A Novel Ensemble Loss Function of Few-Shot Learning for Tomato Leaf Disease Detection

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***Abstract*—This study explores the use of various loss functions, such as Quadratic Loss, Hinge loss, L1 loss, KL divergence loss, and Huber loss, for detecting tomato leaf diseases in Few-Shot Learning (FSL) models. The goal is to create a flexible FSL model that accurately categorizes tomato leaf diseases using a limited number of annotated instances. The authors assess the effectiveness of each loss function separately on datasets of tomato, grapes, apple, and maize leaves. They propose a new method of combining loss functions using exponential transformation to maximize the advantages of each loss function while minimizing their disadvantages. This integrated strategy aims to improve the FSL model's ability to differentiate between healthy and sick leaves. The authors examined five distinct loss functions and combined them using an exponential transformation technique. The results show that the proposed FSL model, which incorporates exponential loss functions, achieves outstanding performance in tasks related to detecting diseases in tomato leaves. This novel strategy is expected to enhance the model's ability to distinguish between healthy and diseased leaves, improving overall disease detection capabilities.**

***Index Terms*—Few-Shot Learning (FSL), Ensemble Loss Function, Image Processing, Machine Learning, Leaf Disease Detection, Tomato Leaf.**

I. Introduction

Accurate identification of plant diseases is crucial for farmers in order to safeguard the quality and yield of their crops [1]. Regardless of the type of crops cultivated, there will be a decrease in the occurrence of diseases, or as a result of early disease diagnosis, there will be a reduction in wastage. An algorithm for automatically classifying plant diseases can be advantageous for monitoring the growth and health condition of plants and detecting plant diseases at an early stage. Detecting plant diseases is a vital undertaking to ensure global food security and alleviate hunger [2]. It can assist farmers in promptly implementing measures to mitigate the spread of illnesses and minimize crop losses. The global rise in food insecurity is a pressing issue that underscores the criticality of guaranteeing food security. Plant diseases have a substantial effect on agricultural yields and, eventually, food production. Through the early identification and prevention of plant diseases, we can effectively reduce crop losses and guarantee a sufficient food supply for the expanding global population. The identification and diagnosis of plant diseases are essential for ensuring farmers can achieve enough food production to sustain the world's expanding population. Plant diseases and pests can result in substantial reductions in crop yield [3], which can lead to food scarcity and increased pricing for consumers. Due to the irregular and complicated structure of the images, the process of dividing the leaves of diseased plants into segments can be pretty challenging [4].

Digital technology and advanced agricultural practices have improved plant disease identification and assessment. Deep learning algorithms can analyze large datasets, identify patterns, and categorize images. However, they require large datasets, increasing costs and time consumption. Various methodologies, including machine learning and computer vision techniques, can be employed to create automated algorithms [5]. A new framework using semi-supervised and ensemble learning is proposed to identify plant diseases using an extensive dataset of plant pictures. This algorithm can monitor plant health and notify farmers of any disease occurrences, which is crucial for early crop productivity [6]. Deep learning for plant disease identification is promising but needs to be more efficient and prone to inaccuracies. FSL algorithms can overcome these limitations by using existing plant disease knowledge and a limited set of annotated images to identify and categorize new diseases quickly [7].

The FSL is a specialized branch of machine learning that focuses on the ability of machines to acquire knowledge and make generalizations based on a limited set of labelled examples [8]. FSL is particularly advantageous in situations where acquiring substantial quantities of labelled data is challenging or costly, such as in the field of agriculture [9]. In recent years, there has been a growing interest in using FSL approaches for plant disease identification. This paradigm shows significant potential for tackling practical difficulties, particularly in situations where data collecting requires extensive tagging and is costly [10]. The agriculture sector plays a crucial role in supplying sustenance for the continuously expanding global populace, but the rapid spread of plant diseases presents a substantial risk to the well-being and output of crops. Swift and precise detection of these illnesses is crucial for implementing suitable actions to reduce their impact and protect agricultural productivity [11].

