Multi-Layered classification of Plant diseases using AI approach

Dr.Medida Jayapal[1], Dr.MadduruSambasivudu[2] ,ChirikiUsha[3*],
Mantri Gayatri[4,] PotuSai Manisha[5]

[1]Assistant Professor,CSE, GITAM University,Hyderabad,A.P, India
jmedida@gitam.edu

[2] Associate Professor, CSE,MRCET,Hyderabad, A.P, India
[3] Assistant professor,Department of CSE,DIET,Visakhapatnam, A.P, India
3*chusha@diet.edu.in
[4] Associate Professor, CSE,MRCET,Hyderabad, A.P, India
gayatricse312@gmail.com
[5]M.Tech Student, CSE,MRCET,Hyderabad A.P, India

Abstract **—** The growth rate of an agricultural sector is related to its capacity for innovation, and vice versa. Our Analysis is focused to employ various deep learning models to create an efficient Plant Disease Detection and Classification Networks (PDDC-Net).Preprocessing is the process of standardizing dataset images by removing various forms of noise.Additionally, the PDDC-Net utilizes a ResidualNetwork-based Convolution Neural Network for efficient feature extraction and classification, ensuring accurate operation. Suggested PDDC-Net model achieved satisfactory accuracy in detecting and classifying plant leaf diseases, as evidenced by test results.

Keywords— *Crop disease detection, Crop disease classification, preprocessing, convolution neural network, Deep learning.*

I. INTRODUCTION

India, contributes more than 20% of the total worlds population and had various challenge of having inadequate resources for cultivatable land [1]. The amount of land accessible for agriculture is 10% less than the entire land area of the nation, according to a survey done by the Ministry of Agriculture, Government of India [7]. Research indicates that the country's land area is primarily composed of mountainous regions, accounting for around two-thirds of the total land area, with plains regions making up only one-third of the total land area [12][4]. Fertile land and mountainous regions make up around one-third of the nation's agricultural population [13]. As a direct result, India's forestry, animal husbandry, and agriculture sectors all have typically poor production conditions [16]. The United Nations Food and Agriculture Organization's research indicates that the quantity of land used for cultivation per person indevelopment [15]. Here is a big challenge to understand the cultivation of various crops in this complicated context in India.

Due to advancement in Artificial intelligence, mainly in analyzing audio , image reorganization, natural language processing and other domains can be used to sort out these challenges. Deep learning is a method that is more effective than the more conventional ways that have been used in the past to discover issues in plants. These approaches have been used in the past. Deep learning is a technique. Deep learning is a methodology. Anyone who is involved in the production of agricultural goods should pay attention to this information [16]. Selected models uses deep learning capability to Supervise, evaluate, and assess crop growth to give a better yield. Using picture identification of insect pests and crop illnesses, farmers may be able to lessen their

K. R. Madhavi et al. (eds.), *Proceedings of the International Conference on Computational Innovations and Emerging Trends (ICCIET 2024)*, Advances in Computer Science Research 112,
https://doi.org/10.2991/978-94-6463-471-6_105

dependency on plant protection specialists in agricultural output. This is one potential benefit of this technology. Farmers would have more time as a result of this to locate and put into action adequate solutions to any challenges that may develop. The rate at which anything can be recognized manually is a great deal slower than the rate at which anything can be identified by making use of an intelligent network, which is a great deal quicker than the rate at which something can be identified artificially. In addition, as a direct consequence of the ongoing development, the level of accuracy of the recognition is continually improving and will continue to do so in the future.In addition to helping to tackle crop yield issues brought on by diseases and insect pests, the development of a stable agricultural network and the integration of the Internet with the agricultural sector can also support the expansion of agricultural information online.

.

