AgriVision: Advancing Agriculture with CNN (GAN model) - Based Leaf Disease Detection

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Abstract - Advances in deep learning (DL) technology have improved our ability to identify and describe objects in images. This development is widely used in agriculture, especially in the detection of harmful diseases. Good disease detection is important for crop management and increased yields. However, the detection of pathogens in plants through image analysis presents inherent problems. Correct detection must not only detect the presence of disease, but also indicate the specific disease associated with the use of appropriate countermeasures. A study of 100 major papers over the past five years showed that CNNs are effective in identifying various leaf diseases. Deep convolutional neural networks (DCNNs) perform well in early disease detection by analyzing image data and have both advantages and disadvantages. The training information is limited. Traditional image classification models often suffer from the problem of small samples, leading to possible overfitting and reduced generalization capabilities. To address this problem, researchers have explored various data augmentation techniques. For example, an improved generative adversarial network (GAN) model based on the Wasserstein GAN loss function was developed to generate synthetic disease images. This model improves the quality of the generated image by adding separate layers to the encoder of the generative network. Generating approximately 3,000 corn disease images from a simple database of 100 healthy images, this method achieved 98.4% recognition on ResNet18 network, showing improvements in model performance.

Using DoubleGAN, a two-level generative adversarial network. In the first stage, models are created using positive and negative leaf images before using Wasserstein GAN. This pattern is used to generate a negative image of a negative leaf. In the second stage, super-resolution GAN (SRGAN) is used to upscale these images. This approach has been proven to be effective in evaluating data with poor image quality. Compared with images generated by deep convolutional GAN (DCGAN), the DoubleGAN method produces clear images with 99.80% accuracy for identifying plant species and 99.53% for identifying diseases., but plant disease research still faces many challenges. Deep learning models usually require extensive hardware, large datasets, and have slow thinking experience, which may hinder practical applications. Network combining GAN modules with a transformer architecture. This new approach involves adding a pre-designed CNN backbone and incorporating GAN modules into the tracking stage. The travolution network combines CNN with Transformer to improve image enhancement and imaging capabilities. Experimental results show that the method achieves a satisfactory balance between accuracy

(51.7%), recall (48.1%), and average accuracy (mAP) (50.3%). Among the various designs, SAGAN performs very well in model tracking, while WGAN is the best in image enhancement. Practicality in the agricultural world. This collaboration demonstrates the potential of deep learning for plant disease detection and management, addresses the limitations of traditional methods, and provides better solutions for crop health monitoring. Generally speaking, the development of deep learning-based GAN methods has stimulated the growth of the field of plant disease detection. Despite the challenges, ongoing research and technology continue to improve the accuracy and efficiency of these methods, paving the way for better agriculture.

I. INTRODUCTION

Global climate change has impacted the natural environment, causing crop yields to declining and making crops more susceptible to pests and diseases. Among the crops affected, soybeans are particularly affected by these changes. This increased risk highlights the urgent need of accurate information about pests and diseases to improve crop production. Measure the problem. This approach requires a lot of skill, knowledge and experience, but is difficult to maintain consistently. In addition, traditional methods are often slow, prone to error and have poor feedback. To overcome these limitations, there is a growing trend towards the use of image processing and information technology in agriculture. The Internet (IE) and cloud computing have had a significant impact on many industries, including agriculture. Artificial intelligence and machine learning, in particular, have made major breakthroughs in the fields of computer vision, speech recognition, and robotics.

Among these advances, generative adversarial networks (GANs) have emerged as a particularly promising approach. GANs provide a great way to generate new models and support data beyond traditional data development methods that rely on geometric transformations and image processing. This capability has proven to be beneficial to modern agriculture and has improved crop yields and quality. Although there are extensive researches on plant diseases, there are still some problems especially in practical use. For example, images stored in archives are affected by different backgrounds, weather conditions and damage levels to obtain the best results. Changes in the appearance, design, form and number of products, together with problems such as lighting and occlusion, increase the difficulty of target detection. They face problems especially in different conditions and backgrounds. Complex algorithm steps may still show low performance and accuracy.

In addition, the time-consuming and difficult collection of information and explanations affects the general competence model. Changes in pests and diseases in different seasons require different deployment methods for pest and disease management and recommend changes. The extracted results are then analyzed using classical methods such as support vector machine (SVM), principal component analysis (PCA), and K-means clustering. The combination of thermal imaging and data depth can improve the lighting conditions and increase the accuracy of detecting poor vegetation. Deep convolutional neural networks (CNN) have shown high accuracy in crop disease classification. For example, a CNN model trained on more than 87,000 images from 25 different plant species achieved 99.53% accuracy in distinguishing healthy leaves from damaged leaves. The rise of GPU, big data, cloud computing, and deep learning like TensorFlow and PyTorch have accelerated progress in many areas like image recognition and driving. Improved accuracy, faster detection times, and improved safety.

