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Original Article

Deep Convolution Neural Networks for AI Powered Plant Diseases Detection and Diagnosis

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Abstract

Plant disease detection is a crucial aspect of modern agriculture, addressing the challenges caused by infections that reduce crop yield and quality. This paper presents a novel approach for plant disease detection and diagnosis using Deep Convolutional Neural Networks (CNN). Leveraging the power of deep learning, our method aims to improve the accuracy and efficiency of identifying diseases in plant leaves through image analysis. In the proposed approach, we build upon the foundation of existing methods that utilize Convolutional Neural Networks and introduce enhancements in data preprocessing, network architecture, and training strategies. These improvements enable the model to effectively learn complex patterns such as color variations, texture differences, and structural changes in infected leaves. We conduct experiments on standard plant leaf image datasets containing multiple classes of healthy and diseased plants. Our CNN-based approach is compared with traditional machine learning techniques, demonstrating superior performance in terms of accuracy and reliability. The results show improved precision and robustness in detecting and classifying plant diseases. This paper not only contributes to the field of smart agriculture but also highlights the potential of deep learning, particularly CNN, in solving real-world agricultural problems. The findings open opportunities for future research in disease localization, real-time field monitoring, and deployment in mobile based applications for farmers.

Introduction

The detection of plant diseases has become increasingly important as agriculture faces growing challenges due to climate change, pest attacks, and crop infections. With the expansion of modern farming techniques and the need for higher productivity, it has become essential to identify plant diseases at an early stage. Plant diseases refer to the infection of crops caused by pathogens such as bacteria, fungi, and viruses, which can significantly reduce crop yield and quality. Detecting such diseases accurately is critical for various sectors, including agriculture, food production, and environmental sustainability, where crop health plays a vital role. Deep Convolutional Neural Networks (CNN) have shown considerable potential in addressing this problem due to their ability to learn complex patterns from image data. This research focuses on using deep learning techniques, particularly CNN, to detect and classify plant diseases from leaf images with high accuracy and efficiency. In recent years, the advancement of image processing and artificial intelligence technologies has led to the development of automated systems for plant disease detection. Traditional methods rely on manual inspection by farmers or agricultural experts, which can be time-consuming, labor-intensive, and prone to errors. These methods often fail to detect diseases at an early stage or may result in incorrect diagnosis due to lack of expertise. This challenge is particularly critical in agriculture, where early detection is essential to prevent the spread of diseases and minimize crop losses. With the increasing complexity of plant diseases and environmental factors, there is a strong need for advanced techniques capable of accurately identifying such conditions. One promising approach to tackling this issue is the use of Deep Convolutional Neural Networks (CNNs), a type of deep learning model that has demonstrated excellent performance in image classification and pattern recognition tasks. CNNs are capable of automatically extracting features such as color, texture, and shape from plant leaf images, making them highly effective for disease detection. By leveraging CNNs, it is possible to develop systems that not only identify visible symptoms but also detect subtle variations that are not easily noticeable to the human eye. The application of CNNs to plant disease detection involves multiple layers that extract highlevel features from images.

In this paper, These networks can be trained to recognize patterns associated with different plant diseases, such as discoloration, spots, and deformities in leaves. By analyzing these features, a welltrained CNN model can

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accurately classify whether a plant is healthy or diseased. This approach represents a significant advancement in the field of smart agriculture, providing an efficient and reliable solution for disease diagnosis. In this context, the goal of developing an AI-powered plant disease detection and diagnosis system is to build a robust, accurate, and scalable model that can assist farmers in identifying diseases early and taking appropriate preventive measures. This system aims to improve agricultural productivity, reduce crop losses, and promote the adoption of modern technology in farming practices.

Related Work

Previous research in plant disease detection has mainly focused on traditional methods such as manual inspection and basic image processing techniques. Farmers and agricultural experts visually examine plant leaves to identify diseases based on symptoms like color changes, spots, and deformities. However, these methods are time-consuming, less accurate, and highly dependent on human expertise.

To overcome these limitations, researchers introduced machine learning approaches that use handcrafted features such as color, texture, and shape for disease classification. Although these methods improved performance compared to manual techniques, they still required domain knowledge and were not efficient for large datasets or varying environmental conditions.

