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Cross-Domain Adaptation Techniques for Robust Plant Disease Detection: A DANN-CORAL Hybrid Approach

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Abstract: Plant disease detection with deep learning models has shown promising results, but these models often struggle with generalizing across diverse agricultural environments due to domain shifts in imaging conditions. This paper presents a novel hybrid approach focusing on cross-domain adaptation techniques to address the challenge of domain shift. Our proposed method combines the Domain-Adversarial Neural Network (DANN) with Correlation Alignment (CORAL) to mitigate domain shifts between datasets. The DANN framework enforces domain-invariant feature learning through adversarial training. Using the PlantVillage Dataset, with controlled environment images, and the New Plant Village Dataset, with varied conditions, the model is first trained on PlantVillage and then adapted to New Plant Village using the CORAL loss to support the second-order statistics. In case of domain shift experiments with various datasets, DANN-CORAL achieved accuracies 91.39%, precision 93.36%, recall 88.9% and F1-scores 91.05% indicating the robustness and generalizability of our model is better than the other baseline models. This approach enhances model robustness and adaptability, providing insights into combining adversarial and statistical alignment for cross-domain adaptation in agricultural imaging.

Introduction

In agricultural environments, the detection of plant species and their diseases plays a vital role, significantly impacting crop yields and global food security. The rise of digital agriculture has brought forth innovative approaches like deep learning, which offer promising solutions for effectively detecting and managing plant species and diseases (Li et al., 2021; Wu et al., 2023). In reality, the implementation of such advanced technologies (Singh et al., 2020) in agriculture presents new hurdles, particularly in ensuring the robust performance of these models across various environmental conditions. This section offers an inclusive overview and significance of plant spices and disease detection (Wu et al., 2023), discusses the role of deep learning, addresses the challenges allied with domain shift and cross-domain adaptation (Huang et al., 2023) and delineates the research objectives and contributions of this study.

Importance of Plant Disease Detection in Agriculture

Efficient detection of plant species and diseases is paramount for preserving high crop yields and quality and ensuring the economic viability of agricultural industries worldwide (Li et al., 2021). Plant diseases can cause significant reductions in yield and compromise produce quality, thereby affecting food supply chains and market prices. Timely and precise disease detection enables prompt intervention, mitigating damage and decreasing reliance on extensive pesticide usage, which can have detrimental environmental consequences (Storey et al., 2022). Moreover, with rising global food demands,

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improvising the dependability and effectiveness of plant spices and disease detection systems becomes imperative for promoting sustainable agricultural practices.

Deep Learning for Plant Disease Detection

Deep learning, a subset of artificial intelligence (AI), has transformed plant disease detection by facilitating automated, highly precise, and efficient analysis of extensive datasets, primarily utilizing imaging techniques. A key advantage of deep learning is its capacity to automatically extract and learn intricate patterns from data without the need for explicit programming for feature identification (Mahmud et al., 2021). This capability will improve the plant species and disease detection accuracy and markedly accelerate the process, enabling real-time decision-making. However, deep learning models heavily rely on data and necessitate substantial annotated datasets (Storey et al., 2022; Mahmud et al., 2021), posing a significant limitation in diverse agricultural settings. Moreover, these models often lack transparency in their decision-making processes and are prone to overfitting, raising concerns about their reliability and broad applicability across varying environmental conditions.

Domain Shift and Cross-Domain Adaptation

In practical applications, the utilization of deep learning models frequently confronts the fundamental obstacle of domain shift (Zhu et al., 2021), which profoundly influences the efficacy of these models when employed across distinct data distributions. Domain shift characterizes the situation wherein the data utilized for training a model (source domain) substantially differs from the new data it encounters (target domain) (Wei, 2023). In the realm of plant spice and disease detection, domain shift can manifest in diverse ways, encompassing variations in imaging conditions, crop types, disease progression stages, and even alterations in camera hardware or settings:

Variations in Imaging Conditions: Differences in lighting, background, and weather conditions between images in training and deployment environments can lead to significant domain shifts (Wei, 2023). For instance, images captured during bright sunlight may differ drastically from those taken on cloudy days or under artificial lighting.

Crop and Disease Variability: The appearance of diseases can vary between different species of plants and even among different strains of the same species. Similarly, the manifestation of symptoms can differ based on the stage of the disease, adding another layer of complexity.

Differences in Data Acquisition: Variations in the equipment used for data collection, such as different camera models or settings, can also cause domain shifts (Zhu et al., 2021). These technical discrepancies can alter the visual appearance of images, thereby confusing the model trained on data from a different setup.

Challenges

Cross-domain adaptation aims to address these issues by enabling a model trained in a particular domain to obtain the same performance on another relevant domain without needing extensive re-labeling or manual adjustment. This adaptation is critical in agricultural applications where conditions are highly variable and continuously changing. The main challenges (Zhu et al., 2021; Wei, 2023; Marvin et al., 2021) include:

Lack of Annotated Data in Target Domain: Acquiring extensive annotated data in the target domain proves costly and time-intensive (Zhu et al., 2021). This scarcity of labeled data constrains deep learning models from effectively learning features that remain consistent across domains.

Complexity of the Adaptation Process: Adapting models across domains entails more than just retraining; it involves modifying the learning process to minimize differences between domains. Techniques like adversarial training or feature alignment demand meticulous tuning (Marvin et al., 2021) and deep comprehension of both the source and target domains.

Balancing Domain-Specific and Domain-Invariant Features: Ensuring that the model retains its capacity to recognize plant species and disease-specific features while adapting to new domain characteristics requires a delicate equilibrium (Wei, 2023). Excessive emphasis on adaptation might cause the model to overlook crucial disease-specific information.

Evaluation of Adapted Models: Evaluating the performance of adapted models presents its own set of challenges, especially in gauging how well these models will fare in real-world agricultural settings that may not be accurately represented in the test data.

Therefore, the need to effectively manage domain shift and perform robust cross-domain adaptation is essential for the success of deep learning applications in plant species and disease detection. Addressing these challenges (Zhu et al., 2021; Wei, 2023) through innovative adaptation strategies forms the core of efforts to enhance model robustness and ensure reliability across diverse agricultural environments.

Proposed DANN-CORAL Hybrid Approach

In this paper, we propose a hybrid model, integrating Domain-Adversarial Neural Networks (DANN) (Wang et al., 2020) with Correlation Alignment (CORAL) (Cheng et al., 2021), to mitigate domain shift challenges (Marvin et al., 2021) in plant spices and disease prediction across diverse agricultural environments. Domain shifts often impair model performance when deployed under varying conditions. Hence, our innovative approach aims to tackle this issue effectively. DANN plays an important role in making the model's features domain-invariant by insisting on adversarial training. This process involves a domain classifier discerning between source and target domain features while the feature extractor learns to confuse this classifier. By doing so, the model can generalize across different agricultural settings and learning features useful for disease classification but invariant to domain differences like lighting variations, camera angles, and background noise (Wang et al., 2020).

Alternatively, CORAL reduces domain shift by aligning the second-order statistics, specifically the covariance, of feature distributions between the source and target domains (Cheng et al., 2021). This statistical alignment facilitates adapting source domain data to resemble the target domain more closely, which is particularly beneficial when dealing with diverse agricultural conditions, such as controlled environment training data versus field deployment images. By combining DANN and CORAL, our model comprehensively leverages adversarial and statistical methods to address domain shifts. While the adversarial component focuses on making high-level representations more generalizable, CORAL adjusts the underlying data distributions. This dual approach ensures the model's high accuracy in detecting various plant diseases across different datasets, making it well-suited for agricultural applications with diverse data.

The main objectives of this research include designing and implementing the hybrid model, testing its effectiveness across various datasets with several categories of leaves and diseases, comparing it with existing baselines, and investigating the impact of individual components on detection accuracy and generalization.