Technologies like transfer learning and selective convolution kernel modules are used to improve the identification of small pests on apple leaves. Similarly, many neural networks have been developed for cucumber disease detection by replacing layers with global average connections to improve the performance of CNN work. These advances address limitations like long running times and generalization ability. Small data can lead to overfitting or underfitting of the model function. Data augmentation can be applied to tackle this problem. For example, the A-WGAN model was proposed to generate images of leaf diseases using deep learning to train the model based on comprehensive data of disease images. Techniques such as spatial affine transformations and color transformation help prevent overfitting, while the Wasserstein GAN (WGAN) network model stabilizes the training and reduces hyperparameter effects. The inclusion of self-guided layers in the generative network further improves feature extraction and global image processing. This approach solves the sample collision problem and improves the identification of small organisms. The shift from traditional methods to AI-based methods has increased the accuracy and efficiency of disease diagnosis. Deep learning models for identifying pests and banana diseases in greenhouses and disease detection have shown good results, demonstrating the potential of AI in pest management in patient farms.

Despite progress, challenges remain, most notably the need for large datasets. Balanced data with sufficient critical information is essential for effective modeling. As seen in repositories like PlantVillage, where thousands of healthy photos are associated with undesirable patterns, small datasets with inconsistent disease patterns can lead to negative results. This uncertainty makes model training difficult and impacts performance. GANs are known for their ability to generate high-quality images, making them useful for image processing. For example, DCGAN (Deep Convolutional GAN) provides a small library that combines CNNs and GANs for unsupervised learning. GANs have been successfully used in many applications, including face recognition and image resolution, and have proven effective in generating data for deep learning models. The competition is especially fierce when working with limited information. Problems such as lack of detail and blurry images can occur when zooming in. Unemployment without any clear signs of progress can also destabilize the education system. To overcome these challenges, researchers have implemented models like DoubleGAN and databases like PlantVillage to generate sharp, high-resolution images.

Using WGAN, the researchers pre-trained healthy leaves and exposed them to a small set of unhealthy samples to improve the quality and resolution of the images. The combination of SRGAN reduces the load and increases the depth of the network. The generated images are combined with the original images and tested separately to verify the performance of the new images. Effective control and management of these diseases is essential to reduce production losses and ensure future food security, especially as the world population grows. The Food and Agriculture Organization (FAO) emphasizes the need to increase food availability while protecting ecosystems through organic farming. To achieve these goals, new approaches to disease diagnosis and crop management are needed. Deep learning models, especially those based on convolutional neural networks (CNNs), offer a state-of-the-art solution to the limitations of traditional classification systems. CNNs are becoming increasingly popular in agricultural research because they have successfully solved image analysis problems and have made significant progress in the field of agricultural disease detection.

II. RELATED WORK

Accurate plant disease identification is essential for effective crop management and ensuring agricultural productivity. Traditional methods often rely on manual inspection, which is both labor-intensive and prone to errors. With advancements in deep learning and image recognition technologies, several innovative approaches have emerged to address the challenges associated with plant disease detection. This section reviews recent developments in this field, focusing on the application of DoubleGANs (a specialized type of Generative Adversarial Network) and other advanced techniques to overcome data scarcity and improve detection accuracy.

Data Scarcity and Unsupervised Learning Approaches

The issue of limited labeled data is a significant challenge in plant disease identification. High-quality labeled images of diseased leaves are crucial for training accurate machine learning models. However, obtaining a large dataset with diverse and accurately labeled examples is often impractical. This scarcity of labeled data has led to the exploration of unsupervised and semi-supervised learning methods.

Unsupervised Learning: Unsupervised learning techniques discover hidden patterns in unlabeled data without predefined labels. These methods are valuable when labeled data is sparse, as they can uncover useful features and relationships within the data. In plant disease detection, unsupervised learning can help identify clusters of similar images or patterns that may correspond to specific diseases, even when labeled examples are limited.

Semi-Supervised Learning: Semi-supervised learning combines a small amount of labeled data with a larger pool of unlabeled data. This approach leverages the available labeled data to guide the learning process while using the unlabeled data to refine and enhance model performance. For plant disease identification, semi-supervised learning can significantly improve model accuracy by providing additional context and variability.

Data Augmentation Techniques

To address the problem of limited data, data augmentation techniques are commonly employed. These techniques generate synthetic variations of existing images, thus expanding the training dataset. Common augmentation methods include geometric transformations (translation, rotation, cropping, scaling) and color adjustments (brightness, contrast, saturation).

