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Analysis of Cotton Leaf Curl Diseases Using Advanced Learning Model

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Abstract: Plant diseases primarily affect society and farmers. Cotton plant diseases have become more complex for cotton farmers and may cause massive damage. Identifying cotton plant diseases in the early stages dramatically impacts the prevention of conditions for plants. Based on living organisms, various diseases cause damage to cotton plants or crops; the other name for this is pathogens when they infect plants. Many state-of-art algorithms failed to detect and recognize cotton plant diseases in the early stages. The most widely used deep learning (DL) domain to find accurate patterns belongs to cotton plant diseases, including bacterial blight, Bacteria, Phytoplasmas, Viruses, leaf curl, and viroids. This paper describes a advanced Learning model to find the specific leaf curl disease or illness in the early stages—ResNet50 is used as a training model to train the cotton plant disease datasets. Image filters remove noise from the input images to improve the disease detection rate. The dataset is the Cotton Dataset collected from the UCI repository. The comparison between the traditional algorithms and ADL is shown in this paper and analyzes the performance.

Keywords: *Diseases, Deep Learning, Agriculture, Crop Yielding.*

1. Introduction

Agriculture is one of the significant economic resources in India. India is also called the land of agriculture. Farmers may select any crop and find the relevant pesticides to reduce diseases and increase crop production [1]. A continuous monitoring system is required to increase crop production to detect plant diseases and prevent steps—diagnosis of plant diseases based on the morphology and other significant factors on the leaves. Visual testing of plants is more critical, which is done by an expert biologist; this may overcome the misdiagnosis of plant diseases and reduce the considerable loss of yield. Continuous monitoring of plant diseases with a specialist biologist is most expensive, but this prevents the spreading and transmission of disease fastly [2]. Artificial intelligence (AI) plays a significant role in complex applications and is integrated into the ML and DL algorithms to find accurate and large patterns. ML and DL algorithms increase plant disease prediction accuracy based on many designs. Deep Learning is one of the significant domains that can better classify disease patterns with the help of multiple layers [3]. Cotton crops became more significant to the farmers, which provided a massive economy to the farmers. The primary use of cotton crops is to make cloths. Based on the cotton crop, the textile industry grew. Preventing the cotton plants' diseases and improving cotton production have more economic impact. Generally, the symptoms of cotton plant diseases are in the form of colored spots identified on the leaves or stems of the plants. Cotton plant diseases are caused by using fungi, bacteria, and viruses. Existing models can be applied to detect these colored spots, but the existing model not shows accurate disease detection.

Several DL algorithms focused on detecting and recognizing plant diseases belonging to various plants. Conditions are different, and every plant is affected by specific diseases [4]. The DL algorithms find an accurate model to detect particular illnesses based on the patterns [5]. This paper mainly focused on filtering the input images. Mean filtering is the technique used in this paper to remove the noise from the input plant images [6]. ResNet50 is the pre-trained model used to train plant diseases called Residual Networks. This model contains many layers that can train on any dataset, such as disease detection, sentiment analysis, and other fields. This paper proposed a combined approach that detects and recognizes the plant-infected regions by highlighting them with red. ResNet50 model trains the plant village images based on the features of the dataset input images. Attributes include image size, shape, format, and type. To detect and remove the noise from input images, the Laplace noise filter and Region based segmentation combined with the CNN model gives the accurate infected regions with disease classification.

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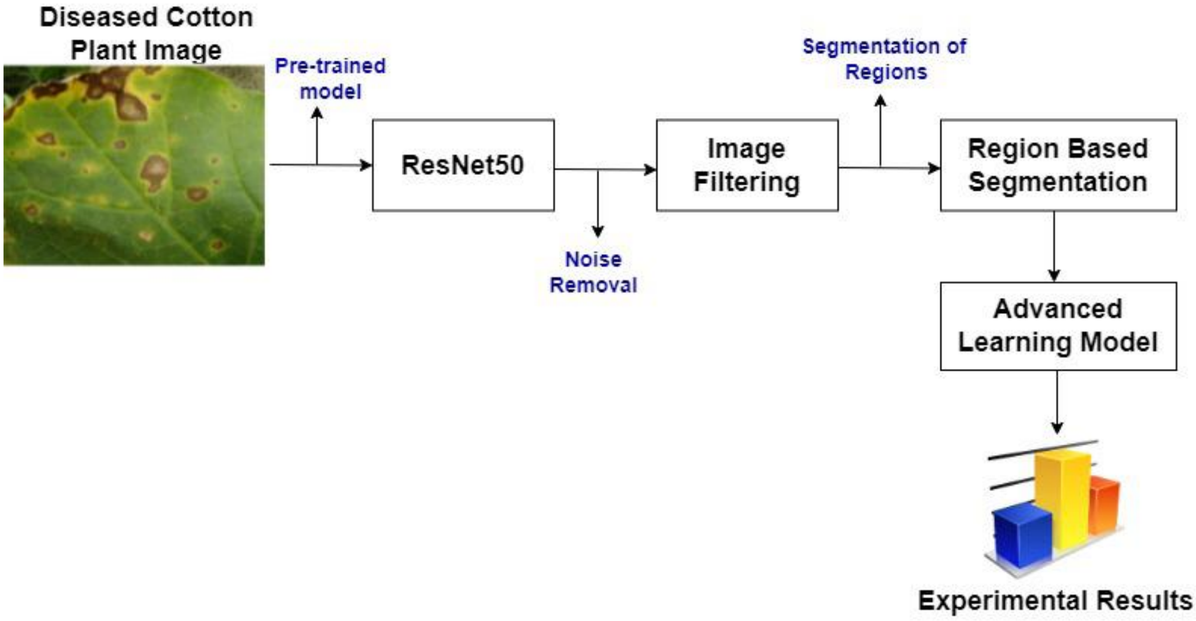

