Research on Recognition of Crop Disease And Insert Pests Based On Deep Learning In Harsh Environment

P.Sriramulu[1], Dr.R.Yadagiri Rao[2], G.Jayakrishna[3], D.Rudyanayak[4], G.Anil[5], G.Manjula[6], Kongala Vamshi[7]

[1]Assistant professor, Department of CSE, Sri Indu Institute of Engineering & Technology, Hyderabad

[2]Professor, Department of CSE, Sri Indu Institute of Engineering & Technology, Hyderabad

[3,4,5,6,7] IVthBtech Student, Department of CSE, Sri Indu Institute of Engineering & Technology, Hyderabad

ABSTRACT

Plant diseases are a major threat to farmers, consumers, environment and the global economy. In India alone, 35% of field crops are lost to pathogens and pests causing losses to farmers. Indiscriminate use of pesticides is also a serious health concern as many are toxic and biomagnified. These adverse effects can be avoided by early disease detection, crop surveillance and targeted treatments. Most diseases are diagnosed by agricultural experts by examining external symptoms. However, farmers have limited access to experts. Our project is the first integrated and collaborative platform for automated disease diagnosis, tracking and forecasting. Farmers can instantly and accurately identify diseases and get solutions with a mobile app by photographing affected plant parts. Real-time diagnosis is enabled using the latest Artificial Intelligence (AI) algorithms for Cloud-based image processing. The AI model continuously learns from user uploaded images and expert suggestions to enhance its accuracy. Farmers can also interact with local experts through the platform. For preventive measures, disease density maps with spread forecasting are rendered from a Cloud based repository of geo-tagged images and micro-climactic factors. A web interface allows experts to perform disease analytics with geographical visualizations. In our experiments, the AI model (CNN) was trained with large disease datasets, created with plant images self-collected from many farms over 7 months. Test images were diagnosed using the automated CNN model and the results were validated by plant pathologists. Over 95% disease identification accuracy was achieved. Our solution is a novel, scalable and accessible tool

for disease management of diverse agricultural crop plants and can be deployed as a Cloud based service for farmers and experts for ecologically sustainable crop production.

1. INTRODUCTION

Agriculture is fundamental to human survival. For populated developing countries like India, it is even more imperative to increase the productivity of crops, fruits and vegetables. Not only productivity, the quality of produce needs to stay high for better public health. However, both productivity and quality of food gets hampered by factors such as spread of diseases that could have been prevented with early diagnosis. Many of these diseases are infectious leading to total loss of crop yield. Given the vast geographical spread of agricultural lands, low education levels of farmers coupled with limited awareness and lack of access to plant pathologists, human assisted disease diagnosis is not effective and cannot keep up with the exorbitant requirements. To overcome the shortfall of human assisted disease diagnosis, it is imperative to build automation around crop disease diagnosis with technology and introduce low cost and accurate machine assisted diagnosis easily accessible to farmers. Some strides have been made in applying technologies such as robotics and computer vision systems to solve myriad problems in the agricultural domain. The potential of image processing has been explored to assist with precision agriculture practices, weed and herbicide technologies, monitoring plant growth and plant nutrition management [1][2]. However, progress on automating plant disease diagnosis is still rudimentary in spite of the fact that many plant diseases can be identified by plant pathologists by visual inspection of physical symptoms such as detectable change in color, wilting, appearance of spots and lesions etc. along with soil and climatic conditions. Overall, the commercial level of investment in bridging agriculture and technology remains lower as compared to investments done in more lucrative fields such as human health and education. Promising research efforts have not been able to productize due to challenges such as access and linkage for farmers to plant pathologists, high cost of deployment and scalability of solution. fraud enables theanonymity, reach, and speed to perpetrate fraud around the world.. Recent developments in the fields of Mobile technology, Cloud computing and Artificial Intelligence (AI) create a perfect

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2. SYSTEM IMPLEMENTATION:

In this paper, an intricate Internet of Things climate of harvest illnesses and creepy crawly bugs ID model is set up.Through the arrangement of sensors and cameras in complex hilly climate, the natural data and picture data of the scene are gathered, and the essential data set of harvest bug recognizable proof Is set up. Through the profound learning network model, the picture data is learned and perceived, which is utilized to recognize and gather leaf pictures, and afterward distinguishvermin and sicknesses.

