMF to the same and different domain datasets; (4) discuss the learning ability and practical application value of PMF for plant and disease recognition.

Results and Analysis Meta-Train In our experiments, DINO-ViT shows the best performance when meta-training on both bark datasets. As shown in Table 1

Domain	Dataset	Collaborators	Categories	Images	Meta-Dataset
Tree species	BarkNJ	Ours	21	24,616	20 × 600
classification	BarkNetV3	Ours	41	13,681	20 × 600
	BarkVN50	Truong Hoang (2017)	51	23,000	40 × 600
	BarkKR	Tae Kyung et al. (2022)	55	5578	50 × 80
Leaf Diseases	PlantVillage	Hughes et al. (2015)	42	6918	25 × 50
Crop Diseases	Agricultural Diseases	Xulang Guan et al. (2021)	61	62,484	38 × 600
Flower Identification	Flowers 102	Nilsback et al. (2008)	103	36,258	55 × 100
mini-ImageNet	mini-ImageNet	Vinyals et al. (2016)	101	8189	85 × 40
Multi-Classification	Full-Dataset	Hu et al. (2022)	8 datasets	60,000	100 × 600

In machine learning, accuracy and loss are key metrics for assessing how effectively a model makes predictions. When examining classification accuracy, the BarkVN50 model consistently outperforms others across various test datasets, both in 1-shot and 5-shot scenarios. Following closely are the mini-ImageNet and BarkNetV3 models, which show slightly lower accuracy—approximately 2–3% less than BarkVN50. This small difference suggests that these models perform comparably well when tested on related domains that share features and classes with their training data.Conversely, the Full-Dataset model struggles with out-of-domain datasets, with the exception of the Flowers dataset. This indicates that merely aggregating diverse source domains into one dataset does not enhance the performance of Conditional Deep Few-Shot Learning (CDFSL) and may even lead to degraded results due to overfitting or conflicting information.In terms of loss metrics, while the BarkVN50 model is well-aligned with its training data, it may struggle to generalize to datasets that differ significantly, particularly those outside its original domain. The mini-ImageNet and Full-Dataset models, though not as adept at predicting bark images, demonstrate superior performance on certain agricultural datasets. Notably, the BarkNetV3 model exhibits lower loss across most test datasets, indicating a robust fit despite varying conditions. The effectiveness of machine learning models in tackling new tasks is closely linked to the separation observed within the distribution of pseudo-classes. A greater distinction among pseudo-classes enhances the model's adaptability to novel tasks.Results indicate that the **BarkVN50 model** achieved strong classification results across most datasets, exhibiting significant segmentation between pseudo-classes. However, its performance declined on the Agricultural Disease dataset. In contrast, the **BarkNetV3 model** ability more stable and adaptable in transfer learning compared to BarkVN50. The **mini-ImageNet** and **Full-Dataset models** performed slightly worse than the other two models. This may be attributed to their pre-training datasets, which likely lacked essential features common in agricultural and forestry images, leading to a weaker ability to distinguish between pseudo-classes. Consequently, their applicability in plant and disease recognition was somewhat limited. However, both models excelled in processing cross- domain datasets like PlantVillage and Flowers, suggesting they may be better suited forfew-shot learning (FSL)tasks with more pronounced distinguishing features.To further illustrate the effectiveness of our trained models, we employed **Smooth Grad CAM++** to visualize the recognition process, as shown in Figure 2. The visualizations revealed a strong correlation between areas of interest and the locations of phenotypic plant diseases, indicating that the model focused on regions exhibiting symptoms such as spots, lesions, discoloration, or deformation.Overall, while the BarkVN50 model excels in certain contexts, the BarkNetV3 model shows greater adaptability, and the mini-ImageNet and Full-Dataset models possess strengths in cross- domain tasks despite some limitations in specific applications.Figure 2.We found that visual attractiveness was highly correlated with the locations of phenotypic plant diseases that occurred biologically, indicating that the model tended to focus more on regions where the plant displayed symptoms of diseases, such as spots, lesions, discoloration, or deformation. Task-specific Fine-tune pseudo-labeling c

