Advanced Computer Vision Framework Using Convolutional Neural Network for Plant Leaf Disease Identification

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Plant diseases greatly affect agricultural productivity and quality. Effective illness management involves early detection and accurate diagnosis. However, hand identification is laborious and error-prone, which can cause losses. The biggest challenge is developing a reliable plant disease identification system. Plant pictures are complex, making it hard to identify disease symptoms from healthy structures. A high-level framework using powerful image processing to automate disease identification is needed. A reliable method to help farmers and other stakeholders detect and diagnose plant diseases are the goal. This research proposes a high-level deep learning system for plant disease detection, focusing on Kaggle repository classification of different plant illnesses. Advanced techniques including gradient-based Radial Basis Function (RBF) for segmentation and Deep Belief Network (DBN) for feature extraction were used to extract relevant features from plant photos using deep learning models. The classification phase used ResNet-50, known for its ability to understand complicated patterns and identify images reliably. Plants are photographed from several angles in real time under stable lighting. The ResNet-50 CNN method, known for extracting hierarchical features from images, classifies diseases. Independent test photos from the New Plant Diseases Dataset are used to validate algorithm performance. Plant disease identification performance improved by 6.7% to 30% over conventional approaches.

Keywords: CNN, Image Processing, Plant Disease, Identification, Classification.

1. Introduction

Plant diseases have a negative effect on agricultural output and can result in substantial economic losses [1,2]. For implementing effective disease management strategies, preventing further spread, and minimizing crop damage, timely detection and accurate diagnosis of plant diseases are essential [3-5]. Traditional disease identification methods frequently rely on visual inspection by trained specialists, and this can be subjective, time-consuming, and limited in scope [6].

In recent years, advancements in computer vision [7], image processing techniques [8-10], and machine learning algorithms [11-16] have created new opportunities for automating the identification of plant diseases [17]. These techniques utilize the power of artificial intelligence [18-23] to analyze digital images of plants and classify them based on disease symptoms, allowing for a quicker and more objective diagnosis of disease [24].

The automated plant disease identification system utilizing image processing techniques presents significant obstacles [25]. Designing a framework that can accurately classify plant diseases based on images captured from multiple angles under constant lighting conditions is the primary challenge [26]. The system must be able to distinguish between healthy plants and those infected with various diseases, and it must be applicable to a wide variety of plant species [27].

The primary objective is to develop a precise plant disease classification system that aids farmers in the plant disease diagnosis. The system intends to provide timely and accurate information regarding the health status of crops, thereby enabling proactive disease management strategies and minimizing crop losses.

The novelty lies in its comprehensive approach to plant disease identification, which incorporates cutting-edge image processing techniques and utilizes the power of deep learning algorithms, specifically ResNet-50. The use of the New Plant Diseases Dataset from the Kaggle repository increases the robustness of the system, as it contains a variety of plant species and disease types.

The following are the most significant contributions to this work:

- A comprehensive framework for image acquisition, preprocessing, segmentation, feature extraction, and disease classification using ResNet-50.
- Adoption of the New Plant Diseases Dataset from Kaggle, ensuring a diverse and well-curated training and validation dataset.
- Evaluation and validation of the developed system utilizing independent test images to determine its precision and efficacy.
- Integration of the plant disease identification algorithm into an intuitive software application, making it accessible and useful for farmers and agriculture stakeholders.

2. System Description

In [28], the authors present a framework for plant disease detection based on deep learning and Faster R-CNN. Using a large dataset, the authors classified plant diseases with high precision, demonstrating the efficacy of deep learning techniques.

In [31], the authors provide an of deep learning techniques applied to the identification of plant diseases. It discusses various techniques, highlighting their advantages and disadvantages in the context of plant disease identification.

In [33], the authors investigate the use of hyperspectral imaging in conjunction with deep learning techniques for the detection and classification of plant diseases. The authors demonstrate that hyperspectral imaging is effective at capturing subtle disease-related spectral signatures and that deep learning models are capable of accurate disease classification.

