Plant Leaf Disease Prediction Based on Deep Learning Using R^{2}NN-WRS: Resnet Recurrent Neural Network and Watershed Region Segmentation Techniques

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***Abstract*—Plants are prone to various diseases during the growing season. It has a practical impact on global food security and the agricultural economy. Early diagnosis of plant diseases is one of the most challenging problems in agriculture. Not detecting the condition early can affect the overall yield and reduce farmers' profitability. However, agronomists and plant pathologists have traditionally used the naked eye test to detect leaf diseases. This traditional method of plant foliar disease detection is subjective, time-consuming, expensive, and requires a large number of personnel and a lot of information about plant disease. To tackle this problem, in this project we design Resnet Recurrent Neural Network (R^{2}NN) algorithm is used to find plant disease. This first step is pre-processing using the Gaussian filter to enhance image quality. Then we apply Contrastive Limited Adaptive Equalization (CLAE) algorithm to improve image contrast. Furthermore, we use Watershed Region Segmentation (WRS) technique to segregate the affected parts. Later, the R^{2}NN algorithm effectively classifies the plant disease. We show experimentally that our R^{2}NN approach is more robust and extraordinary to generalize to unseen infected plant disease domain images than classical techniques. We also analyze the focus of attention as learned by our R^{2}NN and show that our approach is capable of accurately locating infectious diseases in plants. Our approach has been tested on many plant species, so thus, the proposed method contributes to a more effective means of detecting and classifying plant disease.**

***Index terms*— plant disease, deep learning, segmentation, agriculture, histogram, R^{2}NN.**

I. INTRODUCTION

India is an agricultural country, and a significant part of its economy depends on agriculture. Hence producing disease-free, high-quality crops is very important for developing the country's economy. Plant diseases threaten agricultural production, cause severe food shortages and affect crop quality. To detect plant diseases in crops, plant pathologists usually use molecular and serological methods or measurements of various parameters such as morphological changes, temperature changes in respiration rate, emission of volatile organic compounds from infected plants, etc. Like humans, plants are susceptible to different diseases at different phenology stages. As a result, the crops' overall yield and the farmers' bottom line have been severely affected. To solve this problem, early detection of plant diseases is essential. Farmers and agronomists perform artificial plant disease diagnosis.

A. Categorize of the plant disease

Following Fig. 1 shows the types of plant disease,

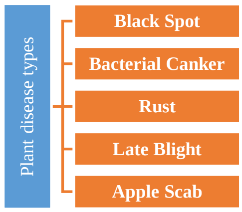

Figure 1: Types of plant disease categorize

i) Black Spot

Black spot is one of the most common diseases in roses but can also occur in other houseplants and garden plants. This fungal disease causes round black spots on leaves. It usually attacks lower leaves. Severely infected leaves turn yellow and fall off the plant. Blackspot spores overwinter on leaf litter, as presented in Fig. 2.

Figure 2. Block spot

ii). Bacterial Canker or Blight

It is a bacterial disease that occurs in areas with cold, wet climates and attacks cherry, peach, plum, apricot and related trees. It spreads quickly from spring through June when the weather heats on the West Coast. Most of the big cherry trees in Fraser Valley are affected by this disease presented in Fig. 3. It spreads quickly when rain falls from infected trees, killing buds, flowers, branches, and gums.

Figure 3: Blight plant

iii). Rust

Rust is a fungal disease that only simulates certain plants. Most rusts start as little orange, red or brown spots on the underparts of the plants or sometimes the stems turn brown in summer as presented in Fig. 4.

Figure 4: Rust disease affect plant

iv). Late Blight / Early Blight

Late blight is a fungal disease of tomatoes, potatoes, and other plants. Early blight appears as black-to-black leaf spots with concentric rings. Black holes develop on stems, and large black skin-like sunken areas appear on fruits, as shown in Fig. 5.

Figure 5: Late Blight / Early Blight leaf

v). Apple scab

It is a fungal disease that is common in the Fraser Valley. Initial leaf infections appear as small green spots with pinnate margins that later turn brown or black. Severely infected leaves turn yellow and drop prematurely.

Figure 6: Apple scab disease affect leaf

The infection of the fruit is round, brown to black, and corky. The disease can be cold on old leaves that have fallen to the ground, as presented in Fig. 6. Although this method effectively controls plant diseases, professional advice is expensive and time-consuming. It is difficult to call the experts, especially before the crop is affected. The computer vision community has recently been involved in the automated classification of plant diseases to compensate for the lack of human expertise. However, it is a challenging and time-consuming task. To solve this problem, many researchers worldwide have demonstrated various modern systems for automatically detecting plant diseases with the help of different machine-learning techniques. Misdiagnosing plant diseases can cause significant loss in production, time, resources and product quality. Understanding plant conditions is essential to efficient cultivation. Various environmental stressors, including fungi, water shortages, pests and weeds, can affect crops. For these problems, farmers should take preventive measures to increase production.