II. LITERATURE SURVEY

K-means clustering was employed by Athanikar et al [21]. as the approach for segmentation, and a neural network-based method was used by these researchers to identify and categorise potato leaf samples. In order to construct a system that is capable of acquiring colour photographs of individual leaf samples and processing those photographs, the creation of algorithms is a must [2]. The research considers a wide variety of leaf types, including those that are beneficial to one's health as well as those that are detrimental to one's wellbeing. The algorithms that were created are used to extract over 24 qualities, some of which include color, texture, and area. These properties may be extracted using the methods. The grey level co-occurrence matrix is the source information that is used for the purpose of extracting the texture characteristics (GLCM). A classifier that is built on a back propagation neural network, also known as a BPNN [8], is used to recognize and categorize a leaf that has not before been seen. Using this classifier, one may establish whether the leaf is in good health. The next stage in the process of diagnosing the ailment is to explain the symptoms that are brought on by the disease after it has been established whether the leaf in question is infected (name, cause, pesticides). The features of the area, as well as the color and texture of the object [3], are shown to the neural network so that it may be taught. After that, the leaf samples that were unable to be recognized are put via a trained network to be categorized and identified. The task of categorizing objects is accomplished with the assistance of many various sets of traits, such as the color, the texture, and the area of anything, in that sequence. The results yield accuracies that are greater than 92% for all the leaf samples when all three feature sets are included in the classification process. [5] This is true regardless of whether the samples originate from healthy plants or plants that have been infected with a disease.

Wang and his colleagues have developed a method to identify plant image ailments. Researchers [18] used four unique kinds of neural networks to identify identify Intervening wheat leaf rust and wheat stripe rust , as well as grape powdery mildew and grape downy mildew . These included neural networks based on back propagation (BP) radial basis function (RBF), generalized regression networks (GRNNs), and probabilistic neural networks (PNNs) [11]. According to the findings, image processing-based BP neural networks, RBF neural networks, GRNNs, and PNNs were shown to be effective tools for the detection and diagnosis of plant ailments. These differences were established with the use of data extracted from the photos that focused on color characteristics, shape attributes, and texture.

Image processing was recommended as a viable way for identifying the scab disease that may harm potatoes [17] by Samantha et al. as a possible method for diagnosing the condition. After being gathered, the photographs that are going to be used in this piece are going to first be acquired from several distinct potato fields, and then they are going to be improved. Image segmentation is then carried out to obtain the target areas once that has been completed (disease spots) [19]. So, a determination of the phase of the illness based on a histogram technique that was performed on the target areas (disease spots) has been finished up with an analysis. After this, a treatment consultative module was developed, which may be developed by agricultural professionals who are looking for farmers who have platefuls of food. This was followed by the development of a treatment consultative module.

The research that was conducted by Too et al. centred on the optimization and testing of a cutting-edge deep convolutional neural network for the image-based classification of plant diseases. This study was carried out by Too et al. It is determined to carry out exhaustive research of the empirical comparison of the structure of the deep learning system [10]. VGG 16, Inception

V4, ResNet with 50, 101, and 152 levels, and DenseNets with 121 layers are among of the architectures that have been investigated, tested, and reviewed. To this study, data were collected from 38 distinct classes. These classes included images of healthy and injured leaf tissue taken from 14 different plant species that were supplied by plant Village. The information was gathered from a total of 38 distinct kinds of plants. For corrective measures to be implemented as soon as realistically feasible, fast and accurate sickness detection algorithms are needed.DenseNets has not shown any evidence of overfitting or performance degradation for the whole of this experiment. As a result, we are making headway toward solving the problem of having an adequate supply of food. In addition to this, it has a trend toward continuing to improve in accuracy as the number of epochs on which it has been trained increases.

III. PROPOSED SYSTEM

In today's world, farmers are confronted with a multitude of significant challenges that prevent them from achieving higher yields. These challenges are the result of rapid climate change and an unexpectedly high population of insects. To achieve higher yields, it is necessary to lower the population of pest insects. The crop disease datasets are then subjected to preprocessing before being fed into ResNet-CNN for feature extraction. Plant leaf images are pre-processed and transfered to ResNet CNN for testing. The trained features that have already been provided with plant diseases are compared with available crop disease datasets and the leaf images. There is some computation and accuracy loss in the retrieved characteristics. The plant disease classes could be predicted from the comparison graph.

