Implementation of an Efficient Low Weighted Network Development in Paddy Disease Detection Prediction, Remedy Guider using Live Mobile Application

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Abstract: *The agriculture industry is the most important industry for society as it serves the most important need of life. But the plant diseases in agriculture lead to a decrease in productivity and hence it is very important to prevent, detect, and get rid of the diseases. Image processing and deep learning are nowadays the buzzwords in the IT industry and their applications in the agriculture industry can enhance decision making in various aspects of the agriculture industry. Paddy crop is one of the most demanding crops especially in South Asia. This paper proposes a predictive model using CNN for classification and prediction of disease in paddy crop. Paddy crop diseases are very fatal and can affect the crops severely if it is not taken care in the initial stages. The proposed model will improve the decision making using CNN in case of various diseases in paddy crop for prediction of diseases in initial stages and prevention of mass loss in productivity of the whole yield.*

Keywords: Convolutional neural networks, Image processing, Paddy crop diseases

I. INTRODUCTION

Agriculture was started during the Neolithic age and is going strong until today. But due to harsh changes in climatic conditions and malpractices by humans the condition of agriculture is worsening day today. As in human beings, the diseases in plants and crops are also fatal and can destroy agriculture if not diagnosed in the early stages. There are number of diseases that prove to be very fatal and cannot only destroy the crop but can also destroy the crops surrounding it. But the diagnosis is not always possible due to lack of education and expertise. So, the experts are trying their best to provide the services to the farmers to get rid of these kinds of diseases.

Since the last few years, the IT industry is also playing a vital role in agriculture as it provides efficient solutions to the various aspects of the agriculture. Machine learning, deep learning, image processing, artificial intelligence, and many more tools are providing very efficient solutions to the problems in agriculture like fighting food scarcity and empowering small farmers by receiving useful data, making yield prediction, coping with climate change, and providing images of crops and land.

Image processing and deep learning are the new trends in agriculture as far as the IT industry is concerned. Image processing and finding out the information about the disease that the plant might be suffering from is one of the major techniques in deep learning domain and then taking precautions is one way to prevent the disease to grow or transmit to another plant.

Heavy weights of the model generated after training process is difficult to deploy in real time processors for applications. Significant losses are incurred by the farmers due to crops being damaged at a very large scale from fatal plant diseases that can be cured if predicted earlier. To overcome these disadvantages in this project the novel architecture can be used to predict and identify nine different types of agriculture diseases. Modified Squeeze net makes the development over larger architectures by replacing large kernel-sized filters with 11 and 5 within the first and second convolutional layer, respectively, with multiple 3 x 3 kernel-sized filters one after another. While Squeeze Net achieves an outstanding accuracy on ImageNet dataset, its deployment on even the foremost modest sized GPUs may be a problem due to huge computational requirements, both in terms of memory and time. Compared to squeeze net the novel model that will be developed is better for developing application because, novel design of architecture approx. images a sparse CNN with a normal dense construction. We use Convolutional layers of different sizes to capture details at varied scales (3X3, 1X1). The proposed system is built with a larger size kernel because multiple non-linear layers increase the depth of the network which enables it to learn more complex features. Since only a little number of neurons are effective as mentioned earlier, the width/number of the convolutional filters of a specific kernel size is kept small. While Squeeze Net achieves an outstanding accuracy on ImageNet dataset, its deployment on even the foremost modest sized GPUs may be a problem due to huge computational requirements, both in terms of memory and time. Also, it uses convolutions of different sizes to capture details at varied scales of 3 x 3, 1 x 1. A mobile application is developed to upload the images of the plant to test for detection and identification of the diseases. A robot has been used to take the fertilizers to the agricultural fields.

This paper is organized as follows: Sect. 1 discusses the introduction, Sect. 2 gives a detail about the related work in the field of crop disease prediction, Sect. 3 explain about the Proposed Model, Sect.4 Contains the Pseudo Code, Sect. 5 Depicts the Result achieved, the conclusion has been detailed in Sect. 6 along with the details of future work.