This study contributes significantly to the field by advancing cross-domain adaptation for agriculture, introducing methodological innovations through the hybrid DANN-CORAL model, enhancing agricultural decision-making, and promoting a sustainable future for farming. By detecting spices and diseases with high accuracy, our research aligns with global sustainability and food security goals, ultimately aiming to create more adaptable, efficient and reliable disease detection methods in agriculture.

Related Work

Deep Learning Techniques for Plant Disease Detection

The advent of deep learning has transformed plant disease detection, providing unmatched precision, speed, and scalability through the analysis of extensive agricultural datasets. Central to this advancement is convolutional neural networks (CNNs) (Laura et al., 2022), which excel in extracting complex features from images, enabling accurate identification of disease indicators on plant foliage and fruits. Trained on extensive agricultural datasets, CNNs discern between healthy and diseased specimens based on nuanced visual cues.

In recent years transfer learning has significantly boosted deep learning's effectiveness in plant species and disease detection. With the help of fine-tuning models pre-trained on generalized datasets like ImageNet, they adapt to specific tasks with limited labeled data, leveraging pre-learned features such as edges and textures. This approach is invaluable in agriculture, where data scarcity is common, enhancing model performance with minimal labeled samples.

Data augmentation techniques (Chlap et al., 2021) are widely employed to address data limitations and enhance model robustness. These methods artificially expand datasets by creating modified image versions through rotations, scaling, and colour adjustments. They bolster model resilience to input variations and improve generalization across diverse agricultural settings.

Despite these strides, deploying DL in plant species and disease detection encounters challenges (Wei, 2023; Marvin et al., 2021). Variability in environmental conditions during data capture, like lighting and camera variations, can affect model performance outside controlled settings (Vijayalakshmi et al., 2020). Moreover, deep learning's computational demands pose challenges in resource-constrained agricultural regions, hindering widespread adoption. Additionally, the opaque nature of deep learning models impedes user trust and understanding, critical for acceptance in agricultural practices.

While deep learning holds immense promise for plant disease detection, ongoing advancements and adaptations are necessary to realize its benefits across diverse agricultural environments. Exploring cross-domain adaptation techniques (Zhu et al., 2021) is vital to enhancing model flexibility and applicability, ensuring their efficacy in real-world agricultural settings.

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Domain Adaptation Techniques for Cross-Domain Image Classification

Methods for domain adaptation are pivotal in overcoming the hurdle of transferring learned knowledge from one domain to another in image classification (Wei, 2023), particularly relevant in agricultural contexts. Variations in environmental conditions (Vijayalakshmi et al., 2020), imaging equipment, and plant characteristics across different datasets can hinder the performance of standard deep-learning models.

Domain adaptation seeks to alleviate the effects of domain shift, wherein a model trained on data from one domain encounters difficulties when applied to another. This challenge holds considerable importance in real-world applications, impacting the scalability and dependability of models under various operational circumstances. Domain adaptation techniques are generally categorized into supervised and unsupervised adaptation. Supervised adaptation involves labeled data in both domains but can be complex due to labelling expenses. On the other hand, unsupervised adaptation utilizes unlabelled data in the target domain, rendering it more suitable for scenarios with limited labeled data availability.

In agriculture, variations in background, lighting conditions, and plant appearance due to genetic or environmental factors can compromise the effectiveness of plant species and disease detection systems. Domain adaptation offers a solution to enhance the robustness of image classification models, enabling them to maintain high accuracy across diverse agricultural settings without extensive retraining or manual adjustments.

Adversarial Domain Adaptation (DANN)

Adversarial domain adaptation, especially through Domain-Adversarial Neural Networks (DANN) (Wang et al., 2020), is a potent strategy for addressing the domain shift problem in machine learning. Inspired by Generative Adversarial Networks (GANs) (Chen et al., 2020), this technique minimizes domain differences, enabling models to generalize across diverse domains.

Principle of Adversarial Adaptation: The Adversarial Adaptation Principle involves training a feature extractor within the DANN framework to generate domain-invariant features, ensuring they cannot be distinguished between the source and target domains. Concurrently, an adversarially trained domain classifier is employed to differentiate between features from the source and target domains. Through this process, the feature extractor aims to deceive the domain classifier by producing consistent features across domains, ultimately achieving domain invariance.

Application in Image Classification: DANN is valuable in image classification, particularly for plant disease detection. For instance, a model trained on high-quality images of diseased plants under controlled conditions (source domain) may struggle in natural settings (target domain) with varying lighting and backgrounds. DANN helps the model extract features that are effective for disease detection regardless of domain-specific characteristics.

Benefits and Challenges: DANN effectively utilizes unlabeled data from the target domain, which is crucial in agriculture where acquiring labeled datasets is costly and time-consuming. However, balancing the adversarial training process is challenging to ensure it doesn't compromise the model's disease detection accuracy. Despite this challenge, DANN enhances the robustness of deep learning models without additional data labelling, making it appealing for improving plant disease detection systems' generalizability across diverse agricultural environments. This approach reduces reliance on extensive labeled datasets and facilitates practical deployment in real-world agricultural settings with inconsistent conditions.

Correlation Alignment (CORAL): The domain adaptation method CORAL (Cheng et al., 2021) aimed at aligning the second-order statistics (covariance) of feature distributions between the source and target domains. Unlike more complex adversarial training methods, CORAL provides a simpler yet effective approach to mitigate domain shifts by directly adjusting the data distributions.

Mechanism of CORAL: CORAL's main objective is to match the covariances of feature distributions between the source and target domains, assuming that aligning these statistics can mitigate the domain gap (Zhao et al., 2022). This is accomplished by transforming features from the source domain to have the same covariance as those from the target domain. The transformation involves a linear operation, making CORAL computationally efficient and easy to integrate into standard deep-learning pipelines.

Application in Plant Disease Detection: In the context of plant disease detection, CORAL can offer notable benefits, particularly when there are disparities in environmental conditions or imaging equipment between the source training data and the operational target environment testing data. For instance, images taken in various seasons or under diverse lighting conditions may exhibit different colour distributions and intensities. CORAL can effectively align these variations (Cheng et al., 2021), enhancing the model's performance without

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requiring extensive retraining. This capability positions CORAL as a valuable tool for enhancing the robustness and generalizability of plant disease detection models across diverse agricultural settings.

Benefits and Considerations: One of the significant advantages of using CORAL for domain adaptation is its simplicity and low computational cost. It does not require additional parameters to be learned, which contrasts with more complex models like DANN (Wang et al., 2020). This simplicity can be particularly advantageous in agricultural settings where computational resources might be limited. However, while CORAL effectively addresses shifts in feature distribution, it assumes that the primary differences between domains can be captured through covariance alone. This may not always hold, especially in cases where higher-order statistics play a crucial role. Thus, while CORAL is a powerful tool for domain adaptation, it is often used in conjunction with other methods to ensure comprehensive adaptation across more complex domain shifts.

By integrating CORAL into the process of plant species and disease detection, the technique offers a promising route to enhance the robustness of diagnostic models against the variations inherent in real-world agricultural data, thereby supporting more accurate and reliable disease management strategies.

Review of Existing Work on Cross-Domain Plant Disease Detection

The integration of cross-domain adaptation techniques in plant disease detection represents an emerging innovative field of research, primarily driven by the necessity to apply deep learning models effectively across varied agricultural environments. Recent advancements in this area have focused on enhancing the adaptability and accuracy of detection systems to cope with the variability introduced by different growth conditions, plant varieties, and imaging technologies.

Recent Developments in Cross-Domain Adaptation: Recent studies (Huang et al., 2023; Zhu et al., 2021) have demonstrated innovative approaches to mitigate the impact of domain shift in agricultural applications. For instance, researchers have explored hybrid models that combine traditional convolutional neural networks (CNNs) with domain adaptation techniques to improve the generalizability of plant disease detection models.