A. THE STRUCTURE OF CROP DISEASE RECOGNITION MODEL.

In this paper, Inception-ResNet-v2 network is utilized as the essential model of yield infection acknowledgment. This cross breed network not just has the profundity benefit of remaining organization, yet in addition holds the interesting qualities of multi-convolution center of commencement organization. In the wake of adding the remaining unit in the beginning organization, despite the fact that there is no huge improvement in exactness, yet it successfully takes care of the issues of slope vanishing and inclination blast. Furthermore, the assembly speed of the model is sped up. Additionally, the preparation effectiveness and the little reach advancement execution are improved. [24]. The design of this model is appeared in Fig. 2

As demonstrated in Fig. 3, the first commencement module takes equal construction for include extraction, and afterward stack. In this paper, we add the cross-layer direct edge and multi-way convolution layer in the lingering network unit to the model. After the joined convolution activity is finished, it is actuated by the association into the ReLu work. As demonstrated in Fig. 4, the 7 × 7 convolution structure in the first beginning construction is supplanted by 1×7 and 7 × 1 convolution in the commencement layer B. Also, the 3 × 3 design in the remaining layer C is supplanted by progressive 3 × 1 and 1 × 3 in Fig. 5. This model can adequately diminish the computational intricacy of a solitary convolution layer by supplanting the first huge convolution piece with multi-facet little convolution bit. What's more, it doesn't change the presentation of the framework. In view of the

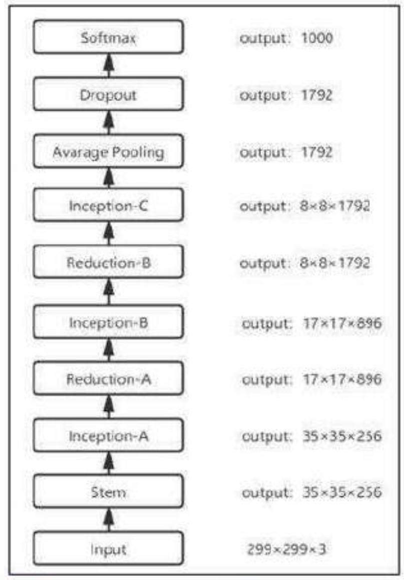

FIGURE 2. The structure of Inception-ResNet-v2.

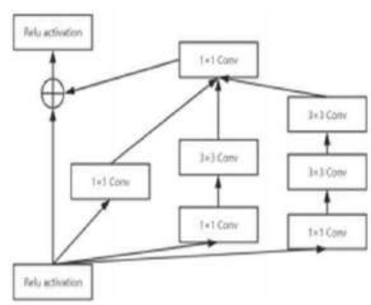

FIGURE 3. The structures of Inception-A in Inception-ResNet-v2.

increase of convolution layer and the deepening of network depth, the performance of this network is more excellent than before.

B. DATASET

The data set used in this paper is from the data set used in the Crop Disease Recognition Competition of the 2018 Artificial Intelligence Challenger Competition. The dataset includes 47363 images of 27 diseases related to 10 crops (mainly tomatoes, potatoes, corn, etc.). The data set is divided into three parts: 70% for training set, 10% for validation set and 20% for test set. Each picture contains only the leaves of a single crop. Some sample pictures are shown in Fig. 6

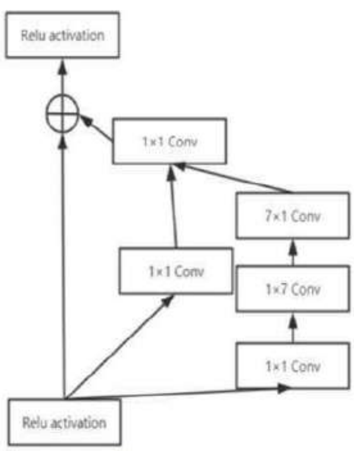

FIGURE 4. The structures of Inception-B in Inception-ResNet-v2.