II. Related Works

Suraksha et al. [5] propose a technique for prediction paddy crop disease using data mining and image processing.

Rajmohan et al. [7] propose a technique for smart paddy crop disease prediction using deep CNN and SVM classifier. In which they have selected 250 images from which 50 are used for training and rest for testing.

Barik [9] proposes a technique for region identification of Rice Diseases using image processing. In this paper, they have presented a model for the identification of disease and region of infection using image processing and classification techniques like SVM classifier and Naive Bayes classifier. Prediction is done and the severity of various diseases is found and then it is classified into different categories.

Jagan Mohan et al. [11] present a technique for disease detection of plants using canny edge detection. It is concluded that this model periodically monitors the cultivated field. The diseases are detected using edge detection in early stage and machine learning is used for training which takes proper decision regarding the diseases.

Badage [10] presents a technique for disease detection in paddy crops which uses Scale Invariant Feature Transform for extracting the features then the features are taken and SVM and K Nearest Neighbors are used to recognize the image.

Dhaygude et al. [12] presented a technique for prediction of diseases in rice plant. This consists of four steps that are color transformation for the RGB image is created then the RGB is converted to HSI then the green pixels are masked and removed using specific threshold value and after that the image is segmented and the useful features are extracted and the texture statistics are computed from SGDM matrices.

III Proposed Model

The objective of this research is to recognize the type of disease that a paddy plant is diagnosed with. Three families of diseases are bacterial, viral, and fungal. We have taken nine diseases into consideration.

3.1 Paddy Crop Disease Modeling

Paddy crops mainly suffer from nine types of diseases which we are using in our dataset for training and testing the data. The detailed discussions of those diseases are

3.1.1 Brown Spot

There also are other symptoms by which it are often identified just like the death of seedlings, death of huge areas of leaf, brown or black spots on grains. It's a kind of mycosis. Everywhere South and South East Asia is does 5% yield loss. Treating seeds chemically also can be proved helpful because it decreases the prospect of the infection.

3.1.2 Bacterial Blight

This disease usually occurs within the leaf of a rice plant and may easily be acknowledged by watching the yellow and white strips on the leaves. This disease is often recognized by watching the youngest leaf which can be straw in color if the plant is affected by bacterial blight. This disease is often prevented by avoiding the utilization of excess nitrogen fertilizer and by plowing stubble and straw into the soil after harvesting the crop.

3.1.3 Leaf Smut

Leaf smut may be a widely spread but a minor disease that happens in paddy. It is often identified by watching the leaf because the leaf is going to be covered by fungus everywhere. This disease is caused by Entyloma oryzae. This disease is often controlled by doing clean cultivation and growing resistant varieties.

3.1.4 Sheath Rot

The panicle doesn't emerge fully from the flag leaf. The glumes are discolored. Grains get discolored. Young panicles might not emerge from infected sheaths.

3.1.5 Grain Discoloration

The grains are discolored red, yellow, orange, pink or black, depending upon the organism involved and therefore the degree of infection. The infection could also be external or internal resulting in discoloration of glumes, kernels or both. Dark brown or black spots appear on grains.

3.1.6 False Smut

Few grains within the ear head exhibit the symptoms. Affected grains get converted into green velvety mass that are much bigger than the normal grains. Spore balls are visible between glumes, and therefore the glumes aren't affected. Rainfall and cloudy weather during flowering and maturity favors the disease development.

3.1.7 Tungro

Infection occurs in nursery and main field. The chief symptoms are stunted growth of plant, reduced till, coloration of leaves in various reminder yellow to orange. The coloration starts from the tip and proceeds downwards. Older leaves exhibit rusty spots or dots of various sizes. The virus is transmitted by green leafhoppers.