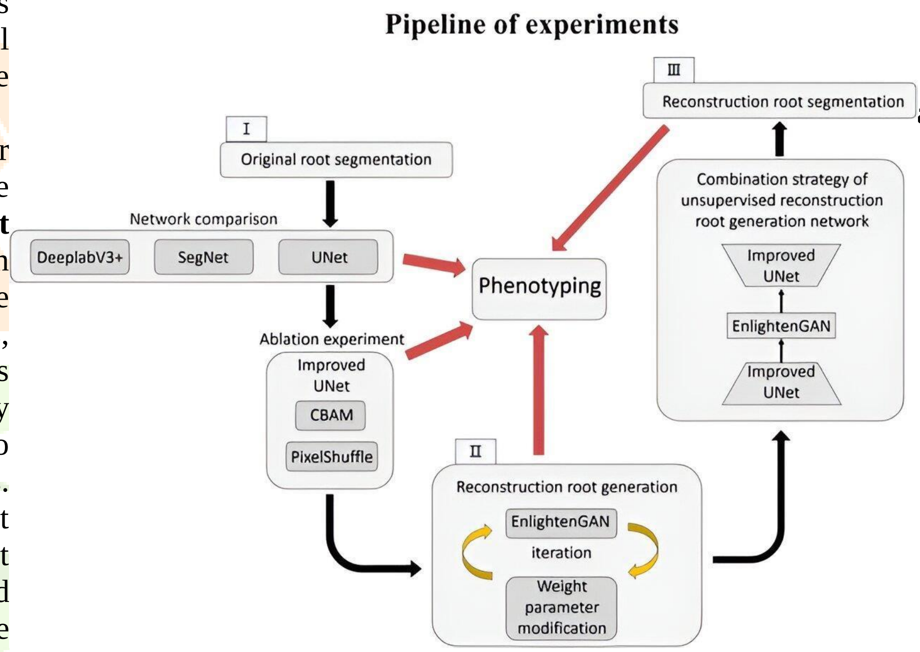


Figure2

lassification chart (5-shot). The caption on the left indicates the dataset used for training, and the caption above the image indicates the dataset used for testing, both using the backbone DINO-ViT. Figure 3. Task-specific Fine-tune pseudo-labeling classification chart (5-shot). The caption on the left indicates the dataset used for training, and the caption above the image indicates the dataset used for testing, both using the backbone DINO-ViT. In the training process of FSL image classification models, the pursuit of enhanced accuracy often leads to various training strategies. However, these strategies may not always improve the performance of the models and may even cause over-training and degradation. To systematically evaluate the consequences of over-training on FSL learning models, we conducted a deliberate