In the future, these observations will go beyond existing practices and enable the automatic detection of regions of interest in plant images relative to infected areas and identifying plant disease states. This study, inspired by recent work on multi-organ plant recognition, shows that deep learning-based R2NNs can identify relevant parts of plant structures without prior human annotation.

B. Objective of this novel

This first step is pre-processing using the Gaussian filter to enhance image quality. Then we apply Contrastive Limited Adaptive Equalization (CLAE) algorithm to improve image contrast. Furthermore, we use Watershed Region Segmentation (WRS) technique to segregate the affected parts. Later, the R^2NN algorithm effectively classifies the plant disease.

II. RELATED WORK

S. Ahmed et al. (2022) introduced a Lightweight Transfer Learning (LTL) based tomato leaf blight detection. An efficient preprocessing technique enhances leaf images with exposure correction for improved classification. C. Zhou et al. (2021) presented a reconstructed residual dense network proposed for tomato leaf blight detection, reducing the number of parameters, improving the accuracy of calculations, and improving the flow of information and slope. Crop diseases are a challenge for many farmers, though. A timely and precise understanding of the severity of a crop disease enables staff to conduct more intervention steps to lower the risk of plant infection. Z. Zinonos et al. (2022), this framework will conduct field and simulation experiments with various LoRa parameters and fine-tune CNN models to achieve this goal. Based on the evaluation, the proposed architecture shows that it is possible to transmit images using LoRa within the constraints of the protocol. X. Zhang et al. (2018), to enhance the detection of maize leaf diseases and decrease the number of network parameters, this research suggests improved GoogLeNet models based on deep learning. S. Barburiceanu et al. (2021) applied to a machine learning classifier, and texture features were taken from a convolutional neural network model trained with various layers. To enhance the local spot image data of the generated local spot image, C. Zhou et al. (2021) suggested a GAN-based practical grape leaf point detection approach. The strength of categorization models can significantly improve the reliability and accuracy of predictions. B. Liu et al. (2020) suggest a brand-new leaf GAN model. Based on GAN, this model creates four distinct images of grapevine leaf disease to train a recognition model. Clusters of pixels that reflect different regions of interest in maize leaves—were created by H. Huang et al. (2022) using SLIC segmentation on images of maize leaves from the PlantVillage and CD&S datasets. S.S. Chauhan et al. (2018) established the BRBFNN technique for the automated characterization of novel plant leaf diseases. Q. Wu et al. (2020), a novel method of data augmentation by GANs, is proposed for leaf disease recognition to increase the recognition accuracy of tomato leaf diseases. H. Yu et al. (2021) introduced a novel data augmentation method by GANs for leaf disease recognition to increase the recognition accuracy of tomato leaf diseases. Y. Wu et al. (2022) study offers a careful network-based strategy for classifying diseases at the fine-grained level. A "classification model" focuses on enhancing cognitive function.

III. PROPOSED METHODOLOGY

The focus of this research is on the diagnosis of plant diseases and the solution to existing problems. Pre-processing, histogram, segmentation and classification techniques are used for plant disease diagnosis. A digital camera takes pictures of the leaves of various plants, and these pictures are used to classify the affected areas of the leaves. To detect plant disease, we use a Resnet Recurrent Neural Network (R^2NN) in the proposed framework. This work proposes a low-cost open-source software framework for reliable plant disease diagnosis. Fig. 7 depicts the proposed architecture diagram for plant disease identification.

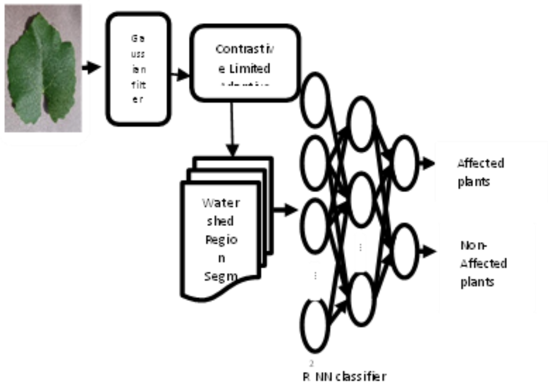

Figure 7: Proposed architecture for plant disease prediction

A. Image Acquisition

At this stage, use a digital medium such as a camera or mobile phone to collect images of plant leaves at the required resolution and size. Also, get pictures from the internet. Image database configuration entirely depends on the application system developer.