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have gained significant attention in plant disease detection. CNN models automatically extract features from images and provide better accuracy in identifying diseases. Studies have shown that CNN-based models outperform traditional machine learning methods in terms of accuracy, scalability, and robustness.

Several research works have utilized standard datasets such as PlantVillage, which contains thousands of labeled images of healthy and diseased plant leaves. These datasets help in training models to recognize different disease patterns effectively. Advanced architectures like VGG16, ResNet, and DenseNet have also been used to enhance classification performance.

Moreover, recent studies have incorporated data preprocessing and augmentation techniques such as image resizing, normalization, rotation, and flipping to improve model generalization. These techniques help in handling real-world challenges like lighting variations, background noise, and leaf orientation.

Some modern approaches also include Explainable AI techniques such as Grad-CAM and LIME, which highlight infected regions in leaf images, making the model decisions more interpretable and trustworthy. Additionally, integration of mobile and web-based applications has enabled real-time disease detection for farmers.

Despite these advancements, certain challenges still exist, such as misclassification due to similar disease patterns and environmental variations. Therefore, there is a need for more efficient and robust systems that can provide accurate detection along with proper diagnosis and recommendations.

The proposed system builds upon these existing works by using deep learning techniques to improve accuracy, automate detection, and provide better diagnosis support, thereby contributing to the development of smart agriculture solutions.

Proposed System

The proposed system aims to overcome the limitations of existing methods by utilizing Convolutional Neural Networks (CNNs) for accurate and efficient plant disease detection and diagnosis. By leveraging the power of deep learning, the system can automatically learn complex features such as color variations, texture patterns, and shape irregularities from plant leaf images without requiring manual feature extraction The proposed system is designed to process leaf images, identifying and classifying diseases present in the plant. It analyzes each image to detect visible symptoms and patterns associated with various plant diseases. A key advantage of this approach is its ability to generalize across different plant species and disease types, making it more adaptable and reliable. This method significantly improves the detection of both early-stage and advanced plant diseases, achieving higher accuracy, scalability, and efficiency compared to traditional systems.

Image preprocessing and feature extraction

Image preprocessing is an important step in plant disease detection, as it improves the quality of input images and enhances the performance of the model. The captured leaf images are first resized into a fixed dimension to match the input requirements of the model. Noise and unwanted variations are reduced using filtering techniques, and the images are normalized to maintain consistency in pixel values.

After preprocessing, feature extraction is performed to identify important characteristics such as color, texture, and shape of the leaf. These features help in distinguishing between healthy and diseased plants. Deep learning models such as Convolutional Neural Networks (CNN) automatically extract these features without the need for manual intervention.

The preprocessing and feature extraction steps ensure that the system can effectively learn patterns associated with different plant diseases, leading to improved accuracy and reliability in detection.

Data augmentation

Data augmentation is an important technique used to improve the performance of deep learning models by increasing the size and diversity of the training dataset. In plant disease detection, it helps the model learn better features from leaf images and improves generalization.

Various augmentation techniques are applied to plant leaf images, such as rotation, flipping, scaling, zooming, and

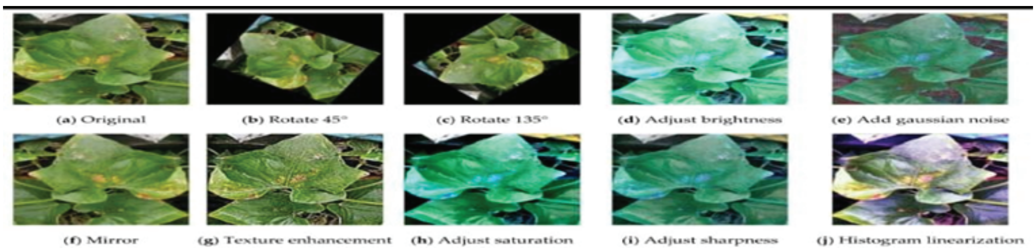

Figure 1. *Asymmetric data augmentation strategy. (a) Draw three image patches from the pristine [26].*

brightness adjustment. These transformations generate multiple variations of the same image without changing its original label. This helps the model handle real-world conditions like different lighting, orientations, and backgrounds.