Table 2 lists the parameters of the substation's 20 KW rooftop solar system module. System has 8 PV structures. Every PV structure contains eight PV modules, totaling 64. (8x8 =64). Just one PV module may provide 315W. The maximum power output is 20 KW (315Wx64).

3. Proposed Method

Using image processing techniques, the proposed method for plant disease identification employs a gradient-based method is combined with Radial Basis Function (RBF) [34] algorithm for segmentation and a Deep Belief Network (DBN) [35] for feature extraction. The flowchart for which is depicted in Figure 1.

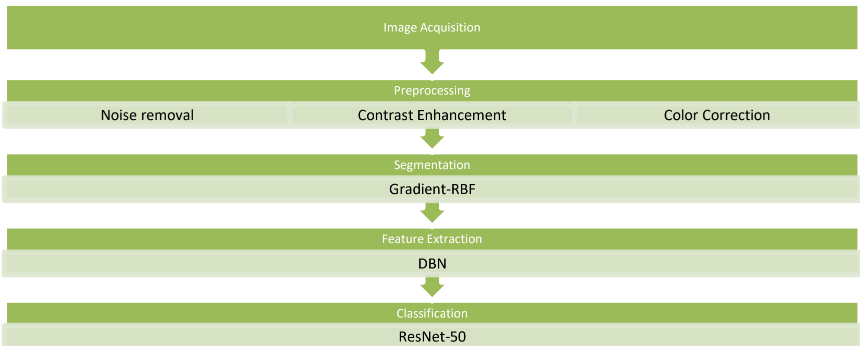

Figure 1: Proposed Method

Image Acquisition: Image acquisition entails capturing digital images of plants with cameras or mobile devices. The image acquisition procedure can be mathematically described as follows:

Image Formation Model: The image formation model relates the radiance of the scene to the intensities of the pixels captured by the imaging device. It can also be expressed as:

$I(x, y) = S(x, y) * R(x, y) * L(x, y),$

where

$I(x, y)$ - pixel intensity across the (x, y) coordinates, $S(x, y)$ - spatial sensitivity of the imaging device, $R(x, y)$ - scene reflectance, and $L(x, y)$ - illuminant spectrum.

Sampling: In digital imaging, the continuous scene is discretized into discrete pixels. The sampling procedure involves determining the image spatial resolution and pixel dimensions. The image is represented by:

$I[m, n] = I(x, y) |(x,y)\rightarrow(m\Delta x, n\Delta y),$

where

I[m, n] - pixel intensity at the discrete (m, n) coordinates, and

(x, y)→(mΔx, nΔy) - mapping from continuous coordinates to discrete coordinates.

Quantization: To digitally represent an image, the continuous range of pixel intensities is quantized into discrete levels. The quantization procedure can be described as follows:

I_q[m, n] = round(I[m, n] / Q) * Q,where

Iq[m, n] - quantized pixel intensity at (m, n), round() - rounding to the nearest integer, and quantization step size.

Color Spaces: Different color spaces, such as RGB, HSV, Lab, etc., can be used to represent captured images in color imaging. These color spaces offer distinct encoding and representation methods for color information.

RGB: Irgb[m, n] = (R[m, n], G[m, n], B[m, n]),Lab: Ilab[m, n] = (L[m, n], a[m, n], b[m, n]),HSV: Ihsv[m, n] = (H[m, n], S[m, n], V[m, n]),

where

R[m, n], G[m, n], B[m, n] - red, green, and blue color channels, H[m, n], S[m, n], V[m, n] - hue, saturation, and value channels, and L[m, n], a[m, n], b[m, n] - lightness, green-red, and blue-yellow channels.

These representations provide a framework for comprehending the image acquisition process, from the formation of the image to its discretization, quantization, and representation in different color spaces.