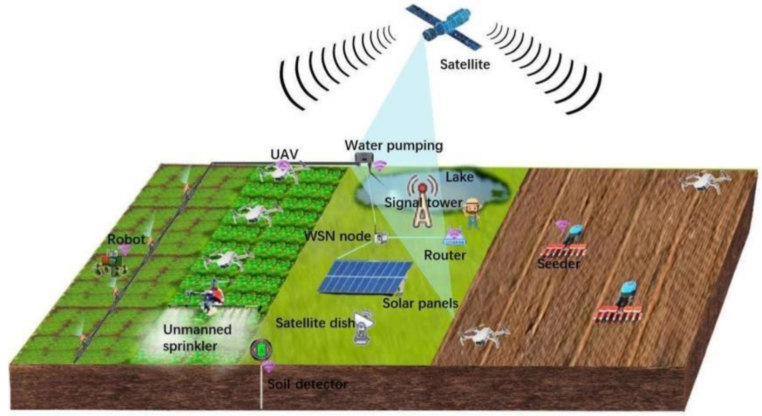


Figure3

experiment by extending the training duration to 30 and 50 epochs, corresponding to episode numbers of 200 and 500, respectively. While this extended training procedure yielded a modest increase in accuracy of about 2.5 percent in our experiments, it also revealed a critical trade-off. Despite the numerical improvement in accuracy, the predictive ability of the model trained in this way showed a significant decline, as visually depicted in Figure 4. It provides a visual representation of the performance degradation observed in the BarkNetV3 and BarkVN50 models due to over-training. Notably, these t-SNE plots reveal significant confusion between pseudo-classes, reflecting a compromised ability of the model to discriminate between classes effectively. Furthermore, the loss values during over-training significantly increase, on average, about 20 percent higher than those of standard training methods. This phenomenon highlights the importance of careful model training strategies to avoid over-fitting, calls for a refined approach to balancing accuracy and generalization in FSL classification tasks, and demonstrates the effectiveness of our parameters setting. The image to the right of each input image is calculated by Smooth Grad CAM++, with the lesion portion highlighted by a heat map. These images were taken from publicly available disease images from the Chinese Academy of Agricultural Research and its affiliates. Moreover, we have specially selected some images with more complex backgrounds to confirm the effectiveness of our visual recognition process. In the training process of FSL image classification models, the pursuit of enhanced accuracy often leads to various training strategies.

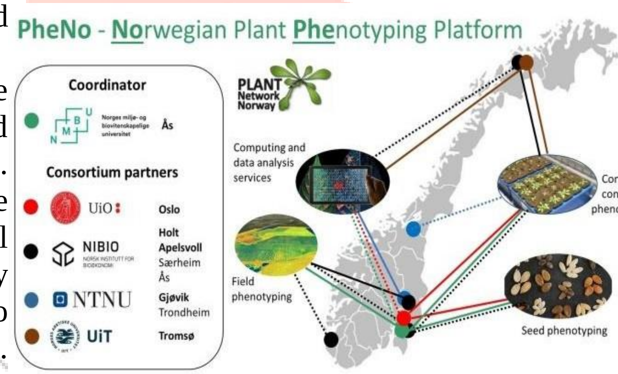


Figure 4

However, these strategies may not always improve the performance of the models and may even cause over-training and degradation. To systematically evaluate the consequences of over-training on FSL learning models, we conducted a deliberate experiment by extendingthe training duration to 30 and 50 epochs, corresponding to episode numbers of 200 and 500, respectively. While this extended training procedure yielded a modest increase in accuracy of about 2.5 percent in our experiments, it also revealed a critical trade-off. Despite the numerical improvement in accuracy, the predictive ability of the model trained in this way showed a significant decline, as visually depicted in Figure 5. Figure 5 provides a visual representation of the performance degradation observed in the BarkNetV3 and BarkVN50 models due to overtraining. Notably, these t-SNE plots reveal significant confusion between pseudo-classes, reflecting a compromised ability of the model to discriminate between classes effectively. Furthermore, the loss values during over-training significantly increase, on average, about 20 percent higher than those of standard training methods. This phenomenon highlights the importance of careful model training strategies to avoid over-fitting, calls for a refined approach to balancing accuracy and generalization in FSL classification tasks, and demonstrates the effectiveness of our parameters setting. Class activation mapping generated via Smooth Grad CAM++. The image to the right of each input image is calculated