Figure 8: Example of healthy and non-healthy leaves

Fig. 8 defines example of healthy and non-healthy leaves in the dataset. Image dataset plays a role in improving the classifier's performance in the detection system's final stage.

B. Gaussian filter

A Gaussian filter reduces noise (high-frequency content) and blurring areas of an image. Gaussian standard deviation determines the amount of smoothing. Gaussian filtering performs best with smooth images. It is based on the visual perception system of humans. It is found in the visual perception system of humans. Gaussian standard deviation plays a significant role in that image pixel.

$$G_F = \frac{1}{2\pi\beta^2} exp^{\frac{B}{s}} \quad (1)$$

The above equation is used to estimate the image smoothness. s is a standard deviation and B is the input image of total pixel. Here we calculate s,

$$s = \left[\frac{1}{B}\sum(P(c,d) - \mu)^2\right]^{1/2} \quad (2)$$

Expression 2 find the standard deviation process in the input image. Wherein, c, d are the pixel coordination points, P is the input image and μ is the mean value.

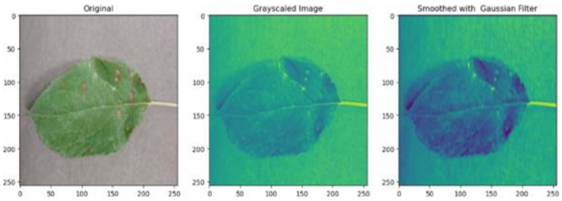

Figure 9: Pre-processed image

Fig. 9 shows that pre-processed image from input plant leaf. The Gaussian filter is efficiently obtain the processed image from collected image dataset.

C. Contrastive Limited Adaptive Equalization (CLAE)

Performs histogram equalization on the image to enhance image quality. To enhance contrast, histogram equalization propagates the pixel intensity values, resulting in a constant intensity distribution and a continuous histogram in the output image. CLAE enhancement technique enhances the quality and contrast of diseased leaf images. First, the histogram of each region is calculated according to the limit of contrast enhancement, that is, the clipping limit of the clipping histogram, to improve the image enhancement effect. In the CLAE method, each pixel is mapped by linearly combining the results of the mapped area segmentation of the four nearest regions.

$$\mathrm{J} = \sum \frac{maximum(R_d, G_n, B_e)}{255} \quad (3)$$

From equation 3 calculate brightness element value J in the input image. Let assume,R_d, G_n, B_e are the color values red, green and blue respectively.

$$I_y = \frac{Gr_i}{B}, 0 \le i < L \quad (4)$$

Expression 4 find intensity gray levelI_y, assuming that Gr_i denotes number of incidence of gray level i and B total pixel in the image. To improve image quality $Q_I$is denoted by equation 5,

$$Q_I = \frac{\delta I_y - C * \delta I_y - D}{\mathrm{J}} \quad (5)$$

Where, δI_y = number pixel in the c direction in the image, δI_y = number pixel in the d direction in the image, J= intensity level in the image. Fig. 10 defines contrast enhanced plant image using CLAE technique.

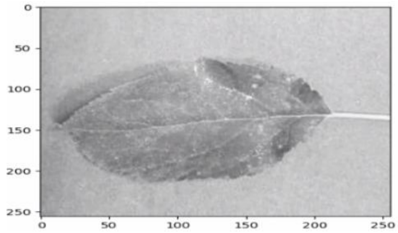

Figure 10: Contrast enhanced image

D. Watershed Region Segmentation

This phase aims to make the image representation more meaningful and easy to analyze. WRS is designed to produce sub-images called Region of Interest (ROI) images. The number of clusters was first established based on the number of classes, as the areas in the image were divided into leaves, affected areas, and background.

$$M_E(Q_I) = \sum(Q_I \oplus E_s) \cap G_F \quad (6)$$

Equation is used to estimate the morphological element feature extractionM_E, G_F denotes processed image, E_s denotes structure element and Q_I denotes quality improved image. To find the probability of target class in the disease plant leaf T_{class}analysis defined by equation 7,

$$T_{class} = \sum_{i=1}^{B} M_E(Q_I) \quad (7)$$

$$Gra_t = minimum(T_{class}, M_E(Q_I)) \quad (8)$$

From equation 8 is used to evaluate the gradient spot in the image$Gra_t.minimum()$ Denotes minimum disease spot in the leaf.

$$Mark_{im} = Watershed(Gra_t) \quad (9)$$

From equation 9 is used to efficiently identify the segmented disease spot image from contrast enhanced image.