Hybrid Adversarial and Statistical Techniques: A notable 2021 study by Zhang et al. integrated adversarial learning with statistical alignment (Zhang et al., 2021) methods, showing that such combinations could significantly enhance model performance across domains by not only aligning feature distributions but also fostering feature invariance. This study underscored the potential of combining different domain adaptation strategies to tackle complex shifts in agricultural datasets.

Transfer Learning Approaches: Another significant line of research has been the use of transfer learning (Talukder et al., 2023) where models pre-trained on large, diverse datasets are fine-tuned for specific agricultural tasks. A 2023 study by Talukder utilized transfer learning to adapt models trained on generic image datasets to specific jute plant disease detection tasks, achieving remarkable improvements in accuracy across unseen data from different environmental conditions.

Domain Adaptation: Research by Hsu et al. (2021) explored the supervised domain adaptation where source data trained model tests against the unknown target domain data. Their work demonstrated that domain gap problems and supervised techniques could effectively bridge the gap between laboratory conditions and field images, thus facilitating the experimental application of DL models in real-life applications.

Challenges and Limitations

While these studies have made significant strides, they also highlight the inherent challenges in cross-domain plant disease detection:

Complexity of Environmental Variability: External factors such as lighting, background, and weather conditions introduce non-trivial variability that complicates the domain adaptation process (Marvin et al., 2021).

Scalability of Models: Although some models perform well in controlled experiments, their scalability and efficiency in diverse, real-world agricultural settings remain a critical concern (Zhao et al., 2022).

Data Availability and Quality: The dependency on high-quality, annotated datasets for training and validation poses significant challenges (Vijayalakshmi et al., 2020), especially in less accessible regions.

Despite significant advancements in deep learning techniques for plant disease detection, the challenge of domain shift remains a substantial barrier, limiting the practical deployment of these models across varying agricultural environments. Current methodologies (Zhu et al., 2021) often fall short in environments that deviate from the conditions under which the models were trained. This decreases accuracy and reliability when confronting real-world agricultural settings with diverse and unpredictable conditions.

The reviewed literature demonstrates substantial progress through approaches like adversarial domain adaptation (Wang et al., 2020) and correlation alignment

(Cheng et al., 2021). However, these methods often address only specific aspects of domain variability, such as image quality or background changes, without a holistic approach to the complex range of variations seen in agricultural fields worldwide. Moreover, most current systems require considerable computational resources and extensive labeled datasets, which are not always feasible in agricultural contexts, especially in resource-constrained settings.

Given these challenges, there is a pressing need for a robust system that can effectively adapt across multiple domains and handle the full spectrum of environmental, genetic, and phenotypic variations inherent in global agricultural settings. The proposed hybrid DANN-CORAL approach aims to fill this gap by providing a versatile, efficient, and scalable solution for cross-domain plant disease detection. This system seeks to combine the strengths of adversarial learning with statistical alignment methods to create a model that is more adaptable to different conditions and more accessible and practical for real-world applications. Our proposed system is designed to address these critical challenges by increasing the generalizability, accuracy, and efficiency of plant species and disease detection models, thus supporting more reliable and sustainable agricultural practices globally.

Hybrid DANN-Coral Model

In this section, we introduce our proposed methodology for addressing the challenge of cross-domain plant disease detection. We begin by mathematically formulating the problem statement, outlining the key objectives and challenges involved in adapting deep learning models to diverse agricultural environments. Subsequently, we present the architecture of our proposed Hybrid DANN-CORAL model, which combines DANN (Wang et al., 2020) with CORAL (Cheng et al., 2021) to mitigate domain shift (Marvin et al., 2021) and enhance model robustness. We elaborate on the components of the model, including the feature extraction network, domain adversarial training with DANN, and correlation alignment with CORAL loss. Finally, we describe the training process and experiments used to gauge the effectiveness of our approach on selected plant leaf images and disease datasets. Through this methodology, we aim to develop a versatile and efficient solution for plant species and disease detection that can adapt seamlessly across different domains.

Problem Formulation: Cross-Domain Plant Disease Detection

Cross-domain plant species and disease detection (Chulif et al., 2023) pose a significant challenge in agriculture, where the deep models trained on one domain struggle to generalize well when deployed in a different domain with distinct characteristics (Farahani et al., 2020). Mathematically, this problem can be formulated as follows:

Let X_S and Y_S specified the source dataset related feature space and label space respectively, where

$$X_S = \left\{ x_i^S \right\}_{i=1}^{N_S} \ \ and \ \ Y_S = \left\{ y_i^S \right\}_{i=1}^{N_S}$$

with N_S representing the source sample count, similarly, let X_t and Y_t represent the target dataset related feature space and label space, where

$$X_t = \left\{ x_i^t \right\}_{i=1}^{N_t} \ \ and \ \ Y_t = \left\{ y_i^t \right\}_{i=1}^{N_t}$$

with N_t denoting the total count of target samples. Learning a mapping function $F: X_S \to Y_S$ is the primary objective of this research, which is to accurately classify plant diseases in the target data X_t with the knowledge transferred from the source data X_S despite the domain shift between the two datasets. Formally, the objective is to reduce the distribution gap between the source and target dataset, expressed as:

$$\min_F \ D(X_S, X_t)$$

where $D(X_S, X_t)$ represents a measure of domain discrepancy, such as the Maximum Mean Discrepancy (MMD) (Wang et al., 2020). The aim is to find a model F that minimizes this domain gap, allowing for effective knowledge transfer between domains and enabling accurate disease detection in the target domain.

Cross-domain adaptation techniques, such as DANN and CORAL, aim to address the domain gap issue by learning domain-invariant representations and aligning the feature distributions between the source and target datasets. By leveraging these techniques, we aim to develop a robust model for plant disease detection that can generalize well across diverse agricultural environments, thereby improving the reliability and effectiveness of disease management strategies.

Network Architecture: Hybrid DANN-CORAL Model

Cross-domain adaptation techniques, including DANN and CORAL are designed to mitigate this challenge by learning features that are invariant across domains (Hongsong et al., 2021) and aligning the feature distributions between the source and target datasets. Through the utilization of these techniques, our goal is to construct a resilient model for plant species and disease detection capable of generalizing effectively across various agricultural settings. This, in turn, enhances the dependability and efficacy of disease management approaches.

Architecture: The Hybrid DANN-CORAL model consists of a feature extraction network, usually a pre-trained CNN, tasked with capturing discriminative features from input images. Domain adversarial training utilizing DANN is incorporated to acquire domain-invariant representations, facilitated by the Gradient Reversal Layer (GRL) (Nam and Suh-Yeon, 2023), which adjusts gradients during backpropagation. Figure 1 illustrates this architecture enables robust feature learning and adaptation, thereby augmenting the model's capacity to generalize across varied agricultural environments for proficient disease detection.

Hybrid DANN-CORAL Algorithm:

Input: Source domain dataset X_S , target domain dataset X_T , domain labels Y_S, Y_T

Output: Trained feature extractor F

1. *Initialize*: Randomly initialize parameters of the feature extractor F and domain classifier D.
2. *Pre-train*: Train F on X_S with supervised learning.
3. *Domain adversarial training*: Repeat until convergence:
   a. Sample a batch of source domain samples X_S and target domain samples X_T
   b. Compute feature representations $F(X_S)$ and $F(X_T)$ using F
   c. Compute domain labels Y_D for source and target domain samples.
   d. Update F to minimize the combined loss:

$$L_{total} = L_{task} + \lambda_1 L_{domain} + \lambda_2 L_{coral}$$

Where:

- L_{task} is the task-specific classification loss.
- L_{domain} is the domain classification loss (using gradient reversal layer).
- L_{coral} is the CORAL loss for domain alignment.
- λ_1 *and* λ_2 are hyperparameters.

4. *Output*: Trained feature extractor F

This algorithm optimizes the feature extractor to learn domain-invariant representations by minimizing the task-specific classification loss L_{task} and maximizing the domain confusion loss L_{domain}. The CORAL loss L_{coral} further aligns the feature distributions between the source and target domains to enhance model generalization. Adjusting the hyper-parameters λ_1 *and* λ_2 , allows for fine-tuning the model's behavior during training.