While data augmentation improves model robustness to various transformations, it may not fully capture the complexity and variability of plant diseases. Traditional methods might not generate sufficiently diverse data to represent the full spectrum of disease symptoms. This limitation highlights the need for advanced methods that can produce more realistic and varied data.

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have emerged as a powerful tool for generating realistic images and data. GANs consist of two neural networks: a generator and a discriminator. The generator creates synthetic data, while the discriminator evaluates whether the data is real or fake. Through this adversarial process, the generator learns to produce data that closely resembles real data, while the discriminator improves its ability to distinguish between real and fake data.

Application of GANs in Plant Disease Detection: GANs can be utilized to generate synthetic images of diseased leaves, augmenting the training dataset and enhancing the model's ability to recognize various plant diseases. By creating diverse and realistic images, GANs help overcome the limitations of traditional data augmentation methods and improve the model's performance in identifying diseases.

DoubleGAN: An Advanced GAN Architecture

DoubleGAN is a specialized variant of GANs that leverages two generators and one discriminator to enhance image generation and recognition capabilities. This architecture provides several advantages for plant disease identification:

1. **Dual Generators:** DoubleGAN employs two generators that create distinct sets of synthetic images. This dual approach can produce a wider variety of images, capturing more diverse aspects of plant diseases. One generator might focus on specific disease features, while the other generates more generalized variations, improving overall data diversity.

2. **Enhanced Discriminator:** The discriminator in DoubleGAN evaluates the synthetic images from both generators, ensuring that the generated data closely resembles real images. This setup improves the quality of the generated images and helps the model better distinguish between genuine and artificial data.

3. **Improved Training Efficiency:** By using two generators, DoubleGAN can more effectively explore the data distribution and generate a richer set of training examples. This approach reduces the risk of overfitting and enhances the model's ability to generalize from limited data.

Anchor-Based and Anchorless Detection Algorithms

Object detection algorithms play a crucial role in identifying and localizing objects within images. These algorithms can be categorized into anchor-based and anchorless methods.

Anchor-Based Methods: Anchor-based methods, such as R-CNN, Fast R-CNN, and Faster R-CNN, use predefined anchor boxes to predict object locations and sizes. Faster R-CNN, with its integrated Region Proposal Networks (RPNs), represents a significant advancement by enabling end-to-end training and improving detection efficiency.

Single-Stage Methods: Single-stage object detection methods, including YOLO (You Only Look Once) and SSD (Single Shot MultiBox Detector), perform object localization and classification in a single step. YOLO-v1, the initial version, divides the image into grids and predicts bounding boxes and probabilities for each grid. Although faster than two-stage methods, YOLO-v1 struggles with accuracy, particularly for small objects. SSD enhances YOLO by incorporating multi-resolution feature maps, improving accuracy for various object sizes.

Anchorless Detection Methods: Anchorless methods, such as CornerNet and CenterNet, simplify object detection by eliminating predefined anchor boxes. CornerNet detects objects by identifying keypoints representing the corners of bounding boxes, while CenterNet focuses on detecting the center of an object and predicting its size and orientation. These methods reduce computational complexity and improve detection efficiency.

Visual Transformers (ViTs)

Visual Transformers (ViTs) offer a novel approach to image classification, segmentation, and rendering by leveraging Transformer models. Transformers, originally designed for natural language processing, have shown promise in computer vision tasks due to their ability to capture long-range dependencies and contextual information.

Application of ViTs in Plant Disease Detection: ViTs treat images as sequences of patches and apply self-attention mechanisms to capture relationships between different regions. This global context is beneficial for understanding complex patterns in plant diseases. Combining Transformers with Convolutional Neural Networks (CNNs) addresses limitations related to local feature capture and enhances overall model performance.

Advanced Methods for Plant Disease Detection

CNN Models: CNN models, such as AlexNet, VGG, and ResNet, have demonstrated significant improvements in plant disease identification. These models leverage convolutional layers to extract features from images and fully connected layers for classification. Combining CNNs with data augmentation and transfer learning techniques has achieved high accuracy in disease detection.

Hyperspectral Data: Hyperspectral imaging provides additional spectral information beyond the visible spectrum, capturing detailed chemical signatures of plant leaves. This data can enhance disease detection by revealing subtle changes in the plant's composition. Specialized sensors and advanced processing techniques are required to fully utilize hyperspectral data.

Cloud-Based Data Management: Cloud storage and management solutions facilitate handling large-scale plant disease datasets. Cloud-based platforms provide scalability, accessibility, and collaboration opportunities for researchers. Integrating cloud storage with deep learning models enables efficient data management and model deployment.