Fig 1: Basic Steps for Plant Disease Detection

2. Literature Survey

D. Das et al. [7] proposed the ML-NN to detect and recognize plant diseases. ML-NN model also extracts the large annotated dataset, which is transferable. The proposed model combined feature extraction and classification based on two levels: training and testing. In the training stage, the features are captured based on the low-dimensional differential space. The testing stage uses the variance of every class. Mahalanobis distance method used to classify plant diseases. Thus this approach achieved a better disease detection rate. V. Singh et al. [8] discussed various current trends in detecting plant diseases using several advanced imaging models. The author mainly focused on detecting diseases based on the significant factors impacting plant disease detection. H. Nazki et al. [9] introduced the Adaptive Re-construction Generative Adversarial Networks (AR-GANs) model that translates the plant disease patterns used for classification. The synthetic dataset used for the experiments is based on the proposed model. The classification accuracy is improved (+5.2%) compared with the existing model. H.-Y. Wu et al. [10] introduced the DL model, which detects tea leaf diseases. The proposed model is a combination of the VGG19 and CNN models. This approach achieved better results compared with state-of-art algorithms.

U. P. Singh et al. [11] developed the Multilayer CNN (M-CNN) introduced for classifying infected mango leaves. The Kaggle dataset used for experiments contains 1070 mango tree leaf images. The dataset consists of two types of leaves, such as healthy and infected leaves. Thus the proposed approach obtained a tremendous accuracy compared with existing models. S. S. Chouhan et al. [12] introduced the integrated system called BRBFNN for finding accurate plant disease detection. The infected regions detected by a part-growing algorithm are used to find the exact areas. The proposed model classifies the fungal diseases based on the color spots. The proposed approach attains high accuracy and classification of plant diseases. Q. Wu et al. [13] introduced DCGAN used to recognize plant diseases. To increase the performance of the disease detection rate, thus DCGAN shows the accurate infected regions. DCGAN can apply to large and complex datasets. B. Liu et al. [14] proposed generative adversarial networks (GANs) to classify grape leaves based on diseases. This approach applies to large datasets of 4,062 grape leaf disease images. GAN combined with Frechet inception distance (FID) to get better results. K. Nagasubramanian et al. [15] proposed the DL model that classifies the eight several soybean stresses. The dataset comprises 16,573 RGB images of healthy and emphasized soybean leaflets under challenging conditions. The proposed approach classifies the soybean leaves based on their features. Thus this approach gives accurate results. C. Bi et al. [16] proposed a combined system consisting of various CNN models. CNN approach combined with advanced models gives the apple leaf diseases. Thus CNN approach achieved better accuracy compared with state-of-art models.

Table 1: Summary of work done using CNN technique

Authors	Methods	Used Plants	Performance
[18]	CNN	Apple, Blueberry, Cherry, Corn, Grapes, Orange, Peach, Potato, Strawberry, Tomato (Dicots)	GoogLeNet accuracy-85.53% to 99.34% AlexNet accuracy-98.21
[19]	Deep-CNN	Rice (Monocot)	Accuracy-95.48% and 93.29%
[20]	CNN with GANs	Multiple Plants	Inception v3-88.6%, MobileNets-92%
[21]	CNN with different architecture	Apple, Blueberry, Corn, Cabbage, Cassava, Cherry, Peach, Strawberry, Tomato (Dicots)	Accuracy-97.26%-99.47%
[22]	CNN and autoencoders	Potato, tomato (Dicots) maize (monocots)	Accuracy-100%
[23]	**CNN**	Distinct plants including Tomato	Modified MobileNet-97.65%, Reduced MobileNet-98.34% and MobileNet-98.65%.