Feature Extraction Network

The core component of the Hybrid DANN-CORAL model is the feature extraction network, crucial for extracting meaningful features from input images. It is vital to employ CNN architecture for this purpose, given its ability to learn hierarchical representations from image data. Consisting of convolutional, pooling, and fully connected layers, the CNN learns to extract relevant features from the input images, laying the groundwork for further analysis.

Convolutional Layer (Conv): The convolutional layer applies a set of learnable filters W to the input image X to produce feature maps. The output of the convolution operation can be represented as:

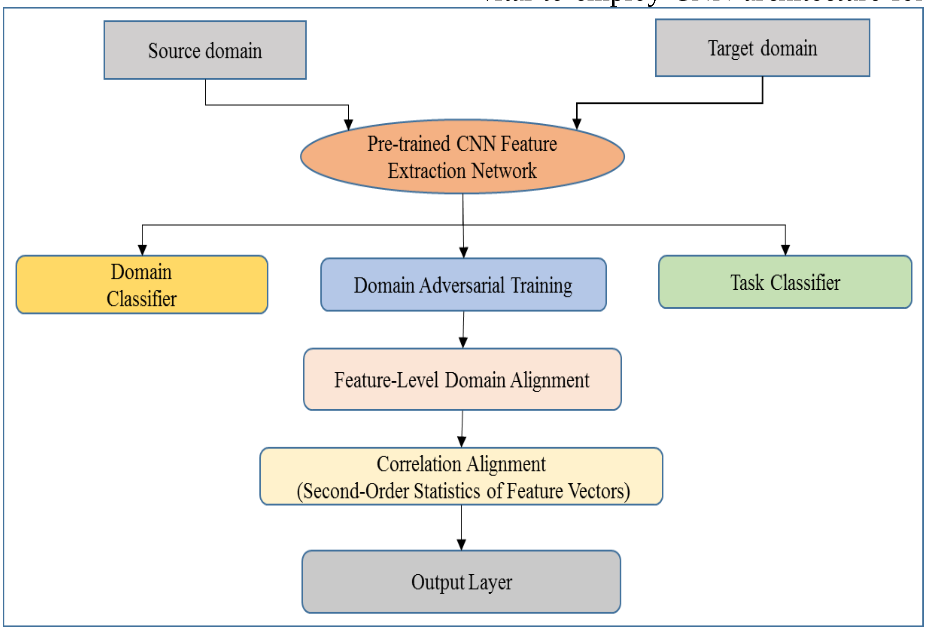

Figure 1. DANN-CORAL Model Architecture for Plant Disease Classification.

$$F_{i,j,k} = \sigma\left(\sum_{m,n} I_{i+m,\,j+n,\,l} \times K_{m,n,l,k} + B_k\right)$$

Where, $F_{i,j,k}$ is the activation function at the place (i, j) in the K^{th} feature map, $I_{i+m,\,j+n,l}$ is the pixel intensity at position $(i+m, j+n)$ in the input image I, $K_{m,n,l,k}$ is the weight corresponding to the (m,n) spatial location of the I^{th} input and output channels. B_k is the bias term for the K^{th} output channel and σ is the activation function (e.g., ReLU).

Pooling Layer: In our DANN-CORAL model, the pooling layer conducts max pooling to decrease the feature maps' spatial dimensions while retaining its crucial information. The max pooling operation for a given stride $'s'$ is applied as follows:

$$F_{i,j,k} = \max\left(F_{(i\times s),(j\times s),k}\right)$$

Fully Connected Layer (FC): This layer, also known as a dense layer (Laura et al., 2022), consolidates the flattened feature maps from the preceding layer into a final feature vector. Denoted by N which represents the number of neurons in the fully connected layer, and W_{fc} be the weight matrix connecting the flattened feature maps to the dense layer. The output of this dense layer is calculated as:

$$Z = W_{fc} \bullet flatten(F) + B_{fc}$$

Where Z is the output feature vector, B_{fc} is the bias term, $flaten(F)$ flattens the feature maps F into a vector. These operations in the feature extraction network allow the model to capture hierarchical features relevant to plant diseases from the input images. The pretrained CNN, initialized with weights learned from a large dataset, is fine-tuned for the task of plant disease detection, enabling it to adapt its learned representations to the specific features associated with plant diseases.

Domain Adversarial Training with DANN

Domain adversarial training is integrated into the Hybrid DANN-CORAL model to facilitate domain-invariant feature learning, addressing the challenge of domain shifts between different agricultural datasets. The feature extraction network is optimized to minimize the standard task loss (e.g., cross-entropy loss) for plant species and disease classification while maximizing the domain confusion loss. This is achieved through the adversarial training paradigm, where the feature extractor is encouraged to produce features that are indistinguishable between the source and target domains. The domain confusion loss L_{adv} is computed as follows (Minghao et al., 2020):

$$L_{adv} = E_{x\sim S}\left[\log D(f(x))\right] + E_{x\sim T}\left[\log(1 - D(f(x)))\right]$$

Here $'S'$ are the labeled source data samples, '*T*' the unlabelled target samples, '*f(x)*' the feature representation extracted by the feature extraction network and the D(•) domain classifier, which is further used to calculate the feature-relevant domain label and 'E' denotes the expectation over the domain data distributions.

The main objective of domain adversarial training (Wang et al., 2020; Zhao et al., 2022) is to reduce the distinction between the distributions of the source and target datasets. This is achieved by instructing the feature extractor to deceive the domain classifier using adversarial learning. The inclusion of the GRL (Nam and Suh-Yeon, 2023) within the network architecture is crucial for facilitating this process. Specifically, the GRL modulates the gradients traversing the network during the backpropagation phase, which effectively reverses their direction. This reversal encourages the feature extractor to produce representations that are invariant to domain variations.

By concurrently optimizing both the task loss and the domain confusion loss (Minghao et al., 2020), the Hybrid DANN-CORAL model was trained to find the representation that is not only discriminative for disease classification but also resilient to changes in the domain. This adaptive capability enhances the model's robustness across a wide range of agricultural environments, allowing for more reliable and accurate disease detection.

Incorporation of the GRL

GRL plays a pivotal role in facilitating effective domain adversarial training within the hybrid DANN-CORAL model (Nam and Suh-Yeon, 2023). Its key function is to invert the gradients during backpropagation, thereby enabling simultaneous optimization of both the feature retrieval system and the domain classifier in opposing directions.

In this adversarial training framework, the feature extractor is encouraged to learn domain-invariant representations (Manh-Ha et al., 2021) while simultaneously training the domain classifier to distinguish between the source and target domains. Mathematically, GRL modifies the gradients passed through it by multiplying them by a negative scalar value λ. This operation effectively reverses the gradients related to the parameters of the domain classifier (Nam and Suh-Yeon, 2023) while leaving the gradients associated with the parameters of the feature extractor unchanged.

As a result, the feature extractor learns to produce features that remain consistent across domain shifts, thereby enhancing the model's ability to generalize across diverse agricultural settings. The modification introduced by the GRL can be mathematically expressed as

$$Modified\,Gradient = -\lambda \bullet Original\,Gradient$$

Where λ is a hyperparameter controlling the magnitude of gradient reversal, $Original\,Gradient$ refers to the gradients computed during backpropagation with respect to the domain classifier's parameters and $Modified\,Gradient$ represents the gradients propagated back through the GRL. By incorporating the GRL into the network architecture, the hybrid DANN-CORAL model is able to effectively learn domain-invariant representations, thereby enhancing its robustness and generalization capabilities across different agricultural environments.