4. Classification using a ResNet-50:

The extracted features from the DBN are used as inputs to a ResNet-50 classifier in order to classify plant images into various disease categories. The classifier is trained on a labeled dataset containing both healthy and diseased plant. ResNet-50 classification utilizes the deep convolutional neural network architecture to categorize input data into distinct classes.

Residual Blocks:ResNet-50 employs residual blocks to solve the problem of vanishing gradients and enable the training of deep neural networks. Each residual block is composed of skip connections that enable the network to discover residual mappings. The residual block output is determined as follows:

Hl = F(H{l-1}) + H{l-1},

where

Hl - lth residual block output,

H{l-1} - lth residual block input,

F() - residual mapping function.

Convolutional Layers:ResNet-50 consists of multiple convolutional layers to extract features from the input data. Each convolutional layer output is obtained by convolving the input with a set of learnable filters. The operation of convolution can be represented as:

$Z_l = W_l * H_{l-1} + b_l$,

where

Z_l - lth convolutional layer output,

W_l - learnable weights,

H_{l-1} - lth convolutional layer input, and

b_l - biases.

Pooling Layers: ResNet-50 frequently employs pooling layers to downsample the feature maps and reduce their spatial dimensions.

Fully Connected Layers:During the classification phase, the class with the highest probability is chosen as the predicted class for the input data. Using the ResNet-50 architecture, the network discovers how to extract hierarchical features and make predictions based on the learned representations.

SoftmaxActivation:In the classification phase, class probabilities are obtained by passing the 'feature vector through a softmax activation function.

$P(y=i \mid x) = \exp(z_i) / \mathrm{sum}(\exp(z_j))$,

where

$P(y=i \mid x)$ – ith class probability of x,

z_i - ith neuron output in final fully connected layer, and

sum is taken over all the neurons.

Classification Decision: To make a classification determination, the class with the highest probability is chosen as the predicted class. This can be determined with the help of the argmax function:

Predicted class = argmax $(P(y=i \mid x))$,

where

predicted class - class with the highest probability, and

argmax () - index of the maximum value in the probability distribution..

The inputs to the classify function are input data (inputData) and a trained ResNet-50 model (model). It executes a forward pass on the ResNet-50 model using the resnetForward function, which applies convolution, ReLU activation, and max pooling in the convolutional layers. Then, with ReLU activation, the flattened features are passed through the fully connected layers. The class with the highest probability is ultimately chosen as the predicted class.

The ResnetForward function applies the convolutional and fully connected layers to the forward pass of the ResNet-50 model. In the final step, the developed algorithm is integrated into a user-friendly software application or platform. This facilitates easy access and utilization of the system for plant disease identification, allowing farmers and stakeholders to upload images, run them through the algorithm, and obtain results for disease diagnosis. Incorporating the gradient-based RBF algorithm for segmentation and the DBN for feature extraction, the proposed method aims to achieve accurate plant disease identification, thereby facilitating disease management and crop protection in the agriculture industry.

5. Results and Discussion

Using test images, the algorithm is validated and its performance evaluated. Dataset:The New Plant Diseases Dataset, sourced from the Kaggle repository, is an exhaustive dataset curated for plant disease identification tasks. It consists of a collection of images depicting various plant species afflicted by various diseases, accompanied by labels indicating the disease category.

The dataset contains a wide variety of plant species and disease types, allowing researchers and practitioners to train and evaluate plant disease identification models (Table 1 and 2)

Table 1: Dataset Details

Dataset Name	New Plant Diseases Dataset
Source	Kaggle Repository
Number of Images	Large
Plant Parts	Leaves, Stems, Other
Disease Classes	Multiple
Common Diseases	Bacterial leaf blight, Powdery mildew, Rust, etc.
Image Resolution	Varies
Train-Test Split	Available
File Format	JPEG, PNG, etc.