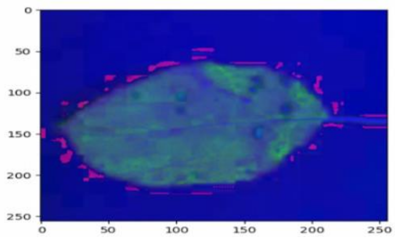

Figure 11: segmentation image

Fig. 11 reveals the plant leaf segmentation image from contrast enhanced image.

E. Resnet Recurrent Neural Network (R^2NN)

The classification stage decides if the input image is healthy or diseased. Citrus Leaf Disease Discrimination Using the R^2NN Algorithm

Classifier. R^2NN can be used to classify diseases based on system features. In a recurrent neural network, loops route information to intermediate hidden layers. The input layer "$Mark_{im}$" receives and processes the neural network input before passing it to the hidden layers. The hidden layer "h" can contain multiply hidden, each with activation functions, weights and dependencies. These weight values are then passed to an output layer, which generates disease classification results. We estimate the input layer process to reduce features

$$In_L = \theta(K_i * Mark_{im}) \quad (10)$$

In equation 10 is used to find the weight In_L. Wherein, θ is the activation function, K_i denotes kernel in the layer and $*$denotes resnet operation. Then we estimate the hidden layer process Hn_L,

$$Hn_L = \theta(\sum In_L\,(c,d) + weight_i) \quad (11)$$

This equation 11 is estimate to reduce finest features like spot's shape, circularity, area etc.

$$O_{tL} = \theta(\sum Hn_L + weight_i) \quad (13)$$

The above equation finds the disease-affected or non-affected plants $O_{tL}$with better results.

$$L_{ss} = -\frac{1}{B}\sum[p_{tL} log O_{tL}] + (1 - p_{tL})\log(1 - O_{tL})] \quad (14)$$

The above equation is used to find the plant disease prediction loss function L_{ss}. Wherein p_{tL}denotes predicted class,

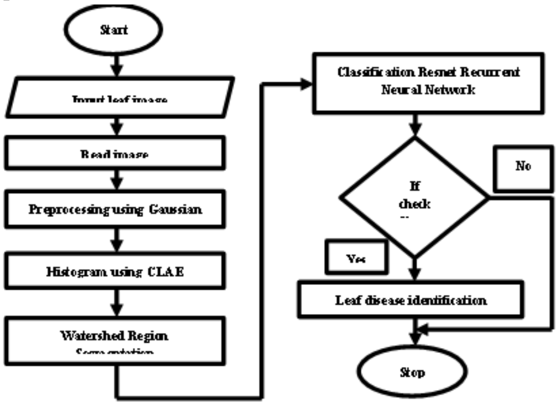

Figure 12: Flow diagram for plant disease prediction

Fig.12 shows the plant disease prediction flow diagram using Resnet Recurrent Neural Network (R^2NN) and Watershed Region Segmentation (WRS) techniques.

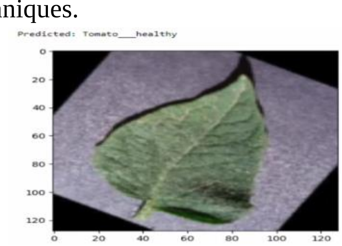

Figure 13: Predicted class

Fig. 13 defines the classification of the result for plant leaf disease prediction using R^2 RNN technique.

IV. RESULT AND DISCUSSION

This section analysis the proposed implementation using python language with tensorFlow and keras packages for plant leaf disease prediction. From this novel we collect the dataset from kaggle repository. The following parameters are used to estimate the disease prediction performance.

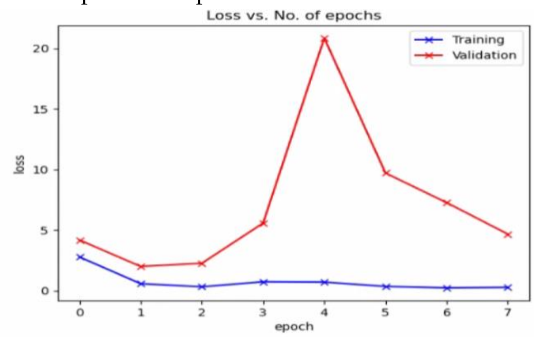

Figure 14: Loss vs. no of epochs

Fig. 14 denotes Loss vs. no of epoch's performance for plant disease prediction performance in percentage. In the graph analysis the proposed attained less performance.