FSL offers a promising resolution to the task of recognizing plant diseases by empowering machines to identify novel

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diseases with little labelled instances [12]. Multiple research has investigated the use of FSL (fluorescence spectroscopy and imaging) for the purpose of detecting plant diseases. Argüeso et al. (2020) [13] employed an FSL methodology to see powdery mildew in tomato plants, achieving a remarkable accuracy of 97.4% by utilizing only five labelled instances for each category. Li and Chao (2021) [14] devised a Few-Shot Learning (FSL) model to classify soybean diseases, achieving an impressive accuracy of 96.0% using only three tagged instances per class. Additional research has investigated the application of FSL for broader identification of plant diseases, with Li and Yahoo (2020) [15] achieving an impressive accuracy of 97.3% using only five tagged instances for each disease class. Nuthalapati and Tunga (2021) [16] devised a method based on Few-Shot Learning (FSL) to identify plant diseases, achieving an accuracy of 97.6% by using only two labelled instances for each category. A new method of combining loss functions influenced by exponential transformations is proposed to efficiently utilize their different contributions, potentially overcoming the limitations of any single loss function. This novel strategy aims to maximize the discriminative power of the FSL model, thus improving its ability to detect diseases.

The research focuses on utilizing loss functions in Few-Shot Learning (FSL) to detect plant diseases, specifically tomato leaf diseases. The aim is to improve the accuracy and efficacy of disease detection models, thereby enhancing machine-learning methodologies in agriculture. This work could transform crop management, guarantee global food security, and underscore the importance of precise disease detection in agriculture. The novelty of the proposed research is given below:

- A comprehensive comparison examination of four various loss functions: Quadratic Loss, hinge loss, L1 loss, KL divergence loss, and Huber loss.
- Conduct a performance evaluation of individual loss functions by training and testing the FSL model using each loss function separately.
- Novel Loss Function Combination Technique: Introduce and execute a pioneering approach to combining loss functions by utilizing exponential transformations.
- Employ a meticulously selected collection of tomato leaf images consisting of both healthy and diseased samples that domain experts have annotated.

The paper is structured as follows: Section I provides an introduction to the research subject, explicitly focusing on the deep learning model FSL, as well as highlighting the unique aspects of the proposed work. The latest advancements have been detailed in section II. The dataset descriptions and techniques are provided in section III. Section IV presents the results and their interpretation through the utilization of diverse graphical representations. Section V ultimately concludes the requested research.

II. Literature Review

The growing global population demands food resources, but plant diseases pose a significant threat to agricultural productivity and food availability. Prompt disease detection is crucial to prevent epidemics and financial damage. Traditional methods require skilled eye examination, which can be time-consuming and subjective. Machine learning, particularly Few-Shot Learning (FSL), offers a solution to data scarcity by acquiring knowledge from limited instances. This study connects advanced machine learning techniques with the urgent needs of the agriculture industry, highlighting the potential of FSL in addressing these challenges. [17]. The analysis of loss functions provides valuable insights into model learning factors, aiding in the development of plant disease identification algorithms. The diversity of the dataset, including visuals of other botanical species, enhances the applicability of findings. This comprehensive approach accurately reflects the complexities of various leaf types, illnesses, and climatic conditions, improving the trustworthiness of the study findings and making them more relevant to practical situations [18].

The exponential loss function combination technique is a groundbreaking development in machine learning algorithms that leverages diversity to create models that outperform their parts. This innovative approach, demonstrated by the exponential transformation method, could potentially enhance model resilience in diverse applications beyond agriculture, demonstrating the potential of machine learning in problem-solving. A streamlined plant disease detection system could revolutionize crop management, enabling farmers to make informed decisions on disease management strategies, optimize pesticide use, and reduce environmental impact. It would also lead to increased productivity and financial stability for individual farmers and the agricultural sector as a whole [19].

The study contributes to the machine-learning community by utilizing two renowned datasets, ImageNet and Open Image, which are ideal for plant disease detection due to their large size. These datasets, which have resolutions greater than 100x100 pixels, are used for everyday image recognition tasks. The authors aim to address a significant challenge in agriculture by integrating machine learning advancements with practical agricultural industry requirements. This approach lays the foundation for sustainable crop management techniques and could revolutionize disease detection, influence agriculture's trajectory, and enhance global food security. As the study progresses, it holds the potential to revolutionize disease detection, influence agriculture's trajectory, and improve global food security [20]. Chen et al. utilized few-shot categorization algorithms (FSL) in agriculture to accurately detect and classify crop illnesses and pests. After a thorough analysis of various FSL algorithms, they concluded that the meta-learning technique is the most effective.