Recent advancements in plant disease identification, including the application of DoubleGANs and other advanced techniques, have significantly improved the accuracy and efficiency of disease detection. Addressing challenges related to data scarcity, computational efficiency, and detection accuracy is crucial for advancing agricultural practices. By leveraging unsupervised and semi-supervised learning, GANs, anchorless detection methods, Visual Transformers, and other innovative approaches, researchers and practitioners can develop more effective solutions for managing plant health and ensuring food security. Future research should focus on refining these techniques, exploring new data sources, and enhancing model robustness to further advance plant disease identification technologies.

III. MATERIAL AND METHODLOGY

A. Self-Attention Mechanism

The self-attention mechanism was introduced to enhance the capabilities of convolutional neural networks (CNNs) by integrating a self-attention layer into the self-coding structure of the generation network. Traditional CNNs, despite their widespread use, have limitations such as handling global feature extraction and overcoming gradient issues in deep architectures. The encoder-decoder structure, commonly used in image processing, often suffers from these issues. It processes the input through convolution, activation, and pooling layers, followed by deconvolution to restore the image size. This symmetric codec structure relies heavily on convolutional layers, which, while simple, may not always provide superior results when faced with complex data.

To address these limitations, the self-attention mechanism, originally developed for natural language processing, has been employed. This approach improves feature extraction by alleviating the traditional convolutional bottlenecks. The self-attention layer creates three convolution channels (F, G, and H) from the feature graph output $x \in \mathbb{R}^{C \times N}$ of the previous convolution layer. The purpose of these channels is to capture comprehensive attention-related content. Attention weights are calculated to focus on different parts of the image, improving the network's ability to generate high-quality images of plant disease leaves. The self-attention mechanism enhances global feature representation, leading to improved network performance in image processing tasks.

Equations are provided to detail the computation of attention weights and the output of the self-attention layer, including the transformations applied to feature spaces and the final attention-weighted output.

B. Wasserstein Distance

Wasserstein distance, introduced in the Wasserstein GAN (WGAN) framework, addresses issues such as training instability and gradient disappearance commonly encountered in traditional GANs. Unlike the Jensen-Shannon (JS) divergence used in conventional GANs, Wasserstein distance uses the Earth-Mover distance to measure the difference between the real data distribution p_r and the generated data distribution p_g. This approach is particularly useful for regression tasks, where the goal is to minimize the distance between generated and true distributions. The Wasserstein distance decreases as the generated images more closely resemble the real images.

The mathematical formulation of Wasserstein distance is provided, illustrating how it measures the discrepancy between the real and generated distributions. Additionally, the loss function for WGAN is described, highlighting the role of Wasserstein distance in stabilizing the training process.

C. AWAGN Network Structure

The Attention Wasserstein Generative Adversarial Network (AWGAN) combines the strengths of attention mechanisms and Wasserstein distance to address the overfitting problem in image-based plant leaf disease recognition. AWGAN generates pseudo-training images with significant variations, focusing on leaf areas while preserving background details. This network builds on the traditional GAN framework by incorporating both Wasserstein distance and a self-attentive mechanism to enhance image quality.

AWGAN uses two discriminators to learn the characteristics of real and generated data from their respective domains. The attention block in AWGAN produces attention-activation graphs that highlight relevant regions in the images, allowing the generator to focus on diseased leaf areas. The AWGAN model is described through its architecture, including the steps involved in generating images of different plant generations and phases. The model utilizes datasets from PlantVillage, consisting of healthy and diseased leaf images, to train and evaluate the network's performance.

The methodology of AWGAN includes a three-step process involving the generation of plant images, classification into different phases, and disease detection. The model architecture and data processing steps are illustrated, showing how AWGAN generates high-resolution images and improves classification accuracy.

D. DoubleGAN Framework

The DoubleGAN framework integrates WGAN and SRGAN (Super-Resolution GAN) to produce high-resolution images with detailed information. This framework operates in two stages:

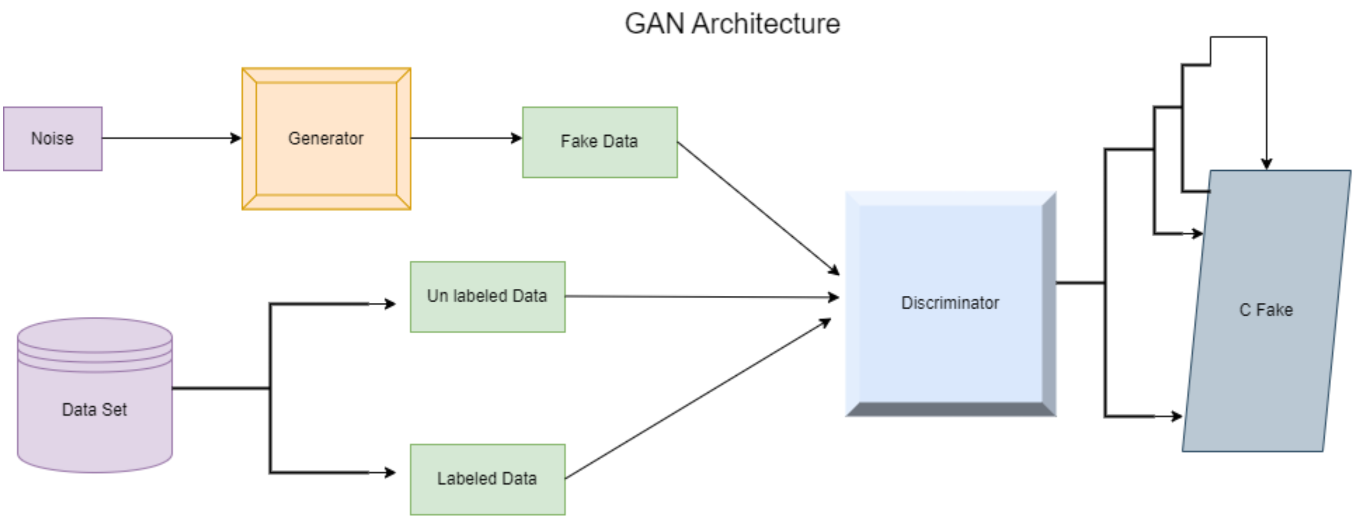
1. First Stage (WGAN): Generates clear, low-resolution images (64x64 pixels) using the Wasserstein distance to measure the similarity between real and generated images. This stage focuses on achieving stable training and minimizing gradient issues.

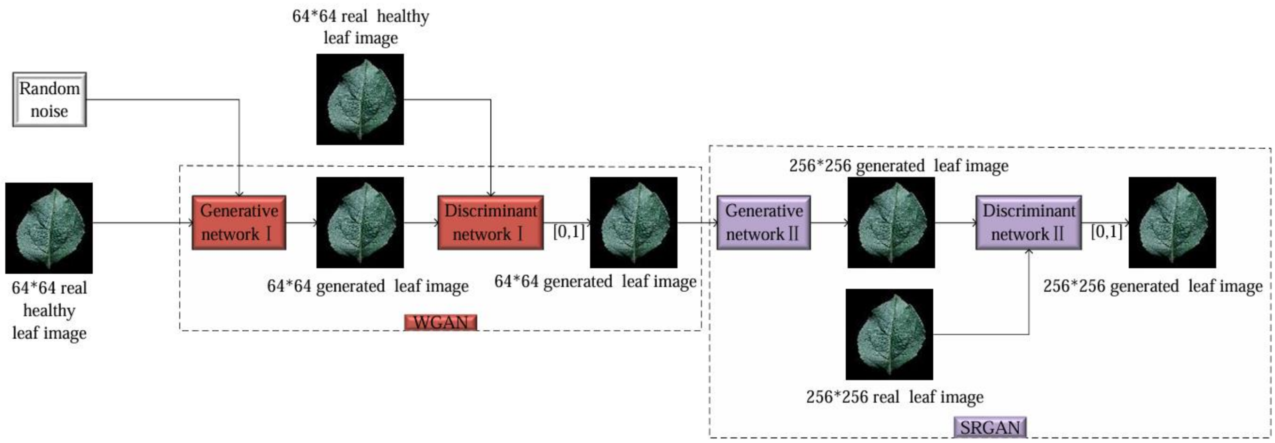
2. Second Stage (SRGAN): Enhances the low-resolution images to high-resolution images (256x256 pixels) using super-resolution techniques. SRGAN improves image detail by combining content loss and adversarial loss, with the latter ensuring that the generated images are indistinguishable from real images.

The DoubleGAN framework involves pretraining the generator, downsampling real images to obtain low-resolution inputs, and using back-propagation to optimize network parameters. The process includes generating high-resolution images and measuring similarity using the MSE and VGG-based feature loss.

Figures and tables illustrate the generation and evaluation of plant leaf images using the DoubleGAN framework, demonstrating its effectiveness in producing high-quality images for plant disease recognition. The results show how the framework improves image clarity and detail, addressing challenges in existing GAN-based approaches.

IV. Architecture





DoubleGAN structural block diagram