by Smooth Grad CAM++, with the lesion portion highlighted by a heat map. These images were taken from publicly available disease images from the Chinese Academy of Agricultural Research and its affiliates. Moreover, we have specially selected some images with more complex backgrounds to confirm the effectiveness of our visual recognition process. An example of over-training. The dataset and corresponding classification accuracy are labeled in ―alpha (beta%)‖ format at the top of the images. Loss indicates the percentage increase in the loss value of the model after over- training. The top and bottom columns of the image show the changes in the test results of the models before and after over-trained on the PlantVillage and Agricultural Disease datasets, respectively. 4. Discussion In this paper, we demonstrated that our meta-trained model could recognize unseen tree species and achieved high accuracy on various plant and disease datasets after finetuning. The results showed that the modified PMF pipeline was able to recognize several cross-domain datasets using generic representations and demonstrated high visual relevance. Moreover, by extending the classes of different semantics within the training dataset, our model can also be generalized to other domains, which implies broad applicability. Our experiments were meta-trained using four backbones, in which DINO-ViT had the highest training accuracy. We speculate that it is based on the following reasons: (1) The structure of DINO-ViT enables it to adapt to new domains and categories with only a small number of labeled examples, eliminating the need for extensive retraining or domain adaptation. (2) Unlike traditional self-supervised learning methods that require a large memory bank to store negative samples, DINO-ViT uses no contrastive loss or dictionary. This reduces the dependence on large-scale labeled data, which is impractical for FSL scenarios. (3) DINO-ViT captures global context and long-range dependencies more effectively than traditional convolutional neural networks such as ResNet. The performance of DeiT-ViT is slightly lower than DINO-ViT. This may be because DeiT-ViT typically requires a large amount of labeled data and a robust CNN teacher network to achieve good results. Thus, the backbone of using DeiT-ViT for FSL may face the problem of attentional collapse, where the model focuses on only a few tokens and ignores the others, thus hindering its ability to capture the global context. In addition, although DINO-ResNet combines DINO and ResNet, DINO-ResNet is still inferior to DINO-ViT in most downstream tasks. This may be because the model is constrained by the shortcomings of ResNet, such as limited receptive fields, spatial resolution, etc., and thus is less capable than DINO-ViT in terms of transfer ability. Notably, instead of optimizing parameters for training accuracy, our experiments emphasized the model's ability to generalize to both the test set and new datasets within the same and different domains. Figure 5 and Table 1 show the test results of the four FSL models through quantification and visualization, respectively. Since the dataset may lack some potential commonuse features of crop images, the BarkVN50 model can not process Agricultural Diseases efficiently, and the generated images are significantly