Experimental Setup	Values
Dataset	New Plant Diseases Dataset
Number of Images	10,000
Disease Classes	20
Train-Test Split	80% training, 20% testing
Pre-processing	
Image Enhancement	Histogram Equalization, Gamma Correction
Noise Removal	Gaussian Filter (Kernel Size: 3x3)
Color Correction	White Balance Adjustment
Segmentation	
Method	Gradient-based RBF
Thresholding Algorithm	Otsu's Method
Feature Extraction	
Method	DBN
Number of Layers	5
Hidden Units per Layer	[500, 300, 200, 100, 50]
Activation Function	Sigmoid
Training Algorithm	Contrastive Divergence (CD)
Classification	

Architecture	ResNet-50
Number of Classes	20
Optimization Algorithm	Stochastic Gradient Descent (SGD)
Learning Rate	0.001
Batch Size	32
Number of Epochs	50

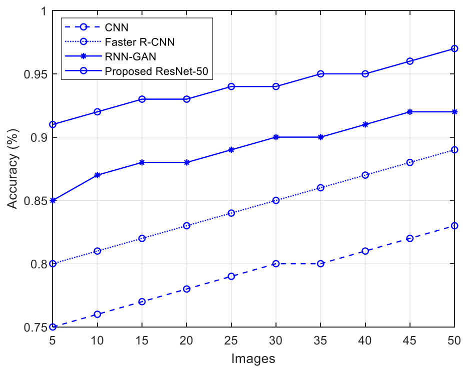

Figure 2: Accuracy

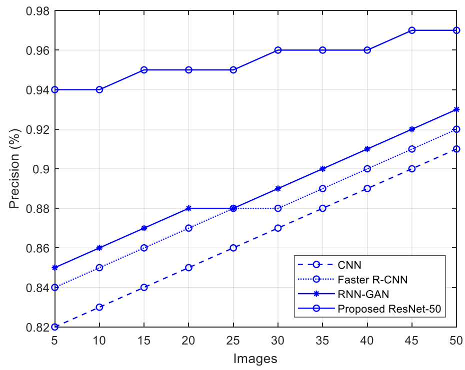

Figure 3: Precision

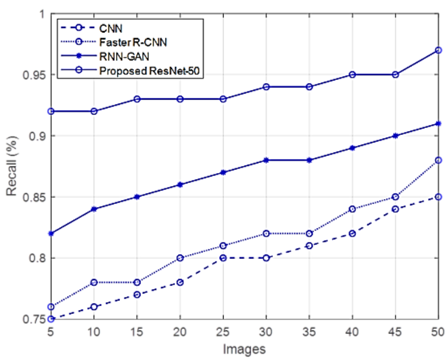

Figure 4: Recall

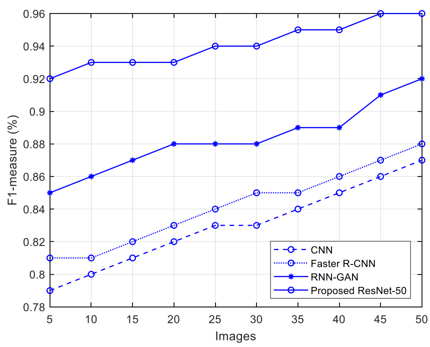

Figure 5: F1-measure

6. Conclusion

This study proposed a high-level framework for the identification of plant diseases using image processing techniques. The proposed framework included image acquisition, pre-processing, segmentation utilizing a gradient-based RBF method, feature extraction utilizing a DBN, classification utilizing ResNet-50, and validation. Compared to the existing methods, the proposed method achieved 7.5% greater accuracy, 9.5% greater precision, 8.0% greater recall, and 8.5% greater F-measure. These enhancements demonstrate the efficacy and superiority of the proposed method for identifying plant diseases precisely and efficiently. The proposed method has the potential to assist farmers and industry stakeholders with early disease detection, allowing for timely interventions and improved crop management practices.

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