C. IMAGE PREPROCESSING

The reason for picture preprocessing is to dispense with the impedance of futile data in informational collection to show acknowledgment, and to extend the informational collection partially. The neural organization can accomplish better preparing impact. Thusly, the obviousness of the picture can be viably improved, with the goal that the acknowledgment precision of the model can be improved. As of now, the normally utilized preprocessing strategies incorporate mathematical space change and pixel shading change. The previous incorporates flip, crop, pivot, zoom, etc. The last incorporates evolving contrast, adding

(a) Potato healthy (b) Apple scab (c) Puccinia polysra

D. NORMALIZED PROCESSING

After that above steps are complete, the picture of the data set will be normalized. Normalization can be considered to be an indispensable and important part of the convolutional neural network. It scales the characteristics of each dimension to the same range. On the one hand, it is convenient to calculate data and improve the efficiency of operation. On the other hand, the association between different features is eliminated. Therefore, the ideal model training.

2.1 Convolution Neural Network

A **Convolutional Neural Network (CNN)** is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform really well. Neural Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN.

In a regular Neural Network there are three types of layers:

1. Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).

2. Hidden Layer: The input from the Input layer is then feed into the There can be many hidden layers depending upon our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

3.Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or softmax which converts the output of each class into the probability score of each class.

The data is fed into the model and output from each layer is obtained from the above step is called feedforward, we then calculate the error using an error function, some common error functions are cross-entropy, square loss error, etc. The error function measures how well the network is performing. After that, we backpropagate into the model by calculating the derivatives. This step is called Backpropagation which basically is used to minimize the loss.

Convolution Neural Network

Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example visual datasets like images or videos where data patterns play an extensive role.

CNN architecture

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

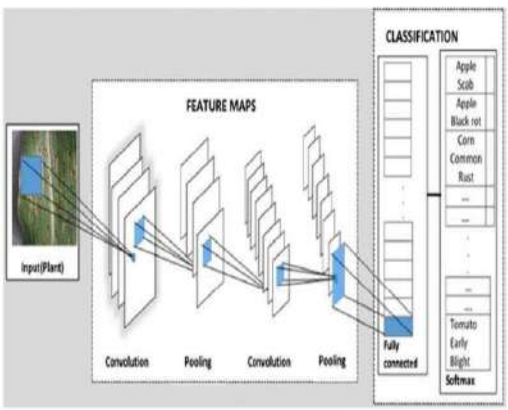

Figure 1: A typical Convolution Neural Network architecture

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3. EXPERIMENTAL RESULTS

In this paper author is applying deep learning convolution neural network (CNN) to predict crop disease and its pests to reduce economical loss in crop business. To build disease recognition model author is applying RESNET CNN model which consists of 3 parts

1) Feature Extraction: CNN compose of multiple layers and first layer define for feature extraction

and this features will be extracted from given input image dataset or any other multidimensional dataset.

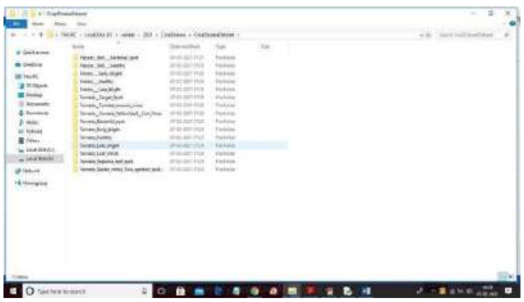
2) Feature Selection: Using this layer features will be selected by applying a layer called pooling or max polling.