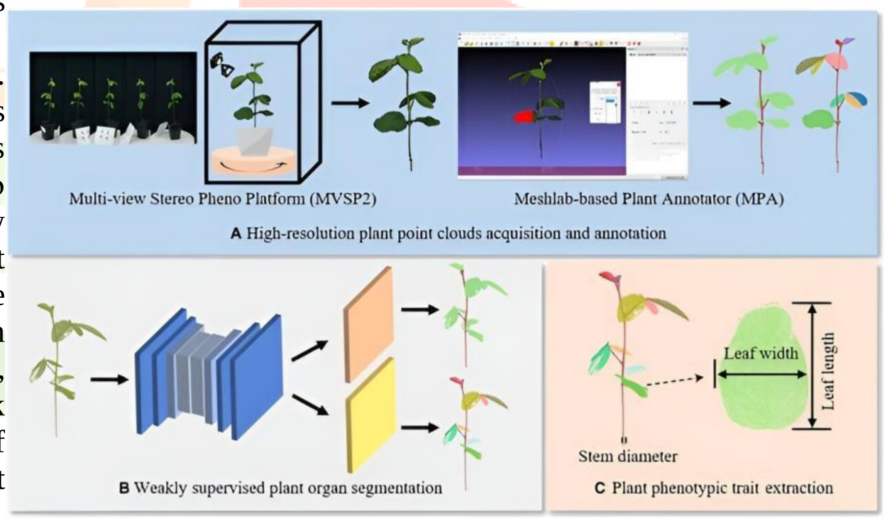


Figure 5

more chaotic than other types of datasets. Similarly, the mini-ImageNet and Full-Dataest models have poor classification capabilities for bark images due to the lack of some common- use features of tree bark. An example of over-training. The dataset and corresponding classification accuracy are labeled in ―alpha (beta%)‖ format at the top of the images. Loss indicates the percentage increase in the loss value of the model after over-training. The top and bottom columns of the image show the changes in the test results of the models before and after over-trained on the PlantVillage and Agricultural Disease datasets, respectively. 4. Discussion In this paper, we demonstrated that our meta-trained model could recognize unseen tree species and achieved high accuracy on various plant and disease datasets after finetuning. The results showed that the modified PMF pipeline was able to recognize several cross-domain datasets using generic representations and demonstrated high visual relevance. Moreover, by extending the classes of different semantics within the training dataset, our model can also be generalized to other domains, which implies broad applicability. Our experiments were meta-trained using four backbones, in which DINO- ViT had the highest training accuracy. We speculate that it is based on the following reasons: Plants 2023, 12, 3280 12 of 16 (1) The structure of DINO-ViT enables it to adapt to new domains and categories with only a small number of labeled examples, eliminating the need for extensive retraining or domain adaptation. (2) Unlike traditional self-supervised learning methods that require a large memory bank to store negative samples, DINO-ViT uses no contrastive loss or dictionary. This reduces the dependence on

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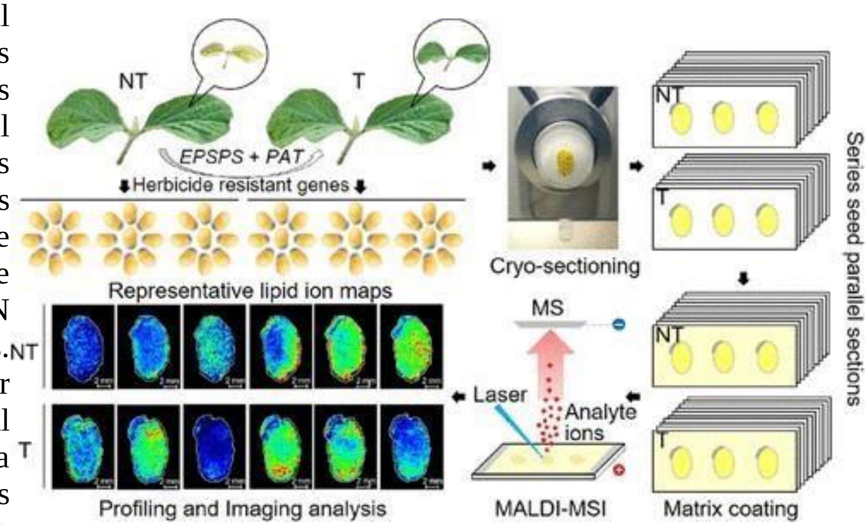

Figure 6

Since the dataset may lack some potential common-use features of crop images, the BarkVN50 model can not process Agricultural Diseases efficiently, and the generated images are significantly more chaotic than other types of datasets. Similarly, the mini-ImageNet and Full- Dataest models have poor classification capabilities for bark images due to the lack of some common-use features of tree bark images. However, the test result of these two models is relatively good for recognizing flowers and crop diseases. This may be because these datasets contain some images of flowers and leaves, so the trained model has a specific classification ability for such images. It is worth mentioning that the BarkNetV3 model achieves more consistent results both for predictions in the same domain (bark) and different domains (plants and diseases), with clear segmentation lines between the pseudo-classes. This indicates that the BarkNetV3 model may be more suitable for plant and disease recognition. Therefore, although mini-ImageNet is considered a more generalized dataset, it may not be as good as specialized datasets for classification in some specific domains. In particular, none of the four models tested well against BarkKR. This may be due to the small size of this dataset and the prevalent existence of images that contain some noise, such as buildings, roads, sidewalks, and cars, which causes the network to fail to capture the key representations. In addition, we analyzed the visual attractiveness of the network using Smooth Grad CAM++, and most lesion occurrence locations were highly correlated with hotspots. This could be because these regions have more distinctive features that can help the model discriminate between different classes of diseases. Alternatively, this could be because these regions have more salient features that can attract the model's attention. In either case, this finding suggests that the model