Few-shot categorization algorithms have been explored in the agricultural field, with recent studies focusing on detecting diseases in tea leaves, classifying leaves, and categorizing leaf diseases. Hu et al. used support vector machines and deep

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networks to identify tea leaf illnesses accurately. Chen et al. used FSL to accurately detect crop illnesses and pests, analyzing various algorithms and determining the meta-learning approach as the most effective. While few-shot categorization algorithms are relatively new, their use in agriculture has been acknowledged [21]. Support Vector Machines (SVMs) and VGG16 networks were used for low-shot segmentation, while conditional deep convolution generative adversarial networks were used to identify patches in images. A Siamese network was used for leaf categorization with restricted samples, and metric learning was used to bring similar leaf samples closer together. FSL is widely used in various domains, including image categorization and object tracking. However, effective use of machine learning and deep learning requires a large amount of data, making deep learning unsuitable [22]. Few-shot categorization algorithms have been used in agriculture for various purposes, such as detecting diseases in tea leaves, classifying leaves, and categorizing leaf diseases. Recent studies have used FSL to accurately detect and classify crop illnesses and pests, with a meta-learning approach being the most effective. However, effective utilization of machine learning and deep learning requires a substantial amount of data, making deep learning an unsuitable option. [23].

III. Data and Methodology

A. Data Description

The tomato leaf disease dataset has been taken from the PlantVillage [24]. Preprocessing involves creating altered replicas of data sets using existing data to enhance the training process. It can be achieved through slight modifications to the dataset or deep learning techniques. Image transformations can be physical, colour, or noise [25]. Physical transformations involve techniques like rotation, cropping, flipping, and reflection. The colour transformation is beneficial for identifying plant illnesses, as it alters the luminous intensity of the image, which factors like weather conditions, viewing angle, and camera distance can influence. Overall, data augmentation is a simple and effective method for enhancing training outcomes [26].

B. Methodology

The process of creating a model with an ensemble loss function entails several vital processes and components, as illustrated in a flowchart (see Figure 1). The procedure commences by collecting foundational learners and initializing their parameters. Subsequently, a composite model is created by amalgamating many individual learners. The base learner is trained on a dataset with a limited number of examples, and the ensemble loss function is optimized to enhance the performance of the model. The predictions of the ensemble are enriched using a fusion method that integrates varied input from each learner. The fusion stage is essential for improving the ensemble's predictive capability and facilitating enhanced generalization. Ultimately, the proficient ensemble model is assessed on a validation set to determine its performance. If the model meets the required standards, it can be utilized in

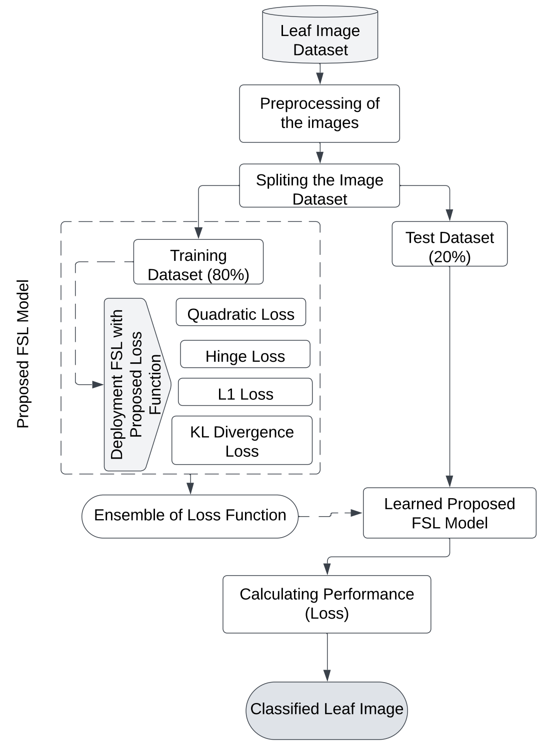

Fig. 1. Flow chart of proposed novel ensemble loss function model to utilizing Few-Shot Learning (FSL)

few-shot learning scenarios, providing enhanced accuracy and resilience in comparison to individual base learners.

- **Quadratic Loss**: The mean squared error (MSE) loss is a commonly employed loss function in regression applications. The metric quantifies the squared discrepancy between the projected value (y) and the goal values ($\hat{y}$). The quadratic Loss is defined as follows:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

The quadratic loss function is more sensitive to outliers since it penalizes more enormous prediction mistakes through the squaring step.