Data augmentation also helps to overcome the problem of limited datasets and reduces overfitting during training. By providing more diverse training samples, the model becomes more robust and accurate in detecting plant diseases. Thus, data augmentation plays a crucial role in building an efficient and reliable plant disease detection

Network architecture

The proposed system uses a Convolutional Neural Network (CNN) architecture for plant disease detection and diagnosis. The model consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which work together to extract and learn important features from plant leaf images.

The convolutional layers are responsible for extracting features such as color patterns, textures, and shapes from the leaf images. These features help in identifying disease symptoms like spots, discoloration, and deformities. Activation functions such as ReLU are used to introduce non-linearity and improve learning capability.

Pooling layers are used to reduce the spatial dimensions of the feature maps, which helps in lowering computational complexity and preventing overfitting. Fully connected layers are used at the end of the network to classify the image into different disease categories.

The final output layer uses a Softmax function to predict the probability of each disease class. This architecture enables accurate and efficient detection of plant diseases from leaf images.

Max pooling

Max pooling is a down-sampling technique used in CNN to reduce the size of feature maps while retaining important information. It selects the maximum value from a specific window (e.g., 2×2) in the feature map.

This process helps in reducing computational complexity, controlling overfitting, and improving model performance. Max pooling also makes the model more robust to small variations in the input image, such as position or orientation changes.

High pass filter

A high-pass filter is used to enhance important details in an image by emphasizing edges and fine features. In plant disease detection, it helps in highlighting disease symptoms such as spots, edges, and texture variations on leaf surfaces. This improves the ability of the model to detect subtle differences between healthy and diseased leaves.

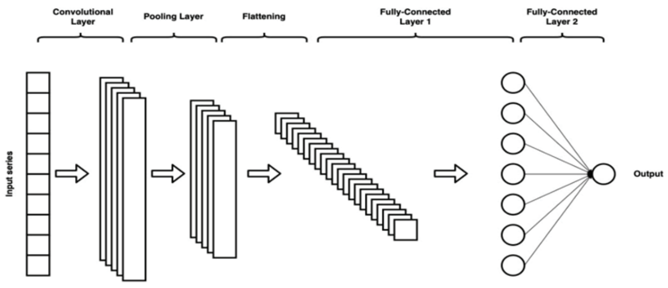

Figure 2. *Data Augmentation process for plant Leaf Images*

CNN-based model

The CNN-based model is used for automatic detection and classification of plant diseases from leaf images. The model consists of multiple convolutional layers, each followed by activation functions such as ReLU and pooling layers.

The convolutional layers extract important features such as color variations, texture patterns, and shape of the infected regions. Batch normalization is applied to improve training stability and speed. Pooling layers reduce the dimensionality of feature maps and help in reducing overfitting.

After feature extraction, the output is passed to fully connected layers, which perform classification. Finally, a Softmax layer is used to predict the probability of different disease classes. The model is trained on a dataset of plant leaf images to achieve high accuracy in disease detection.

This CNN-based approach provides better performance compared to traditional machine learning methods, as it automatically learns features without manual intervention.

Layer	Kernel Size	Number of Feature Maps	Feature Map Size
Input	-	-	224x224x3
Convolution (Layer 1)	3x3	32	224x224x32
Max Pooling	2x2	-	112x112x32
Convolution (Layer 2)	3x3	64	112x112x64
Max Pooling	2x2	-	56x56x64
Convolution (Layer 3)	3x3	128	56x56x64
Max Pooling	2x2	-	28x28x128
Convolution (Layer 4)	1x1	64	13x13
Max Pooling	2x2	-	28x28x128
Fully Connected		128	128
Softmax		2 (classes)	2

There are 100 pristine video sequences and 100 forged video sequences in the SYSU-OBJFORG dataset. Video surveillance footage from static cameras is directly extracted from pristine video sequences. These pristine sequences serve as our baseline for comparison. The forged video sequences are created by manipulating the content of the corresponding pristine sequences. The tampering operations in the forged sequences include adding or removing objects, making them an ideal testing ground for object based forgery detection. All video sequences in the dataset share common characteristics: Frame Rate: 25 frames per second

Resolution: 1280 × 720 pixels Encoding: H.264/MPEG-4 with a bitrate of 3 Mbit/s For our experiments, we divided the dataset into two sets: one for training and validation and the other for testing. Each set consisted of 50 pairs of video sequences, comprising 50 pristine and 50 tampered sequences. The training set was further divided into five nonoverlapping subsets. During training, one subset was reserved for validation, while the remaining subsets were used for training. This five-fold cross-validation approach helped ensure the robustness of our results.