Correlation Alignment with CORAL Loss

In the Hybrid DANN-CORAL model, Correlation Alignment with CORAL Loss functions is complementary to Domain Adversarial Training, aiming to further mitigate domain shift and bolster the model's adaptability across diverse agricultural environments. The CORAL loss functions to reduce the distribution gap between the source and target datasets by aligning their second-order statistics, specifically targeting the covariance matrices of the feature representations.

Mathematically, the CORAL loss is computed as the squared Frobenius norm of the discrepancy between the covariance matrices of the feature representations extracted from the source and target domains, denoted as XS and XT, respectively.

Mathematically, the CORAL loss is calculated as the squared Frobenius norm of the difference between the covariance matrices of the feature representations from the source and target dataset domains. Let XS and XT denote the feature representations extracted from the source and target dataset domains, respectively. Then, the CORAL loss (Preciado-Grijalva and Venkata Santosh, 2021) can be formulated as:

$$L_{CORAL} = \frac{1}{4d^2}\|C_S - C_t\|_F^2$$

Where $C_S = \frac{1}{n_s} X_S^T X_S$ and $C_t = \frac{1}{n_t} X_t^T X_t$ specifies the source and target domain features related covariance matrices. $\|\bullet\|_F$ denotes the Frobenius norm, d represents the dimensionality of the feature representations, n_S and n_t are the number of samples identified in the source and target dataset domains, respectively. The objective of minimizing the CORAL loss is to encourage the feature extractor to learn representations that not only align in terms of mean values but also in terms of second-order statistics, thus reducing domain shift and promoting domain-invariant feature learning. By incorporating the CORAL loss into the training process alongside Domain Adversarial Training with DANN, the Hybrid DANN-CORAL model achieves a comprehensive approach to domain adaptation, effectively addressing different aspects of domain shift and enhancing its robustness in plant disease detection across diverse agricultural settings.

The training process of the Hybrid DANN-CORAL model involves optimizing the feature extraction network, domain classifier, and auxiliary layers to minimize the classification loss while simultaneously aligning domain distributions using domain adversarial training with DANN and correlation alignment with CORAL Loss. By optimizing the model parameters using the described training process, the Hybrid DANN-CORAL model learns to extract domain-invariant features (Chen et al., 2020) while effectively classifying plant diseases, enhancing its robustness and generalization across diverse agricultural environments.

Experiments and Results

As part of the experiments and results section, we conduct an evaluation of the proposed Hybrid DANN-CORAL model for robust plant disease detection. Utilizing cross-domain adaptation techniques, we assess the model's performance on different datasets, including both the PlantVillage dataset (Hughes and Salathe, 2015) serving as the source domain and the New PlantVillage dataset (Samir Bhattarai, 2019) acting as the source domain. In vice versa, we made the New PlantVillage dataset (Samir Bhattarai, 2019) serve as the source domain and the PlantVillage dataset (Hughes and Salathe, 2015) serve as the target domain for second-level experiments. Additionally, we explore the integration of both datasets as integrated datasets to evaluate the model's performance comprehensively. Through thorough analysis and comparison with baseline models, we gauge the effectiveness of our approach in tackling domain shift challenges and improving disease detection accuracy.

Datasets and Preprocessing

This section details the datasets used in our experiments and the preprocessing steps applied to prepare the data for training and evaluation.

Table 1 illustrates the distribution of images across various plant diseases, including Potato Healthy, Potato Early Blight, Tomato Healthy, Tomato Yellow Leaf, Pepper Healthy, and Pepper Bacteria Spot. The numbers highlight the variations in dataset sizes and the availability of images for each category, which are essential considerations for training and testing the model ability in plant species and disease detection.

may exhibit differences in lighting conditions, background clutter, and plant phenotypes compared to the source domain, necessitating domain adaptation techniques for effective model transfer.

Table 1. Selection of Leaf Categories across Datasets for Experiments.

Leaf Categories	Plant Village Dataset [30]	New Plant Village Dataset [31]
Potato Healthy	1824	1520
Potato Early Blight	1000	1939
Tomato Healthy	1591	1926
Tomato Yellow Leaf	3209	1961
Pepper Healthy	1478	1988
Pepper Bacteria Spot	997	1913

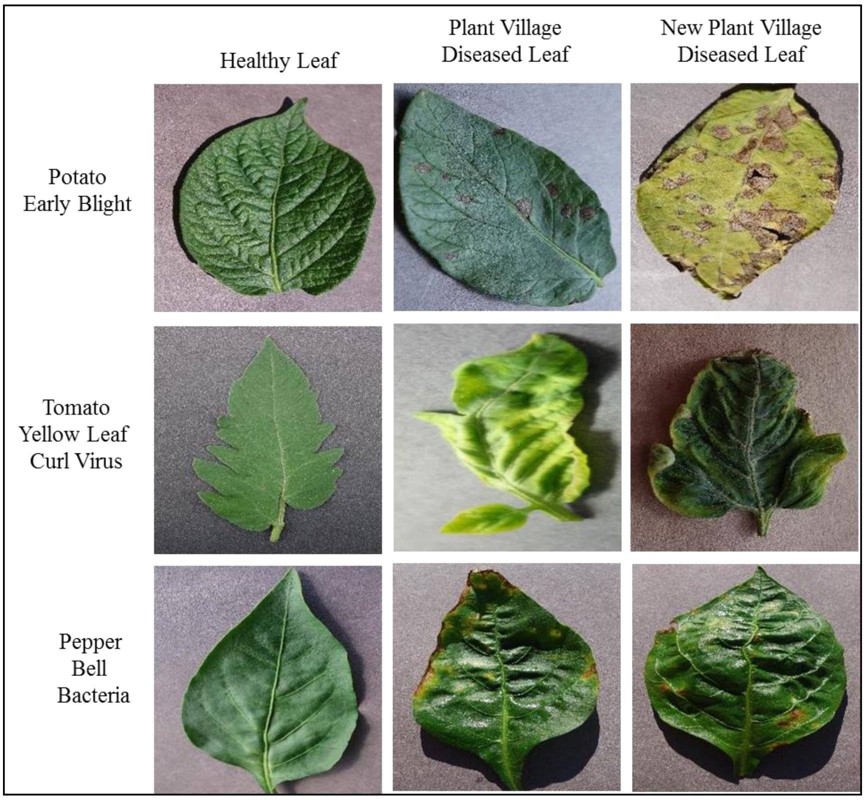

Figure 2. Leaf Images from Plant Village and New Plant Village Datasets.

PlantVillage Dataset: Figure 2 presents the PlantVillage dataset (Hughes and Salathe, 2015), which contains a diverse collection of images depicting various plant diseases across multiple plant species (Minghao et al., 2020). This dataset is widely used for plant species and disease detection tasks and comprises high-quality images annotated with disease labels. Every image within the dataset is linked to a particular plant species and disease classification, offering essential data for training our model.

New Plant Village Dataset: The New Plant Village dataset (Samir Bhattarai, 2019) consists of images (Figure 2) collected from different geographic regions or environmental conditions than the PlantVillage dataset. These images capture additional disease types or variations not present in the source domain, thereby introducing domain shift challenges. The target dataset

Preprocessing: To enrich the diversity and resilience of our training data, we utilize different types of data augmentation techniques, such as rotation, scaling, flipping, and colour jittering. These augmentation methods are instrumental in mitigating overfitting and enhancing the DANN_CORAL capacity to generalize across diverse dataset images. Moreover, by simulating variations in the target domain, data augmentation aids in fostering domain adaptation during training.

As part of the preprocessing stage, we resize all dataset images to a standardized dimension of 224x224 pixels to ensure uniformity in input dimensions. Following resizing, normalization techniques (Chlap et al., 2021) are applied to scale pixel values to a consistent range, which promotes model convergence and enhances performance.