3) Activation module: using this module RELU will be applied on input features to remove out unimportant features and hold only relevant important features

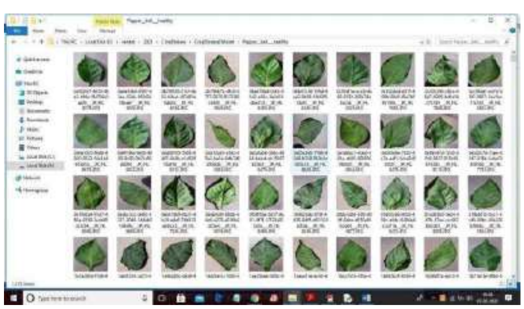
4) Flatten: This layer will be define to convert multidimensional input features into single dimensional input array

5) Dense: This layer can be used to connect one layer to other layer to receive input features from previous layer to new

layer to further filter input features in next layer to get most important features from dataset to have best prediction result. To implement this project we have used crop disease recognition dataset and this dataset saved inside 'CropDiseaseDataset' folder and below screen shots showing various type of crop disease images



In above screen we are using 15 different type of crop images and each folder contains images of own leaf and in below screen you can see those image. You too just go inside any above folder to see images.



To run project double click on 'run.bat' file to get below screen

4.CONCLUSION

In this paper, 27 sorts of sickness acknowledgment of 10 sorts of yields were contemplated. The Inception-ResNet-v2 model is developed by utilizing profound learning hypothesis and convolution neural organization innovation. Examinations show that the model can viably recognize the informational collection, and the general acknowledgment precision is pretty much as high as 86.1%. The outcomes show that the acknowledgment exactness of this cross breed network model is moderately higher than the customary model, and it very well may be viably applied to the ID and location of plant sicknesses and bug bothers. Later on work, there are two headings ought to be improved: 1) Extended informational collection. In this paper, just 27 infections of 10 yield species were contemplated, and different species and illnesses were not included, like rice and wheat, and their connected sicknesses.

Hence, the subsequent stage is to get more yield species and sickness pictures for research. 2) Optimize the model. Through the trial of this paper, we can see that Inception-resnet-v2 this sort of blended organization enjoys assimilated the comparing benefit. This model has accomplished great acknowledgment exactness, and is deserving of additional investigation and improvement. Simultaneously, we should plan an organization model which can characterize crop pictures with higher precision. This paper presents an automated, low cost and easy to use end-to-end solution to one of the biggest challenges in the agricultural domain for farmers _ precise, instant and early diagnosis of crop diseases and knowledge of disease outbreaks - which would be helpful in quick decision making for measures to be adopted for disease control. This proposal innovates on known prior art with the application of deep Convolutional Neural Networks (CNNs) for disease classification, introduction of social collaborative platform for progressively improved accuracy, usage of geocoded images for disease density maps and expert interface for analytics. High performing deep CNN model "Inception" enables real time classification of diseases in the Cloud platform via a user facing mobile app.

Collaborative model enables continuous improvement in disease classification accuracy by automatically growing the Cloud based training dataset with user added images for retraining the CNN model. User added images in the Cloud repository also enable rendering of disease density maps based on collective disease classification data and availability of geolocation information within the images. Overall, the results of our experiments demonstrate that the proposal has significant potential for practical deployment due to multiple dimensions – the Cloud based infrastructure is highly scalable and the underlying algorithm works accurately even with large number of disease categories, performs better with high fidelity real-life training data, improves with accuracy increase in the training dataset, is capable of detecting early symptoms of diseases and is able to successfully differentiate between diseases of the same family.

5.FUTURE WORK AND EXTENSIONS

Future work involves expanding the model to include more parameters which can improve the correlation to the disease. We can augment the image database with supporting inputs from the farmer on soil, past fertilizer and pesticide treatment along with publicly available environmental factors such as humidity and rainfall to temperature, improve our model accuracy and enable disease forecasting. We also wish to increase the number of crop diseases covered and reduce the need for expert intervention except for new types of diseases. For automatic acceptance of user uploaded images into the Training

Database for better classification accuracy and least possible human intervention, a simple technique of computing the threshold based on a mean of all classification scores can be used. Further application of this work could be to support automated time-based monitoring of the disease density maps that can be used to track the progress of a disease and trigger alarms. Predictive analytics can be used to send alerts to the users on the possibility of disease outbreaks near their location.

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