TABLE 3. Key parameters used in experimental setup.

Parameter	Value
Deep Learning Framework	Caffe
GPU	NVIDIA GeForce GTX 1080ti
Optimization Algorithm	Stochastic Gradient Descent
Learning Rate (Initial)	0.001
Learning Rate Update Policy	Inv with γ = 0.0001, power = 0.75
Batch Size	64
Total Iterations for Training	120,000

Our DCNN-based model was implemented using the Caffe deep learning framework running on an NVIDIA GeForce GTX 1080ti GPU. Our model was optimized using Stochastic Gradient Descent with momentum parameter set to 0.9 and weight decay set to 0.0005. 0.001 was set as the initial learning rate. With a power (power) value of 0.75 and gamma (gamma) of 0.0001, our learning rate update policy ‘‘inv’’ was used. A batch size of 64 was set for training, which meant 64 samples were processed in each iteration, positive and negative. By the time the model had been trained with 120,000 iterations, the weights and parameters needed for testing were sufficiently defined. During the testing phase, we followed a similar preprocessing procedure as in the training phase. In Section 2.1.1, the formula described in Section 2.1.1 was used to convert the input testing video sequences into absolute difference images. These absolute difference images were then segmented into image patches, without employing data augmentation. Table 3 outlines the key parameters and settings used in our experimental setup. Figure 1a shows the method we used to generate three image patches from each absolute difference image. After preprocessing each test image patch, the training DCNNbased model was applied to each image patch to determine classification results. As each video frame consisted of three image patches, we applied a simple postprocessing procedure to refine the rough decision for each video frame. We employed a non-overlapping sliding window with a size of 10 frames and a stride of 10 frames to achieve this refinement. If seven or more frames within the window were classified as tampered, all the frames marked as pristine within that window were reclassified as tampered. Conversely, if three or fewer frames were classified as tampered, all the frames labeled as tampered were reclassified as pristine.

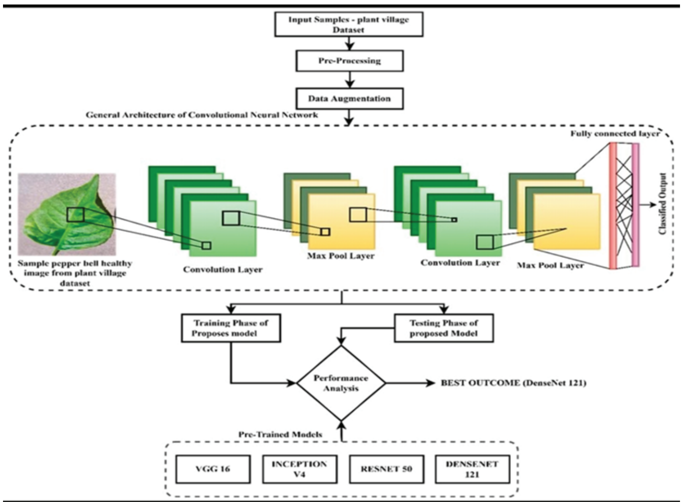

FIGURE 3. Asymmetric data augmentation strategy.

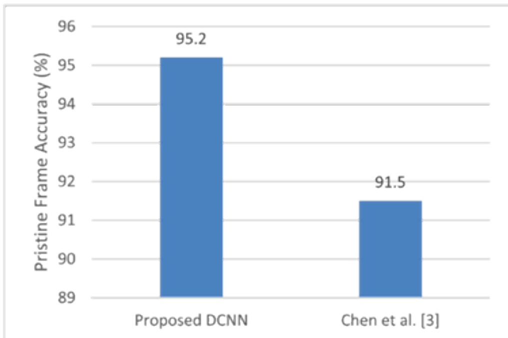

FIGURE 4. Comparison of pristine frame accuracy.