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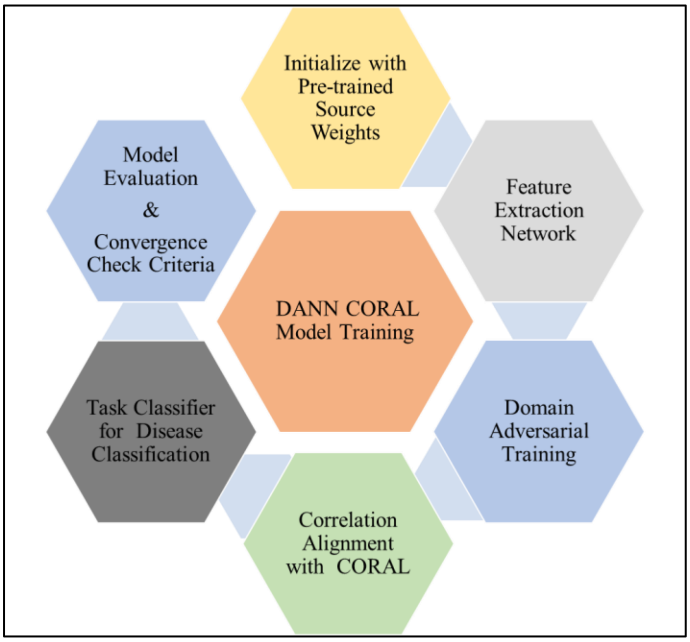

Figure 3. Training Process Flow of Hybrid DANN-CORAL model.

Standardization procedures are also implemented to centre the pixel distributions on zero mean and unit variance, facilitating effective feature learning and bolstering the model's flexibility to fluctuations with image input conditions.

Metrics: Evaluation metrics like accuracy, precision, recall, and F1 score assess cross-domain adaptation techniques for plant disease detection. These metrics provide insights into the model's overall correctness, ability to identify true positives, and balance between precision and recall. Additionally, metrics like the confusion matrix aid in assessing the model's discrimination ability and understanding its strengths and weaknesses. Network hyperparameters, including the CNN's layer number, filter sizes, and activation functions, are adjusted to optimize disease prediction performance.

Model Training

To train the Hybrid DANN-CORAL model for plant spices and disease detection, we adhere to a systematic approach illustrated in Figure-3, incorporating both domain adversarial training (Nam and Suh-Yeon, 2023) with DANN and correlation alignment with CORAL. This ensures that the model learns domain-invariant representations, enabling effective generalization across diverse agricultural environments. The Hybrid DANN-CORAL model consists of key elements: a feature extraction network, a domain classifier, and a task classifier. The feature extraction network captures essential features from input images, while the domain classifier distinguishes between source and target domain samples. The task classifier is tasked with predicting the presence of plant diseases.

We start by initializing the model with weights pre-trained on the source domain dataset to capture basic visual patterns, speeding up convergence during training. Domain adversarial training via DANN (Wang et al., 2020) aims to narrow the domain gap between the source and target domains by training the feature extractor to produce domain-invariant representations while minimizing standard task loss (e.g., cross-entropy loss) (Minghao et al., 2020). Additionally, correlation alignment with CORAL is employed to further mitigate domain shift by aligning second-order feature statistics, enhancing adaptability to agricultural environment variations. Training iteratively optimizes model parameters using gradient descent algorithms, carefully tuning learning rates and regularization parameters to ensure stable convergence and prevent overfitting. This integrated approach fosters the learning of robust and domain-invariant representations (Manh-Ha et al., 2020), improving generalization performance across diverse agricultural domains.

Domain Shift Experiments and Results

In our domain shift experiments, we conducted three sets of trials to evaluate the Hybrid DANN-CORAL model's performance in robust plant disease detection. The first set involved training the model on the New Plant Village Dataset (Samir Bhattarai, 2019) and testing it on the Plant Village Dataset (Hughes and Salath, 2015), assessing its adaptability to new environments. Conversely, in the second set, we trained the model on the Plant Village Dataset and tested it on the New Plant Village Dataset, examining its ability to generalize to unseen data from a different domain. Finally, the third set entailed training the model on an integrated dataset comprising both datasets, demonstrating its performance in a merged domain context with broader environmental conditions and disease manifestations. By systematically evaluating the model across these settings, we comprehensively understood its robustness and generalization capabilities in diverse agricultural environments.

Set-I Results: In the first set of experiments, we trained the model on the New Plant Village Dataset (Samir Bhattarai, 2019) and tested it on the Plant Village Dataset (Hughes and Salathe, 2015). Employing domain adversarial training with DANN and correlation alignment with CORAL during training, we assessed its performance using metrics defined in metrics (Xiaoxu et al., 2023) section to evaluate its effectiveness.

Table 2. Results of Disease Detection Modules on Plant Village Dataset.

Plant Village Dataset Modules	TP	FP	FN	TN	ACC	Precision	Recall	F1-score
Tomato Healthy and Yellow Leaf	1423	146	227	3004	92.23%	90.71	86.24	88.41
Pepper Healthy and Bacteria Spot	1351	93	141	890	90.55%	93.56	90.55	92.03
Potato Healthy and Early Blight	1654	76	187	907	90.69%	95.61	89.84	92.64
Integrated Score	4428	315	555	4801	91.39%	93.36	88.86	91.05

In this evaluation, the model demonstrated strong performance across various plant disease categories is listed in table-2 and clearly visualized in figure 4 and 5. For the "Tomato Healthy and Yellow Leaf" module, the DANN-CORAL model achieved an accuracy of 92.23%, with high precision (90.71%) and recall (86.24%), indicating DANN-CORAL ability to effectively identify both healthy and diseased tomato leaves. Similarly, in the "Pepper Healthy and Bacteria Spot" module, the model attained an accuracy of 90.55%, with impressive precision (93.56%) and recall (90.55%), highlighting its robustness in distinguishing between healthy and infected pepper leaves. Moreover, for the "Potato Healthy and Early Blight" module, the model exhibited an accuracy of 90.69%, with notable precision (95.61%) and recall (89.84%), underscoring its proficiency in detecting potato diseases.

Integrated across all modules, the model achieved an accuracy of 91.39%, with consistent precision (93.36%) and recall (88.86%). These results signify the effectiveness of the Hybrid DANN-CORAL model in cross-domain adaptation for plant disease detection.

Set-II Results: For the second set of trials, we reversed the training and testing datasets, training the Hybrid DANN-CORAL model on the Plant Village Dataset (Hughes and Salathe, 2015) and the same is testing on the New Plant Village Dataset. Similar to the first set, we incorporated domain adversarial training and correlation alignment (Preciado-Grijalva and Venkata Santosh, 2021) during training and evaluated the model's performance on the New Plant Village Dataset using the aforementioned metrics (Xiaoxu et al., 2023) is shown in table-3 and visualized the comparison in figure 6 and 7.

In the second set of experiments, the DANN-CORAL model exhibited notable performance across diverse plant disease categories (Table 3). Notably, it achieved an accuracy of 85.36% for the "Tomato Healthy and Yellow Leaf" module, indicating its effectiveness in classifying tomato leaf diseases. Additionally, strong performance was observed in the "Pepper Healthy and Bacteria Spot" module, with an accuracy of 93.98%, showcasing the model's robustness in distinguishing between healthy and infected pepper leaves. Similarly, the model exhibited promising results in detecting potato diseases, achieving an accuracy of 91.21% for the "Potato Healthy and Early Blight" module. Overall, the integrated score across all modules yielded an accuracy of 86.98%, demonstrating the model's consistent performance in cross-domain adaptation for plant disease detection. These results underscore the model's versatility and potential to tackle the issues encountered in real-life applications in plant leaf and disease classification.

Table 3. Results of Disease Detection Modules on New Plant Village Dataset.