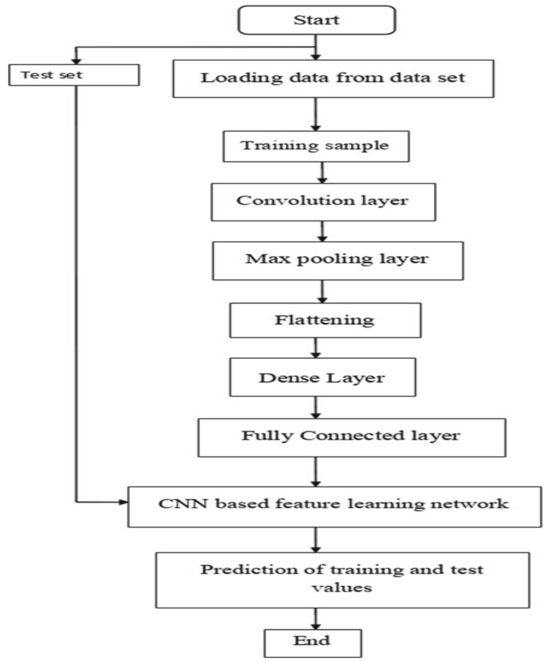
3.1.8 Blast

On leaves, the spots are typically spindle shaped (Eye shaped) with dark brown margin and grey center.

3.1.9 Sheath Blight

Leaf smut may be a widely spread but a minor disease that happens in paddy. It’s often identified by watching the leaf because the leaf is getting to be covered by fungus everywhere. This disease is caused by Entyloma oryzae. This disease is often controlled by doing clean cultivation and growing resistant varieties. That, the presence of disease in the leaf is evaluated

3.2 Process Flow Model



3.3 Image Generation and Augmentation

Neural networks processes images using CNN and therefore the CNN model interprets the image within the sort of matrices and every one the operations are performed on the matrix formed by the image. The pictures are generated and augmentation is performed. Images are augmented to extend the quantity of coaching data. We've performed the horizontal flip, vertical flip, shearing, and brightening of images within the augmentation process.

3.4 Convolution Step

The model gets a picture as its input within the sort of matrices. During a CNN model, matrices play a key role. Within the convolution step, a filter or kernel matrix is taken and convolution is performed with the input image matrix by sliding the filter over the input image. Allow us to consider

x Input
a^k After convoluted image
k Index of kernel (weight filter)
W Kernel (weight filter)
b Bias
E Cost function.

3.5 Pooling Step

Pooling is one among the foremost important building blocks of a CNN model. The most objective of applying pooling is to scale back the spatial size of a picture .therefore the depth of the image remains intact. There are three sorts of pooling: Max pooling, Min pooling, and Average pooling. In our model, we have implemented the max-pooling technique

Forward Propagation:

$$a_{ij} = \max(0, x_{(i+s)(j+t)}) \quad (1)$$

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3.6 Fully Connected Layers

The output of the pooling step may be a matrix that ought to be mapped into a knowledge structure which is possible for classification and prediction and therefore the vector is employed for that. A totally connected layer is employed to map a matrix to a one-dimensional vector. A matrix gets converted to a vector employing a flatten() function and a few linear operations are performed within the hidden layers using the Dense() function. In one of the Dense layer, we have used 'ReLU' as an activation function and 'Softmax' for the other Dense layer.

ReLU activation function:

$$\text{ReLU}(x) = \max(0, x) \tag{2}$$

Forward Propagation:

$$a_{ij} = \text{ReLU}(\text{x}) = \max(0, x_{ij}) \tag{3}$$

Backward Propagation:

$$\frac{\partial E}{}$$

$$\partial x_{ij} \qquad \partial a_{ij}\, \partial x_{ij} \qquad\qquad 0\ (Otherwise)$$

3.7 Disease Prediction

After training the info assail the training set and classifying the disease on test set we've predicted the disease present during a random paddy crop image using the predict() function and therefore the results were obtained within the sort of a binary vector with three classes. If any disease is present within the crop then the corresponding element within the output vector are going to be 1 and every one the opposite are 0.