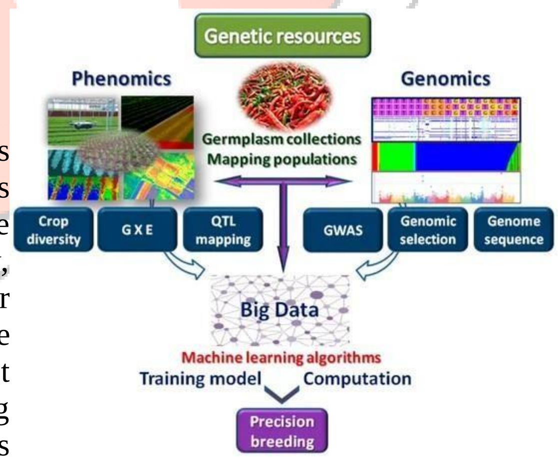

Figure 7

has learned some useful information about the occurrence and distribution of plant diseases from the training data, and is also suitable for practical field-based disease recognition applications. We believe that the success of the model is due to the fact that bark images have rich texture and color features that can help the model learn more discriminative and generic representations of plants. Compared to previous studies [30–40], our experiments achieved similar or even better results in terms of (1) the accuracy of prediction, despite being trained from bark, our tests on some public datasets (such as Agricultural Disease, PlantVillage, and Flowers) yielded promising results, with an average 5-shot accuracy of about 93%; (2) the ability of domain adaptation; while other methods may rely on more specific or domain-dependent features, our method can adapt to different regions, environments, and seasons more effectively than other methods; (3) the amount of data required (e.g., BarkVN50 has only 4000 images), reduce the cost and time for data collection and annotation; and (4) the transfer capability, as shown in the t-SNE visualization, the performance of the model is more stable in the transfer between domains. It is important to note that, unlike previous studies on FSL in agriculture, our work focuses on CDFSL. However, there are fewer studies in this area, so the comparisons with similar work may not be comprehensive. Nevertheless, the application value of CDFSL image classification in plant and disease recognition is considerably broad. When staff need to recognize a species that is not included in the dataset, they only need to input five labeled images as learning samples, and the fine- tuned model can be applied to the recognition of this new category. Using this technique, staff can collect images in the field and later upload them to the server for recognition.

Through optimizing data acquisition and image processing, our FSL model can meet the needs of fieldwork in terms of efficiency and accuracy. In addition, by accumulating a large amount of data and model optimization, the model's generalization performance can be continuously improved, and the model can be transferred to applications in different scenarios. Plant and disease recognition covers a wide range of species and symptoms, and our experiments are insufficient to generalize the features of all the classes. Thus, our method still has some drawbacks: (1) we did not test on a CDFSL image dataset covering multiple semantics classes in other domains, which limits the ability to use our trained models in specific domains; (2) our method may not be able to handle some complex or rare plants and diseases that require more specialized knowledge or features; (3) our method may not be able to capture some contextual or temporal information that may affect plant health or disease diagnosis; (4) the predictions or reasoning process in a transparent or interpretable way. In our future research, we will utilize prior knowledge from similar domains as auxiliary data to enhance both the data efficiency and generalization capability of our model, while also conducting further optimizations of the FSL algorithm. 5. Conclusions In this paper, we modified an effective pipeline of CDFSL for plant and disease recognition, and analyzed and visualized the model's performance on multiple datasets from the same and different domains. In our experiments, we exploited the rich texture and color features of bark images to learn more discriminative and generalizable representations for plant and disease recognition. In addition, we used some visualization techniques to analyze the stability of the model on the novel dataset, as well as the recognition process of the neural network. We evaluated our method on various plant and disease datasets and obtained similar or even better results than previous studies in terms of the ability of domain adaptation, the amount of data required, and the transfer capability. Furthermore, we demonstrated the effectiveness of the recognition process using Grad CAM, revealing a strong correlation between the feature location of plant diseases and visual attractiveness. Based on our modified PMF pipeline, integrating diverse images with various agricultural and forestry semantics into the meta-dataset can enhance the model's ability to generalize comprehensive recognition features, expanding its applicability to a broader range of application scenarios.