New Plant Village Dataset Modules	TP	FP	FN	TN	ACC	Precision	Recall	F1-score
Tomato Healthy and Yellow Leaf	1518	211	358	1800	85.36%	87.81	80.92	84.22
Pepper Healthy and Bacteria Spot	1872	72	163	1794	93.98%	96.31	91.99	94.11
Potato Healthy and Early Blight	1443	106	198	1712	91.21%	93.16	87.93	90.47
Integrated Score	5158	621	843	4625	86.98%	89.25	85.95	87.57

Set-III Results: In our third set of scheduled experiments, we merged the New Plant Village Dataset (Samir Bhattarai., 2019) and the Plant Village Dataset (Hughes and Salathe, 2015) to create an integrated dataset. This merged dataset was split into training and testing sets.

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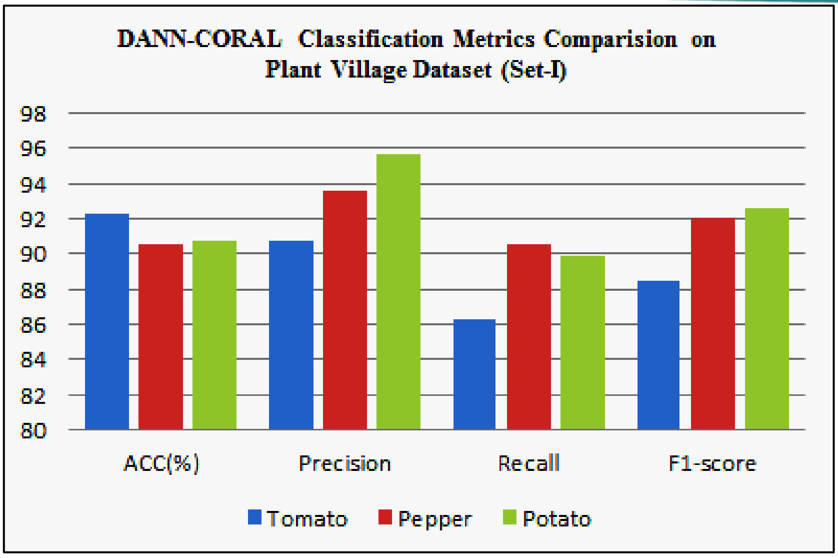

Figure 4. DANN-CORAL Classification Metrics Comparison on Plant Village Dataset (Set-I).

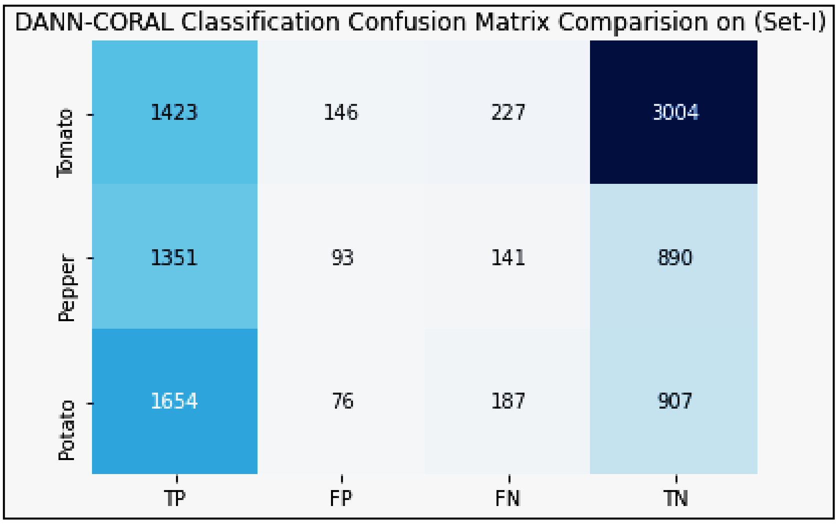

Figure 5. DANN-CORAL Classification Confusion Matrix Comparison on Set-I.

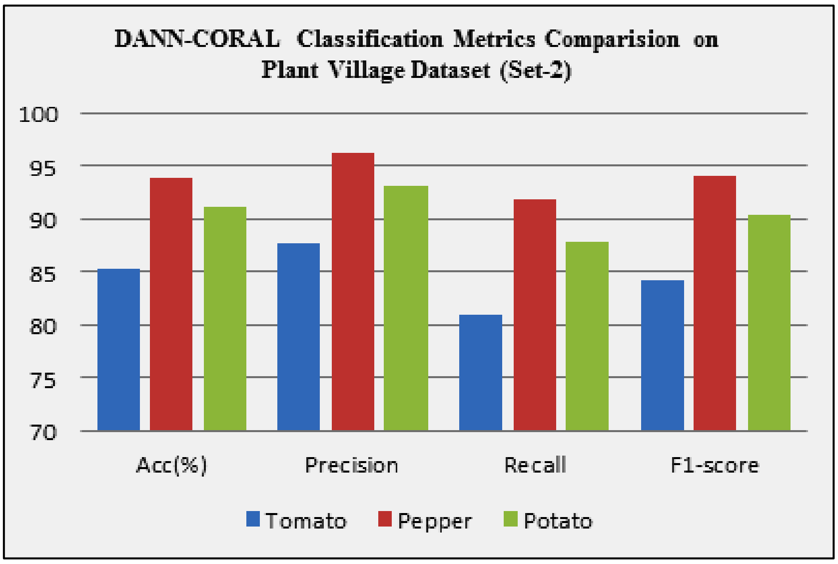

Figure 6. DANN-CORAL Classification Metrics Comparison on New Plant Village Dataset (Set-II).

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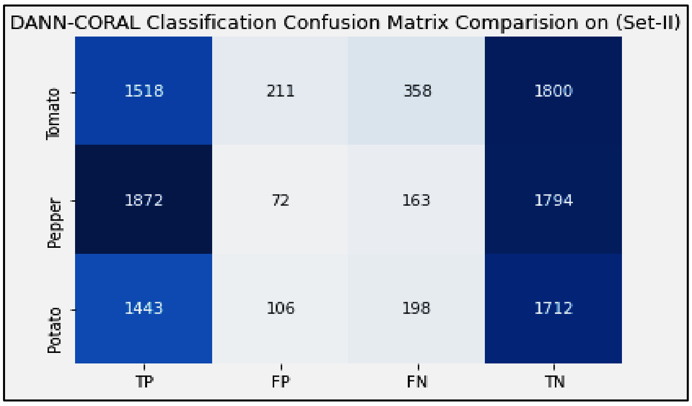

Figure 7. DANN-CORAL Classification Confusion Matrix Comparison on Set-II.

The Hybrid DANN-CORAL model was trained on the merged dataset, leveraging domain adversarial training and correlation alignment techniques. Subsequently, we tested the trained model on the split integrated dataset and computed the performance metrics (Xiaoxu et al., 2023) (Table 4) to analyze its effectiveness in cross-domain adaptation for plant disease detection. The comparison metrics of results are visualized through Figures 8 and 9 for better understanding. The DANN-CORAL model exhibited notable performance across diverse plant disease categories in the third set of experiments. Notably, for "Tomato and Yellow Leaf," the model achieved 92.53% accuracy, showcasing effective classification of tomato leaf diseases. Strong performance was also observed for "Pepper Healthy and Bacteria Spot," with an accuracy of 93.61%, demonstrating the model's robustness in distinguishing between healthy and infected pepper leaves. Additionally, the model showed promising results for "Potato Healthy and Early Blight," achieving 92.74% accuracy. When considering all modules, the model attained an accuracy of 92.91%, emphasizing its cross-domain adaptation capabilities. Overall, these findings highlight the model's versatility and potential for real-world applications in agriculture.

Table 4. Results of Disease Detection Modules on Integrated Dataset.

Integrated Dataset Modules	TP	FP	FN	TN	ACC	Precision	Recall	F1-score
Tomato and Yellow Leaf	3216	204	445	4822	92.53%	94.04	87.84	90.83
Pepper Healthy and Bacteria Spot	3149	266	142	2819	93.61%	92.21	95.69	93.92
Potato Healthy and Early Blight	3108	282	174	2719	92.74%	91.68	94.71	93.17
Integrated Score	9473	752	761	10360	92.91%	92.65	92.56	92.62

Finally, these experiments provided insights into the model's ability to adapt to domain shifts and generalize across different agricultural environments. By assessing its performance on varied datasets and comparing the results, we comprehensively understood the Hybrid DANN-CORAL model's efficacy in robust plant disease detection.