- **Hinge Loss**: It is frequently employed in Support Vector Machines (SVMs) for jobs involving binary classification. The system encourages the accurate categorization of examples by applying a penalty depending on the margin to incorrectly identified samples. The hinge loss is defined as:

$$Z = \max(0, 1 - y \cdot z) \tag{2}$$

where y is the correct label (1 for positive class, -1 for negative class).

- **L1 Loss**: The mean absolute error (MAE), usually referred to as the average absolute deviation, is a loss function commonly employed in a range of machine learning applications, including in regression issues. The

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metric quantifies the mean absolute deviation between the projected values and the actual (ground truth) values. The L1 loss is defined as follows:

$$\text{L1 loss} = \sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{3}$$

where: n is the number of data points or samples in the dataset Y_{pred} represents the predicted values by the model. Y_{true} represents the actual value from the dataset.

- **Kullback-Leibler Divergence**: It is typically utilized to compare a predicted probability distribution with a target (actual) probability distribution. Suppose we are given two probability distributions, P and Q, which represent the likelihood of different occurrences or outcomes occurring. Kullback-Leibler Divergence quantifies the amount of information that is not captured when using Q as an approximation for P. The definition is as follows.

$$\text{KL}(P||Q) = D_{\text{KL}}(P \parallel Q) = \sum_{x} P(x) \log\left(\frac{Q(x)}{P(x)}\right) \tag{4}$$

where: P(i) is the probability of event I in distribution P, Q(i) is the probability of the event in distribution Q. It is the summation of all events or outcomes in the distribution. It's important to note that KL Divergence is not symmetric, meaning KL $(P||Q)$ is not necessarily equal to KL $(Q||P)$.

C. Experiments Design and Parameter Setting

In this section, the experimental setup and parameters are described as given below:

- **Data Collection and Preprocessing** Acquire a varied array of tomato leaf photos encompassing both healthy and damaged leaf samples. Engage in collaboration with specialists in the field to guarantee precise categorization of each sample by assigning appropriate illness classes. Conduct data preprocessing to standardize the sizes of images, employ data augmentation techniques to enhance the variety of the dataset, and normalize pixel values to facilitate practical training of the model.
- **FSL Framework** Develop and apply a cutting-edge FSL framework specifically designed for image classification applications. Use well-established topologies like Prototypical Networks, Matching Networks, or Relation Networks as a starting point for our studies. Make the required adjustments to suit various loss functions and the suggested technique for combining loss functions.
- **Loss Function Selection and Implementation** Incorporate the following loss functions into the FSL framework: Quadratic Loss, hinge loss, L1 loss, KL divergence loss, and Huber loss. Formulate precise mathematical definitions for each loss function and verify their correct integration into the training process.
- **Model Training and Validation** Partition the dataset into training, validation, and test sets. The training set is utilized to optimize the model, whilst the validation set assists in fine-tuning the hyperparameters and implementing early stopping. Individually train the FSL model using each loss function and periodically evaluate the model's performance on the validation set. Perform a thorough exploration of hyperparameters to enhance the design of the model and optimize hyperparameters that are specific to the loss function.
- **Exponential Loss Function Combination** Suggest a novel strategy for combining loss functions by utilizing exponential transformations of separate loss function outcomes. Aggregate the outcomes of the loss function using the exponential method and assess the model's performance on the validation dataset.
- **Evaluation Metrics** Evaluate the performance of the FSL model by employing commonly used assessment metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). Calculate confusion matrices to obtain a deeper understanding of the model's capacity to differentiate between healthy and diseased tomato leaves.
- **Hardware and Software Requirements for the Experimentation** The experiments are conducted on a high-performance CPU and GPU computer to facilitate efficient model training and evaluation. We utilize popular deep learning frameworks such as TensorFlow or PyTorch to implement the FSL framework and loss functions. Hyperparameters such as learning rate, batch size, number of training epochs, and Loss function-specific parameters are tuned using a grid search or random search strategy. We use cross-validation to validate hyperparameter configuration and ensure model stability.

IV. Result Analysis

The research aimed to develop a robust model for identifying diseases in tomato leaves using four loss functions: Quadratic Loss, L1 Loss, and KL Divergence Loss. The model showed a progressive decline in Quadratic Loss values as iterations progressed, indicating successful knowledge acquisition and dataset adjustment. The model began with less precise predictions but gradually improved its understanding of fundamental patterns, demonstrating its ability to forecast disease classification accurately.