References

1. Liu, J.; Wang, X. Plant Diseases and Pests Detection Based on Deep Learning: A Review. Plant Methods 2021, 17, 22. [CrossRef] [PubMed]

2. Benos, L.; Tagarakis, A.C.; Dolias, G.; Berruto, R.; Kateris, D.; Bochtis, D. Machine Learning in Agriculture: A Comprehensive Updated Review. Sensors 2021, 21, 3758. [CrossRef]

3. van Dijk, A.D.J.; Kootstra, G.; Kruijer, W.; de Ridder, D. Machine Learning in Plant Science and Plant Breeding. iScience 2021, 24, 101890. [CrossRef] [PubMed]

5. Singh, A.; Ganapathysubramanian, B.; Singh, A.K.; Sarkar, S. Machine Learning for High-Throughput Stress Phenotyping in Plants. Trends Plant Sci. 2016, 21, 110–124. [CrossRef

8. Grinblat, G.L.; Uzal, L.C.; Larese, M.G.; Granitto, P.M. Deep Learning for Plant Identification Using Vein Morphological Patterns. Comput. Electron. Agric. 2016, 127, 418–424. [CrossRef]

9. Hesami, M.; Alizadeh, M.; Naderi, R.; Tohidfar, M. Forecasting and Optimizing Agrobacterium-Mediated Genetic Transformation via Ensemble Model-Fruit Fly Optimization Algorithm: A Data Mining Approach Using Chrysanthemum Databases. PLoS ONE 2020, 15, e0239901. [CrossRef]

10. Mishra, B.; Kumar, N.; Mukhtar, M.S. Systems Biology and Machine Learning in Plant–Pathogen Interactions. MPMI 2019, 32, 45–55. [CrossRef]

11. Sarker, I.H. Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Comput. Sci. 2021, 2, 160. [CrossRef] [PubMed]

12. Alzubaidi, L.; Zhang, J.; Humaidi, A.J.; Al-Dujaili, A.; Duan, Y.; Al-Shamma, O.; Santamaría, J.; Fadhel, M.A.; Al-Amidie, M.; Farhan, L. Review of Deep Learning: Concepts, CNN Architectures, Challenges, Applications, Future Directions. J. Big Data 2021, 8, 53. [CrossRef] [PubMed]

13. Hatcher, W.G.; Yu, W. A Survey of Deep Learning: Platforms, Applications and Emerging Research Trends. IEEE Access 2018, 6, 24411–24432. [CrossRef]

14. Deng, L.; Yu, D. Deep Learning: Methods and Applications. Found. Trends®Signal Process. 2014, 7, 197–387. [CrossRef]

15. Wang, Y.; Zhang, W.; Gao, R.; Jin, Z.; Wang, X. Recent Advances in the Application of Deep Learning Methods to Forestry. Wood Sci. Technol. 2021, 55, 1171–1202. [CrossRef]

16. Ferentinos, K.P. Deep Learning Models for Plant Disease Detection and Diagnosis. Comput. Electron. Agric. 2018, 145, 311–318. [CrossRef]

17. Santos, L.; Santos, F.N.; Oliveira, P.M.; Shinde, P. Deep Learning Applications in Agriculture: A Short Review. In Proceedings of the Robot 2019: Fourth Iberian Robotics Conference, Porto, Portugal, 20–22 November 2019; Silva, M.F., Luís Lima, J., Reis, L.P., Sanfeliu, A., Tardioli, D., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 139–151. [CrossRef]

18. Bouguettaya, A.; Zarzour, H.; Kechida, A.; Taberkit, A.M. Deep Learning Techniques to Classify Agricultural Crops through UAV Imagery: A Review. Neural Comput. Applic. 2022, 34, 9511–9536. [CrossRef]

19. Wang, D.; Cao, W.; Zhang, F.; Li, Z.; Xu, S.; Wu, X. A Review of Deep Learning in Multiscale Agricultural Sensing. Remote Sens. 2022, 14, 559. [CrossRef] Plants 2023, 12, 3280 15 of 16