IV. Algorithm of the Model

Input: A dataset with images of infected paddy crop leaves.

Output: A predicted value of disease.

Start

Step 1. Import necessary libraries

Step 2. Add a 2-dimensional convolution layer using conv2D() in the neural network

Step 3. Add a 2-dimensional max pooling layer using maxpooling2D() in the neural network

Step 4. Add a flattening layer using Flatten()

Step 5. Repeat step 2,3 and 4

Step 6. Add a fully connected layer with an activation function of ReLu

Step 7. Add a dense layer using dense() with an activation function of Softmax

Step 8. Perform image augmentation using ImageDataGenerator() by Horizontal flip, vertical flip, brightening, shearing

Step 9. Load the images as training and test sets and load them in different Variables

Step 10. Fit the data and train the model on training dataset using fit generator()

Step11. Test the accuracy of the model on the test set.

Step 12. Predict the disease on a random image and print the output.

Stop

V. Result

After the model is trained the app is opened and photo of diseased paddy plant is captured and the name of the disease will be predicted and the remedy is given. A robot is used to spray the pesticides in the field.

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Figure: Home Page of Paddy Disease Detection

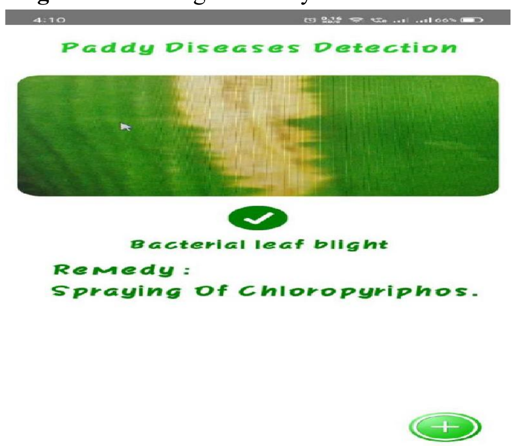

Figure: Disease Predicted and Remedy is given

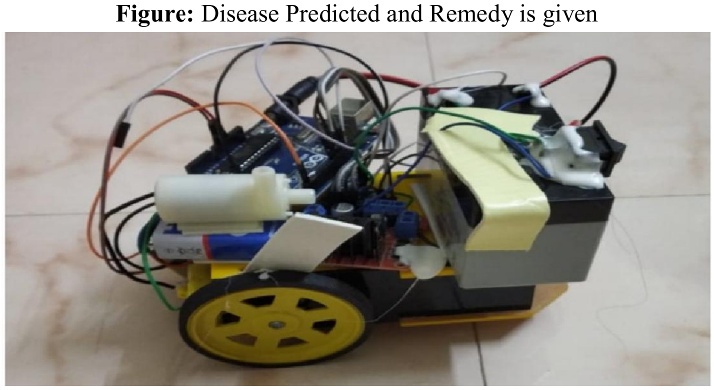

Figure: Robotic Car Setup

VI. Conclusion and Future Work

Agriculture plays a very important role in the lives of living beings as it provides food to all the living organisms. As it is important not only for humans to survive and also for animals so it must be protected and means should be created to protect agriculture from different types of diseases. In this project we suggest a method of dissimilar disease cataloguing for the nine different types of diseases in the infected plants. It also recommends and assesses an instinctive image dissection and cataloguing techniques by framing a layered set of rules for the infected plants. From the execution point of view, the proposed methodology was tried and verified on various kinds of rice leaf diseases like bacterial blight, brown spot, leaf scald and leaf blast successfully. Over and above it has been seen that, by means of least methodical pains the finest outcome can be gained resourcefully to verify the productivity of methods. In the future the methodology can be further trained to obtain the maximum accuracy of the model generated in this project.

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We can also incorporate further more diseases and build an effective way to classify viral and bacterial infections in paddy to take a step towards saving the crop and leading to the increase in productivity.

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