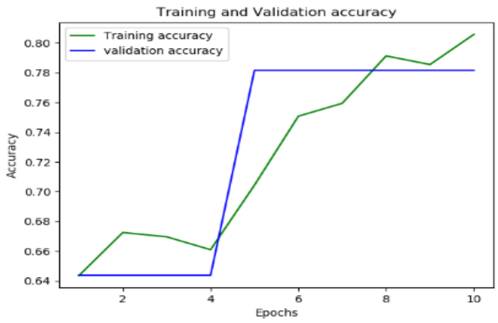

Figure 15: Impact of accuracy performance

Fig. 15 denotes accuracy performance for plant disease prediction performance in percentage. In the graph analysis the proposed attained 95% of accuracy performance.

V. CONCLUSION

To conclude this work Resnet Recurrent Neural Network (R^2NN) algorithm is used to find plant disease. This first step is pre-processing using the Gaussian filter to enhance image quality. Then we apply Contrastive Limited Adaptive Equalization (CLAE) algorithm to improve image contrast. Furthermore, we use Watershed Region Segmentation (WRS) technique to segregate the affected parts. Later, the R^2NN algorithm effectively classifies the plant disease. Our approach has been tested on many plant species, so thus, the proposed method contributes to a more effective means of detecting and classifying plant disease. Therefore the proposed method produce high performance than previous methods.

REFERENCE

[1] S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony and M. H. Kabir, "Less is More: Lighter and Faster Deep Neural Architecture for Tomato Leaf Disease Classification," in IEEE Access, vol. 10, pp. 68868-68884, 2022.

[2] C. Zhou, S. Zhou, J. Xing and J. Song, "Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network," in IEEE Access, vol. 9, pp. 28822-28831, 2021.

[3] Z. Zinonos, S. Gkelios, A. F. Khalifeh, D. G. Hadjimitsis, Y. S. Boutalis and S. A. Chatzichristofis, "Grape Leaf Diseases Identification System Using Convolutional Neural Networks and LoRa Technology," in IEEE Access, vol. 10, pp. 122-133, 2022.

[4] X. Zhang, Y. Qiao, F. Meng, C. Fan and M. Zhang, "Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks," in IEEE Access, vol. 6, pp. 30370-30377, 2018.

[5] S. Barburiceanu, S. Meza, B. Orza, R. Malutan and R. Terebes, "Convolutional Neural Networks for Texture Feature Extraction. Applications to Leaf Disease Classification in Precision Agriculture," in IEEE Access, vol. 9, pp. 160085-160103, 2021.

[6] C. Zhou, Z. Zhang, S. Zhou, J. Xing, Q. Wu and J. Song, "Grape Leaf Spot Identification Under Limited Samples by Fine Grained-GAN," in IEEE Access, vol. 9, pp. 100480-100489, 2021.

[7] B. Liu, C. Tan, S. Li, J. He and H. Wang, "A Data Augmentation Method Based on Generative Adversarial Networks for Grape Leaf Disease Identification," in *IEEE Access*, vol. 8, pp. 102188-102198, 2020.

[8] H. Phan, A. Ahmad and D. Saraswat, "Identification of Foliar Disease Regions on Corn Leaves Using SLIC Segmentation and Deep Learning Under Uniform Background and Field Conditions," in IEEE Access, vol. 10, pp. 111985-111995, 2022.

[9] S. S. Chouhan, A. Kaul, U. P. Singh and S. Jain, "Bacterial Foraging Optimization Based Radial Basis Function Neural Network (BRBFNN) for Identification and Classification of Plant Leaf Diseases: An Automatic Approach Towards Plant Pathology," in IEEE Access, vol. 6, pp. 8852-8863, 2018.

[10] Q. Wu, Y. Chen and J. Meng, "DCGAN-Based Data Augmentation for Tomato Leaf Disease Identification," in IEEE Access, vol. 8, pp. 98716-98728, 2020.

[11] H. Yu *et al.*, "Corn Leaf Diseases Diagnosis Based on K-Means Clustering and Deep Learning," in *IEEE Access*, vol. 9, pp. 143824-143835, 2021.

[12] Y. Wu, X. Feng and G. Chen, "Plant Leaf Diseases Fine-Grained Categorization Using Convolutional Neural Networks," in *IEEE Access*, vol. 10, pp. 41087-41096, 2022.