This research study investigates the performance features of the Quadratic Loss Function, a loss function used in regression applications to quantify the squared discrepancy between anticipated and actual values. The study found consistent performance across the sample and compared it to other loss functions, providing valuable insights into its behaviour and implications. (see Figure 2). The L1 loss function, a key tool in regression and optimization tasks, quantifies the absolute discrepancy between expected and actual values. Its unique attributes distinguish it from other loss functions. Examining the set of L1 loss values provides a deeper understanding of its behaviour and usefulness, demonstrating that quadratic and L1 losses consistently minimize differences between expected

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and actual values. (see Figure 3). The KL Divergence loss, used for measuring the difference between two probability distributions, showcases slightly higher average values than quadratic and L1 losses. It might indicate a more sensitive response to deviations, potentially making it suitable for critical distribution comparison tasks. In exploring diverse loss functions, we delve into the intricate characteristics of the KL Divergence Loss function. KL Divergence is pivotal in information theory and probabilistic modelling to measure dissimilarity between probability distributions (see Figure 4). To summarise, KL Divergence Loss Functions provide a distinct perspective for analyzing differences in distributions. Their emphasis on acquiring knowledge, ability to perceive subtle distinctions, and involvement in Probabilistic modelling provide them with a strong sense of authority and capability.

The Hinge Loss, a key component of support vector machines and binary classification tasks, exhibits heterogeneity in average values across datasets. It is more responsive to specific data points, resulting in larger mean values. Studying Hinge Loss values provides crucial information about their properties and usefulness, especially in classification problems (see Figure 5). This analysis enhances understanding of Hinge Loss's properties and enables researchers and practitioners to utilize its capabilities effectively. By aligning with the geometric knowledge of Hinge Loss, resilient classification models can be created, achieving a balance between accuracy and margin optimization.

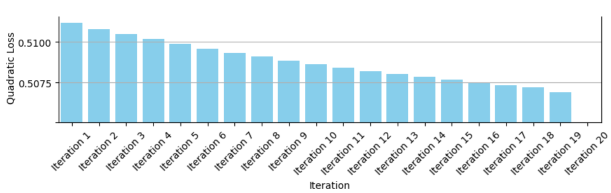

Fig. 2. Quadratic loss distribution over tomato leaf dataset with utilization of iterations.

The aggregate loss numbers are a comprehensive metric that combines various loss components, with the mean value of the combined Loss remaining within the range of individual losses. The Exponential Form Combined Loss Function (see Figure 6) is an innovative method that integrates separate elements of Loss using an exponential formulation, creating a composite loss function. By examining the given values of this combined Loss, valuable insights are obtained on its unique features and benefits. The mean value of the Hinge

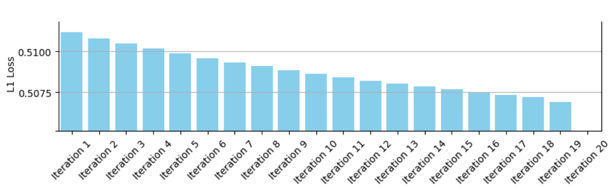

Fig. 3. L1 loss distribution over tomato leaf dataset with utilization of iterations.

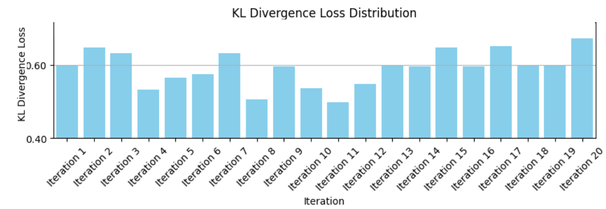

Fig. 4. KL divergence loss distribution over tomato leaf dataset with utilization of iterations.

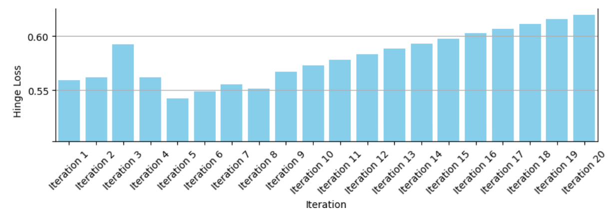

Fig. 5. Hinge divergence loss distribution with utilization of iterations over tomato leaf dataset.