Baseline Models Comparison

Following the domain shift experiments, we proceeded to compare the performance of our DANN-CORAL model with baseline models: DABAN (Wang et al., 2022), DL-DA (Soto et al., 2022), and DANN (Ida et al., 2020). All models were trained on the Plant Village Dataset (Hughes and Salathe., 2015) and evaluated on the New Plant Village Dataset (Samir Bhattarai, 2019). Various performance metrics (Xiaoxu et al., 2023), including accuracy, precision, recall, and F1-score, were computed to gauge the models' effectiveness in classifying plant diseases across datasets.

The results of these experiments, including the performance metrics for each model, are summarized in Table 5. This comprehensive analysis allowed us to determine our DANN-CORAL model's relative strengths and weaknesses compared to the baseline approaches, providing valuable insights into its efficacy for robust plant disease detection.

Table 5. Classification Results obtained from various domain adaption baseline models.

Model	Accuracy	Precision	Recall	F1-Score
DANN-CORAL	91.39%	93.36	88.9	91.05
DABA [33]	89.75%	92.1	87.5	89.7
DL-DA[34]	88.62%	91.8	86.2	88.9
DANN[35]	90.15%	91.5	88	89.7

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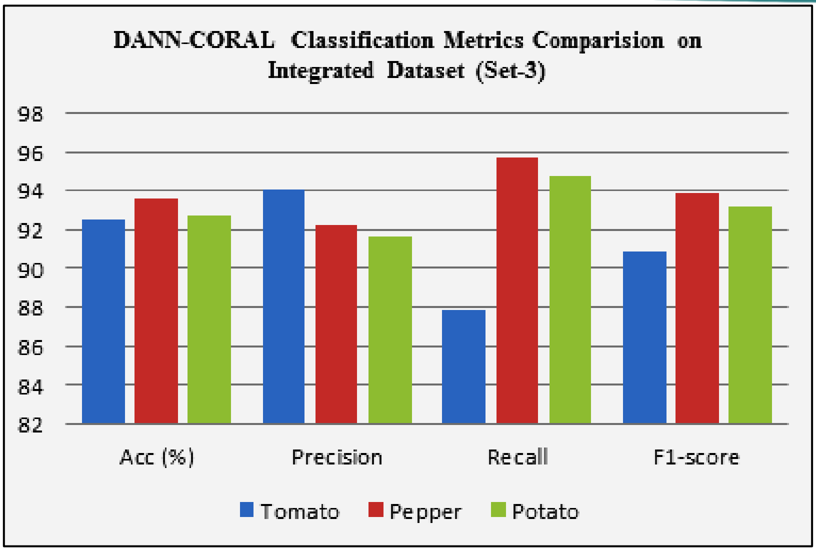

Figure 8. DANN-CORAL Classification Metrics Comparison on Integrated Dataset (Set-III).

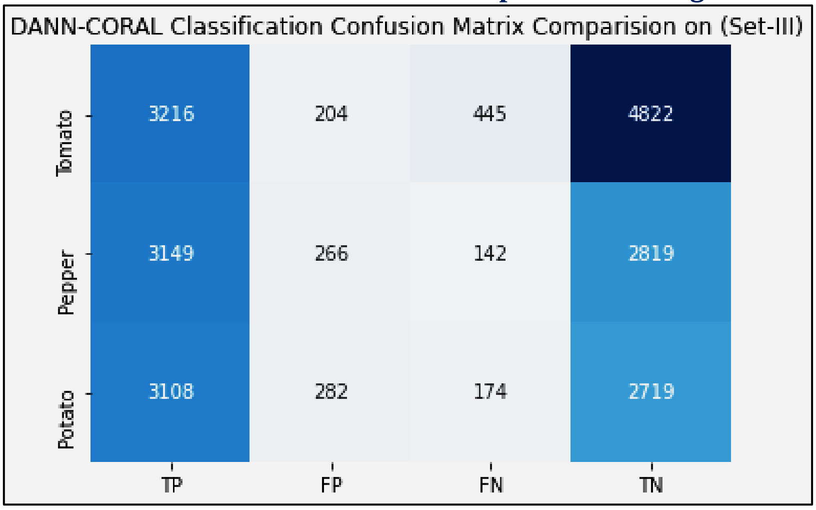

Figure 9. DANN-CORAL Classification Confusion Matrix Comparison on Integrated Datasets (Set-III).

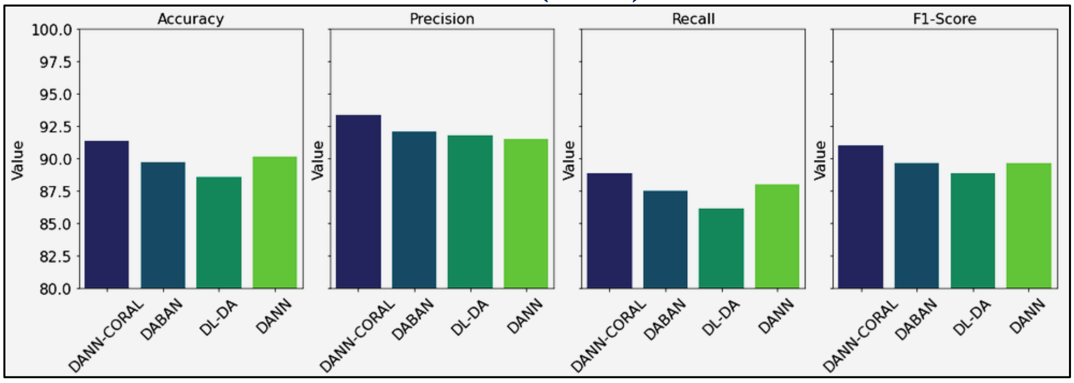

Figure 10. DANN-CORAL performance comparison with Baseline Models.

Table 5 and figure-10 provide a comprehensive overview of the performance metrics for our DANN-CORAL model and three baseline models (Wang et al., 2022; Soto et al., 2022; Ida et al., 2020). Notably, the DANN-CORAL model achieved the highest accuracy at 91.39%, indicating its exceptional ability to accurately classify plant diseases across diverse datasets. In terms of precision, the DANN-CORAL model demonstrated superior performance with a score of 93.36%, highlighting its ability to correctly identify positive cases while decreasing the false positives. Moreover, the recall score of 88.9% for DANN-CORAL underscores its effectiveness in capturing true positive cases from the dataset. This balanced measure of precision and recall is further reflected in the model's F1-score of 91.05%, signifying its robust performance in disease classification (Hughes and Salathe, 2015) tasks.

Conclusion

In this paper, we proposed a novel hybrid deep model for robust plant disease detection using cross-domain adaptation techniques. By leveraging a Hybrid DANN-

CORAL model, we aimed to address the challenge of domain shift between different agricultural environments. Our methodology involved the integration of domain adversarial training with DANN and correlation alignment with CORAL to learn domain-invariant representations. Conducting the comprehensive experiments and results analysis, we demonstrated the efficiency and robustness of our approach in detecting various plant diseases across different datasets. The DANN-CORAL achieved accuracies of 91.39%, precision of 93.36%, recall of 88.9%, and F1-scores of 91.05%, indicating the robustness and generalizability of our model. Furthermore, our experiments revealed the significance of individual leaf categories as well as the integrated dataset in enhancing disease detection performance. Future research could explore advanced fusion techniques to integrate multi-modal data sources, thereby enhancing disease detection accuracy. Additionally, investigating semi-supervised learning approaches could leverage unlabelled agricultural data, optimizing model performance in data-scarce scenarios. In addition, integrating the advanced transfer learning techniques with domain shift models to boost the performance while expanding to more image datasets is another prominent future work.

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