20. Kamilaris, A.; Prenafeta-Boldú, F.X. Deep Learning in Agriculture: A Survey. Comput. Electron. Agric. 2018, 147, 70–90. [CrossRef]

21. LeCun, Y.; Bengio, Y.; Hinton, G. Deep Learning. Nature 2015, 521, 436–444. [CrossRef]

22. O'Mahony, N.; Campbell, S.; Carvalho, A.; Harapanahalli, S.; Hernandez, G.V.; Krpalkova, L.; Riordan, D.; Walsh, J. Deep Learning vs. Traditional Computer Vision. In Proceedings of the Advances in Computer Vision, Las Vegas, NV, USA, 2–3 May 2019; Arai, K., Kapoor, S., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 128–144. [CrossRef]

23. Sarker, I.H. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN Comput. Sci. 2021, 2, 420. [CrossRef] [PubMed]

24. Wang, Y.; Yao, Q.; Kwok, J.T.; Ni, L.M. Generalizing from a Few Examples: A Survey on Few-Shot Learning. ACM Comput. Surv. 2020, 53, 63:1–63:34. [CrossRef]

25. Hospedales, T.; Antoniou, A.; Micaelli, P.; Storkey, A. Meta-Learning in Neural Networks: A Survey. IEEE Trans. Pattern Anal. Mach. Intell. 2022, 44, 5149–5169. [CrossRef] [PubMed]

26. Wang, J.X. Meta-Learning in Natural and Artificial Intelligence. Curr. Opin. Behav. Sci. 2021, 38, 90–95. [CrossRef]

27. Tian, Y.; Zhao, X.; Huang, W. Meta-Learning Approaches for Learning-to-Learn in Deep Learning: A Survey. Neurocomputing 2022, 494, 203–223. [CrossRef] 28. Wang, S.; Fang, H.; Khabsa, M.; Mao, H.; Ma, H. Entailment as Few-Shot Learner. arXiv 2021, arXiv:2104.14690. 29. Song, Y.; Wang, T.; Cai, P.; Mondal, S.K.; Sahoo, J.P. A Comprehensive Survey of Few-Shot Learning: Evolution, Applications, Challenges, and Opportunities. ACM Comput. Surv. 2023, 55, 271:1–271:40. [CrossRef] 30. Yang, J.; Guo, X.; Li, Y.; Marinello, F.; Ercisli, S.; Zhang, Z. A Survey of Few-Shot Learning in Smart Agriculture: Developments, Applications, and Challenges. Plant Methods 2022, 18,

28. [CrossRef] 31. Sun, J.; Cao, W.; Fu, X.; Ochi, S.; Yamanaka, T. Few-Shot Learning for Plant Disease Recognition: A Review. Agron. J. 2023. [CrossRef]

32. Lin, H.; Tse, R.; Tang, S.-K.; Qiang, Z.; Pau, G. Few-Shot Learning for Plant-Disease Recognition in the Frequency Domain. Plants 2022, 11, 2814. [CrossRef]

33. Egusquiza, I.; Picon, A.; Irusta, U.; Bereciartua-Perez, A.; Eggers, T.; Klukas, C.; Aramendi, E.; Navarra-Mestre,

R. Analysis of Few-Shot Techniques for Fungal Plant Disease Classification and Evaluation of Clustering Capabilities Over Real Datasets. Front. Plant Sci. 2022, 13, 813237. [CrossRef] [PubMed]

34. Li, X.; Xiao, S.; Kumar, P.; Demir, B. Data-Driven Few-Shot Crop Pest Detection Based on Object Pyramid for Smart Agriculture. JEI 2023, 32, 052403. [CrossRef]

35. Ragu, N.; Teo, J. Object Detection and Classification Using Few-Shot Learning in Smart Agriculture: A Scoping Mini Review. Front. Sustain. Food Syst. 2023, 6, 1039299. [CrossRef]