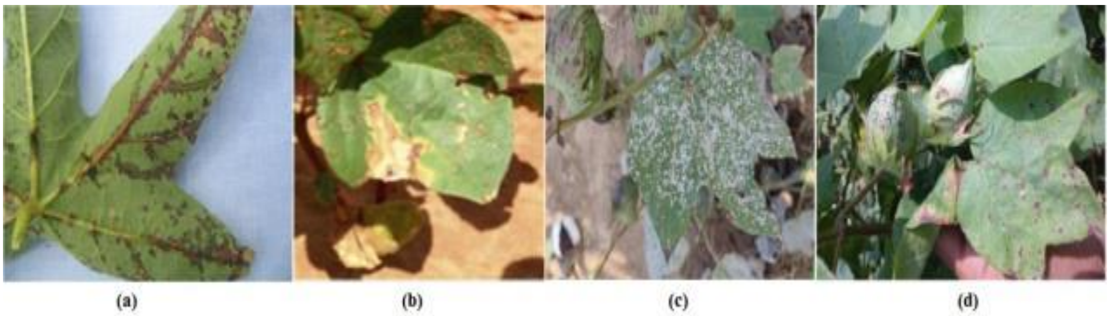

Fig 2: (a) Angular leaf spot, (b) vascular wilt, (c) grey mildew, (d) anthracnose, (e) root rot.

3. Pre-Trained Model

A. ResNet-50

The other name for ResNet is Residual Neural Network. ResNet-50 consists of 50 deep layers. This model contains various residual blocks that process the input images. The residual blocks used to increase the accuracy of the proposed model. In these blocks, the plant disease features are analyzed and extract the features of the plant diseases are. The skip connections are placed at the residual blocks and increase the power of the neural network. This model can also learn the identity function. In other words, the skip connections add more outputs from the previous layers trained with deeper networks. Thus this can be used as a pre-trained model for the plant disease datasets.

B. Laplacian Noise Filter

Laplacian operator noise filters play a significant role in removing the noise from the input plant images. Noise filters will reduce the noise, sharpening, and edge detection. This paper uses a Laplace filter to remove the image's noise. The smoothing technique also finds the edges of the input plant image. This operator gives the abnormalities in the gray level. The Laplacian operator is a second spatial derivation of the extracted input image. The Laplacian operator represents:

$$Laplace\ (f) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (1)$$

C. Region Based Segmentation

Region-based segmentation (RBS): This segmentation model divides the input plant images into unique segments. The regions consider components that find high-intensity pixels that detect abnormal areas. Based on the seed points, the locations are recognized. RBS helps the CNN for better classification. After the noise filter step, RBS measures and gather the intensity, color Etc. Threshold plays a significant role in finding abnormal regions by using RBS. Equation 2 used to measure the maximum and minimum values of image intensity.

$$|X_{max} - X_{min}| <= Threshold \quad (2)$$

D. Advanced Deep Learning Algorithm (ADL)

In Deep Learning (DL), RBFNs are the neural network based on the feed-forward (FF) approach and make utilization of radial functions as activation functions. This model contains three layers input layer, hidden layer, and output layer. RBFN mainly focused on measuring the plant disease abnormalities from the training set. This generally presents the input vector which sustains the data to the input layer by approving the identification of results by comparing the previous datasets. The neurons in the input have efficient nodes that efficiently classify the data based on class. All the neurons are present in the hidden layer and connected with the input layer. Gaussian transfer functions are part of the hidden layer. Thus the following layers are as follows:

Input layer: This consists of N_i nodes from the source, where N_i is the range of input vector v.

Hidden Layer: In this layer, the count values are computed by comparing the training attributes, which is M. Every attribute in this divided with RBF.

$$\varphi(v) = \varphi\left(||v - vj||\right), \quad Where\ j = 1,2, \ldots\ldots, N \quad (2)$$

Equation 2 represents the following variables such that, the j^{th} point is the input vector,

Output Layer: In this layer, there is no limit for the output layer. The size of the output layer is very shorter than the hidden layer. In the hidden layer, the RBF is used in every computation attribute.