Loss and Exponential from Combined Loss provides valuable insights into their respective performance, with the disparity in their mean values highlighting their diversity in reaction to variations. The Hinge Loss's susceptibility to particular data points, particularly those close to the decision boundary, is also highlighted. The discrepancy between the average value of the Hinge Loss and the value of the Exponential Form Combined Loss can guide in selecting a model. The elevated mean value of the Hinge loss indicates its capacity to emphasize certain misclassifications, while the Exponential Form Combined Loss offers a flexible and comprehensive method. Understanding the disparities in mean loss values is crucial for model training and assessment, allowing for the customization of modelling

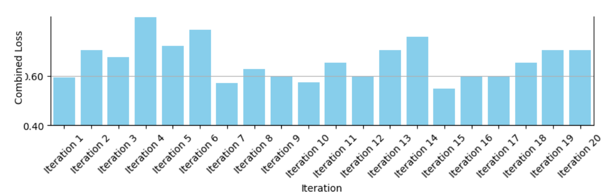

Fig. 6. Combined loss distribution with the utilization of iterations over tomato leaf dataset.

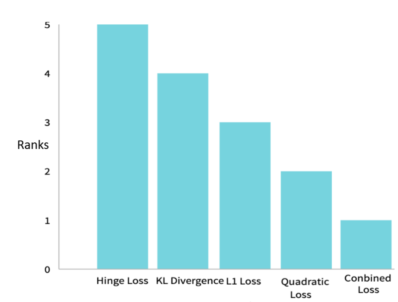

Fig. 7. Rank of loss function over tomato leaf dataset to the comparison of all loss functions.

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TABLE I
AVERAGE OF LOSSES OF TRADITIONAL AND PROPOSED LOSS FUNCTION

S.N.	Loss Function	Average Loss value
1	Quadratic Loss	0.507
2	L1 Loss	0.517
3	KL Divergence Loss	0.570
4	Hinge Loss	0.601
5	**Proposed method**	**0.078**

techniques to achieve the ideal balance between minimizing errors and ensuring model resilience.

Table-I shows that the proposed ensemble strategy has the lowest average loss value (specifically, 0.078) compared to the other loss functions. The Quadratic Loss function has reached the second highest Loss, specifically 0.507. Throughout several iterations of the trials, the losses of the function (as indicated in Table- I) were recorded. The Friedman ranking method was then applied to determine the Rank of the loss function, as shown in Figure 7. The lowest ranking values indicate the best performance. Thus, it can be inferred that the suggested technique surpasses previous loss functions in terms of performance.

V. CONCLUSION

The research introduces a unique technique that combines exponential loss functions to enhance the precision and resilience of Few-Shot Learning (FSL) models for detecting plant diseases. This method addresses the challenge of selecting a singular loss function that meets all conditions, enhancing the overall disease-detection capabilities of the FSL model. The study investigates quadratic Loss, hinge loss, L1 loss, KL divergence loss, and Huber loss, highlighting their impact on understanding illness patterns from limited data sets. The inclusion of a varied data set, including many plant species, enhances the generalizability of the findings and their application to a broad spectrum of plant disease detection scenarios. The findings provide insight into the relationship between loss functions and few-shot learning (FSL) in plant disease detection, with the L1 loss being a promising candidate due to its robustness against extrinsic influences. The findings demonstrate the potency of interdisciplinary collaboration, extending beyond its direct use in agriculture. The study establishes a model for innovation in other industries by applying advanced machine-learning techniques to address real-world issues in the agriculture sector.

REFERENCES

[1] D. Varghese, A. Jain, and R. Buyya, "Few-shot learning for plant disease classification using ILP," in *International Advanced Computing Conference*, Cham: Springer Nature Switzerland, 2022.

[2] R. Rani, P. Jain, V. Singh, and P. Kumar, "Role of artificial intelligence in agriculture: An analysis and advancements with focus on plant diseases," *IEEE Access*, 2023.

[3] R. Satya Rajendra Singh and R. Kumar Sanodiya, "Zero-shot transfer learning framework for plant leaf disease classification," *IEEE Access*, 2023.

[4] Y. Lee, X. Sun, Q. Wang, Y. Zhang, and T. Mei, "Meta pseudo labels," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 6523-6532.

[5] P. Sharma and A. Sharma, "A novel plant disease diagnosis framework by integrating semi-supervised and ensemble learning," *Journal of Plant Diseases and Protection*, 2023, pp. 1-22.