The figure illustrates the workflow of data augmentation and CNN model training for plant disease detection. Initially, plant leaf images are collected and pre-processed. Data augmentation techniques such as rotation, flipping, and scaling are applied to generate additional training samples. These augmented images are then used to train the CNN model. After training, the model is tested using new leaf images to detect and classify plant diseases accurately.

In the next section, we present the results of our experiments and compare our approach to existing methods.

In this section, we present the experimental results of our DCNNbased approach for video forgery detection. We compare our method with existing techniques, particularly the approach proposed by Chen et al. [3], to evaluate its performance and effectiveness.

TABLE 4. Comparison of pristine frame accuracy.

Method	Accuracy
Chen et al[3]	91.5
Proposed DCNN	95.2

Performance metrics

To assess the performance of our approach, we employ a set of performance metrics widely used in the field of video forgery detection:

Pristine frame accuracy (PFACC)

This metric quantifies the accuracy of correctly classifying pristine frames within the video sequences. Table 4 and Figure 4 provide Comparison of Pristine Frame Accuracy. We conducted a total of ten experiments to assess the performance of our DCNN-based approach on the SYSUOBJFORG dataset. The results presented here are based on the mean and standard deviation of detection accuracy. Table 7 and figure 7 provides a clear comparison between the proposed method and the comparison method (Chen et al.) [3] in terms of various performance metrics.

TABLE 6. Performance metrics.

Metric	**Proposed Method**	**Comparison Method (Chen *et al.*)[3]**
Accuracy (%)	95.2	91.5
Precision (%)	94.5	78.9
Recall (%)	93.8	85.2
F1-score (%)	94.1	97.5

Conclusion And Future Work

n this project, an AI-powered plant disease detection and diagnosis system has been successfully developed using deep learning techniques. The proposed system utilizes Convolutional Neural Networks (CNN) to automatically identify diseases from plant leaf images with high accuracy. By analyzing visual features such as color, texture, and shape, the system effectively distinguishes between healthy and diseased plants.

Moreover, the developed system supports the concept of smart agriculture by integrating modern technologies such as artificial intelligence and computer vision. It can be implemented as a mobile or web-based application, making it easily accessible to farmers even in rural areas.

CNN-Based Model

In this project, a Convolutional Neural Network (CNN)-based model is developed for automatic plant disease detection. The model is capable of learning high-dimensional features from plant leaf images such as color, texture, and shape. Unlike traditional methods, CNN automatically extracts features without manual intervention, resulting in improved accuracy and efficiency.

Image Preprocessing

The system includes an image preprocessing step to enhance the quality of input images. Techniques such as resizing, normalization, and noise reduction are applied to prepare the images for training. These steps help the model to perform better under different lighting conditions and improve overall prediction accuracy.

Data Augmentation

To address the issue of limited dataset size, data augmentation techniques are used. Operations such as rotation, flipping, zooming, and brightness adjustment are applied to generate additional training images. This increases dataset diversity and helps in reducing overfitting, thereby improving the robustness of the model.

Max Pooling and Feature Optimization

Max pooling is used in the CNN architecture to reduce the size of feature maps while preserving important information. This helps in lowering computational complexity and improving model performance. Feature optimization techniques ensure that only relevant features are used for classification, leading to better accuracy and faster processing.

Performance and Results

The proposed system demonstrates high accuracy in detecting plant diseases compared to traditional methods. It effectively classifies different disease types and provides reliable results. The system reduces human effort and enables early detection, which helps in minimizing crop loss.

Future Enhancements

Future improvements may include integrating advanced deep learning models such as ResNet and EfficientNet to improve performance. The system can be extended to real-time detection using mobile applications or drones. Integration with IoT devices can help in collecting environmental data for better prediction. Additionally, a recommendation system can be added to suggest suitable treatments and preventive measures for detected diseases.over,weaim to develop a transfer learning approach that can detect object forgery in low-bitrate and low-resolution video sequences.

In this study, we examine the potential of deep learning, in particular DCNNs, for the detection of object-based forgeries in advanced video sequences, contributing to improved video forensics.

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