$$\varphi i(v) = \varphi(v - vj) \quad (3)$$

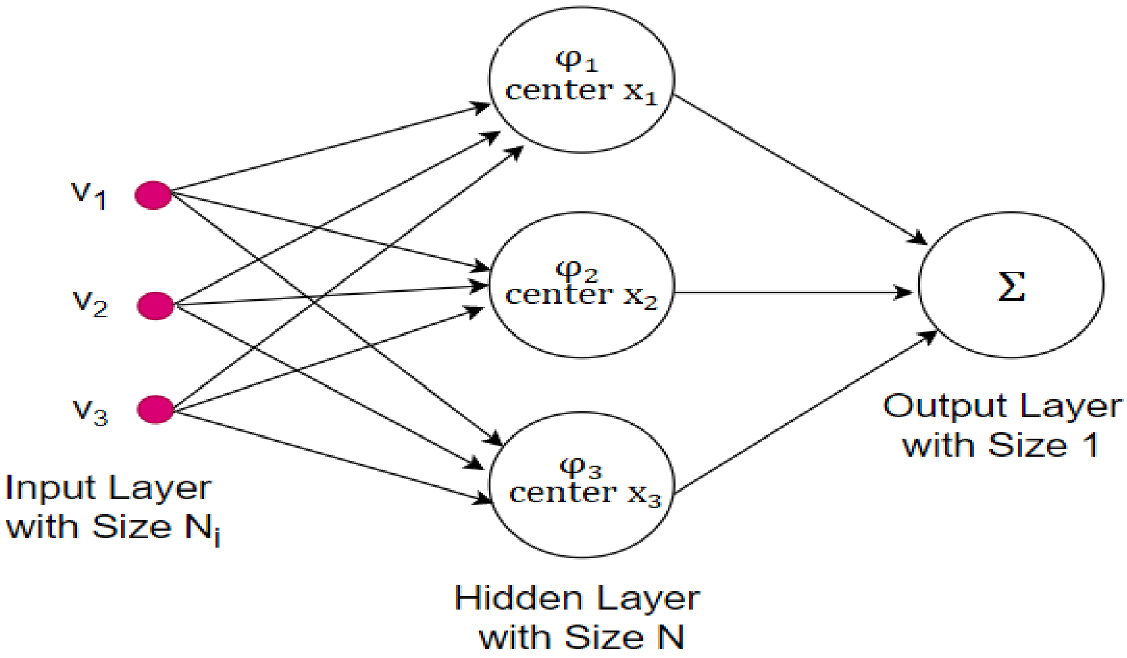

Fig 3: Structure of RBF

E. Dataset description and Experimental Results

The cotton plant dataset contains 2384 cotton leaves divided into seven types of classes (Healthy, Leafspot, Nutrient Deficiency, Powdery mildew, Target spot, Verticillium Wilt, and Leaf curl). These images are collected from Matiari city from pakistan. These images are captured in the morning, afternoon, evening. The pixels of the images are 3120 x 4160. A confusion matrix is applied to analyze the model performance for the testing set data. This also initializes the true values for the testing data. This is also called an error matrix if the model shows the errors. The true and false values of the model are given in performance metrics section. Figure 3 shows the plant leaf images from dataset.

Fig 4: Cotton Plant Dataset Diseases [17]

F. Performance Evolution

The performance of models are analyzed by using the following count values given in below table

True Positive (TP)	**True Negative (TN)**
False Positive (FP)	**False Negative (FN)**

TP: The predicted value is true, and it is true.

TN: The predicted values is no and it is false.

FP: The predicted values is yes, originally it is not true.

FN: The predicted values is no, but the values are true.

Precision: The total positives measured from the overall positives give precision.

$$Precision = \frac{TP}{TP + FP}$$

Accuracy: The model accuracy is identified.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Recall: The overall TPs are identified.

$$Recall = \frac{TP}{TP + \ FN}$$

Specificity: The overall false values are correctly identified.

$$Specificity = \frac{No\ of\ TN}{No\ of\ TN +\ No\ of\ FP}$$

F1-Score: This measure the coherence mean of Precision and Recall achieved the better computation which is incorrectly classified cases than the Accuracy.

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

Table 1: Comparison table with performance metrics

Algorithms	Precision	Accuracy	Recall	Specificity	F1-Score
CNN	93.21	92.23`	90.45	93.89	94.9
ALM	97.45	98.45	96.89	98.67	98.45

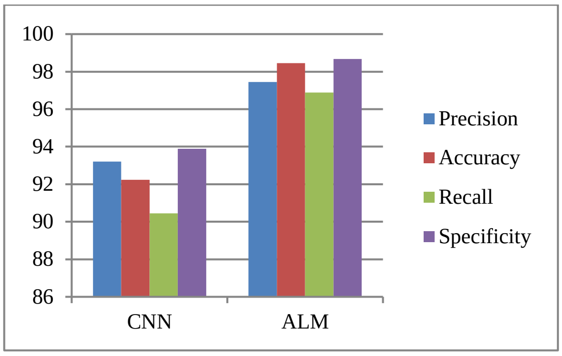

Fig 5: Comparative Performance

4. Conclusion

This paper describes the advanced learning model (ALM) developed to overcome various issues in cotton plant disease detection. MF is the automated approach that detects and recognizes the specific disease from the input images. MF classification based on healthy and disease-infected leaf images. The image filters are most widely used to improve the MF's performance by removing the image's noise. The pre-trained model ResNet50 trains the plant disease dataset images, extracts the disease images' features and detects the infected regions. The proposed model achieved an accuracy of 98.45%; precision is 97.45%; Recall is 96.89%; specificity is 98.67%, and F1-Score is 98.45%.

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