[6] L. Li, S. Zhang, and B. Wang, "Plant disease detection and classification by deep learning—A review," *IEEE Access*, vol. 9, pp. 56683-56698, 2021.

[7] D. Argüeso, A. Picon, A. Irusta, A. Santesteban, J. G. Pajares, U. Perallos, and A. Herrero, "Few-shot learning approach for plant disease classification using images taken in the field," *Computers and Electronics in Agriculture*, vol. 175, p. 105542, 2020.

[8] Y. Lee, X. Sun, Q. Wang, Y. Zhang, and T. Mei, "Model-agnostic meta-learning via adversarial function augmentation," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2021, pp. 14571-14580.

[9] B. M. Lake, R. Salakhutdinov, and J. B. Tenenbaum, "Human-level concept learning through probabilistic program induction," *Science*, vol. 350, no. 6266, pp. 1332-1338, 2015.

[10] O. Vinyals, C. Blundell, T. Lillicrap, K. Kavukcuoglu, and D. Wierstra, "Matching networks for one shot learning," in *Proceedings of the 30th International Conference on Neural Information Processing Systems*, 2016, pp. 3630-3638.

[11] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," in *Proceedings of the 34th International Conference on Machine Learning*, 2017, pp. 1126-1135.

[12] J. Snell, K. Swersky, and R. S. Zemel, "Prototypical networks for few-shot learning," in *Proceedings of the 31st International Conference on Neural Information Processing Systems*, 2017, pp. 4077-4087.

[13] F. Sung, Y. Yang, L. Zhang, T. Xiang, P. H. Torr, and T. M. Hospedales, "Learning to compare: Relation network for few-shot learning," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 1199-1208.

[14] A. Nichol, J. Achiam, and J. Schulman, "On first-order meta-learning algorithms," *arXiv preprint arXiv:1803.02999*, 2018.

[15] H. Kim, H. Park, and J. Kim, "Edge-labeling graph neural network for few-shot learning," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 11698-11707.

[16] S. Qiao, C. Liu, W. S. Chen, and A. L. Yuille, "Few-shot image recognition by predicting parameters from activations," in *Proceedings of the IEEE International Conference on Computer Vision*, 2019, pp. 7229-7238.

[17] C. Finn, A. Rajeswaran, S. M. Kakade, and S. Levine, "Online meta-learning," *arXiv preprint arXiv:1902.08438*, 2019.

[18] A. A. Rusu, N. C. Rabinowitz, G. Desjardins, H. Soyer, J. Kirkpatrick, K. Kavukcuoglu, and R. Hadsell, "Meta-learning with latent embedding optimization," in *Proceedings of the 36th International Conference on Machine Learning*, 2019, vol. 97, pp. 5635-5644.

[19] Y. Lee, X. Sun, Q. Wang, Y. Zhang, and T. Mei, "Efficient and effective few-shot learning with model-based meta-learning," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2020, pp. 7729-7738.

[20] Y. Tian and C. Liu, "Conditional few-shot learning with local adaptation," in *Proceedings of the European Conference on Computer Vision*, 2020, pp. 307-323.

[21] T. Chen and A. Gupta, "Efficient few-shot image recognition with attention-based meta-regularization," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019.

[22] A. V. Uzhinskiy, D. S. Nasonov, P. A. Pustovalov, and S. Y. Marshak, "One-shot learning with triplet loss for vegetation classification tasks," *Remote Sensing*, vol. 13, no. 4, pp. 608-614, 2021.

[23] H. Wang, X. Yun, Y. Tai, M. E. Khan, M. Li, and J. Li, "A comparison of machine learning methods for cross-domain few-shot learning," in *AI 2020: Advances in Artificial Intelligence*, Canberra, ACT, Australia: Springer International Publishing, 2020, pp. 463-474.

[24] Y. Li and X. Chao, "Semi-supervised few-shot learning approach for plant diseases recognition," *Plant Methods*, vol. 17, no. 1, pp. 1-10, 2021.

[25] P. Nuthalapati and K. Tunga, "Few-shot learning for plant disease detection with scarce data," in *Proceedings of the 16th International Conference on Precision Agriculture*, 2021, pp. 413-419.

[26] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," *arXiv preprint arXiv:1511.08060*, 2015.

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