A. Crop disease dataset

Total dataset is classified into 15 classes of diseases, such as 'PotatoHealthy ','PotatoEarlyBlight ' , ' PotatoLateBlight ' , 'PepperBellHealthy ', ’ PepperBellBacterialSpot ' , ' TomatoHealthy ', 'TomatoEarlyBlight ' , 'Tomato_Bacterial_spot ' , 'TomatoTomatoYellowLeafCurlVirus ' , 'TomatoTomatoMosaicVirus ', 'TomatoTargetSpot ', 'TomatoLeafMold' , 'TomatoSpiderMitesTwoSpottedSpiderMite' , 'TomatoSeptoriaLeafSpot' , 'TomatoLateBlight ' .

Here Tomato, potato and Pepper are the major crop classes with different disease sub-types.

B. pre-processing of Image.

The term "Image processing" refers to practice to applying certain image processing procedures to digital images by specific computer algorithms. Analogue image processing is superior to its digital equivalent, digital image processing, in a number of respects, including the fact that digital image processing is a subset of digital signal processing. It makes it possible to apply a considerably greater range of algorithms to the data that is being entered. The objective of image processing is to make the data better by eliminating undesired noise while extracting picture characteristics. This is accomplished via a combination of the two. Because of this, our artificial intelligence and computer vision models will be able to make greater use of the upgraded data that they are working with. Pre requisite is input image size should match with the size of the network's input to train successfully and afterwards make predictions based on newly collected data. In the case that we need to adjust the size of the images to make them compatible with the network, we may either rescale or crop the data in order to acquire the necessary size. This will depend on which option will provide the best results.

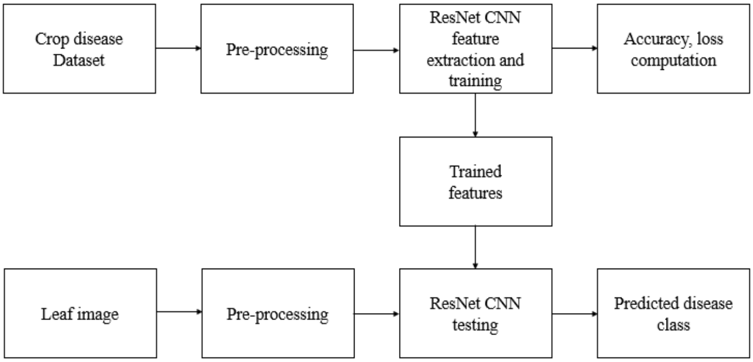
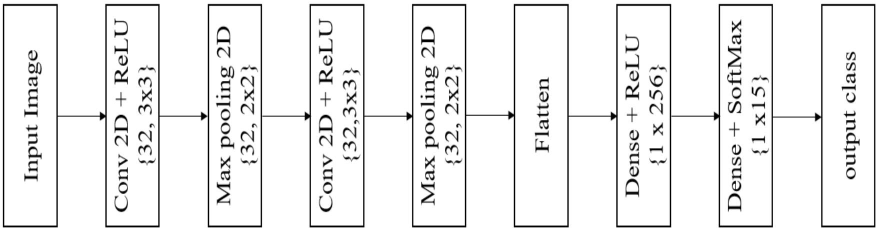


Figure 1.Proposed PDDC-Net model.

C. *Proposed ResNet-CNN*

Deep neural networks are currently being included into the process of identifying the causes of plant diseases and insect parasites, which was previously done using traditional methods. A subclass of artificial neural networks known as deep neural networks uses learnable parameters to replace the connections that would normally link neurons in an attempt to mimic how the human brain operates. Artificial neural networks called deep neural networks are made to resemble biological neural networks in terms of structure.. This is done by modelling the structure of biological neural networks after their artificial counterparts. One of the most prevalent kinds of structures that can be found in deep neural networks is referred to as a convolution neural network, which is the name of the structure. This structure is a subset of the category known as feed forward neural networks. Successes of the AlexNet network model gave more evidence for the convolution NN model's usefulness in the context of machine learning. The convolution neural networks have undergone significant development and have found widespread application in various contexts, including the monitoring of



financial transactions, the recognition of text and speech, the creation of smart homes, the diagnosis of medical conditions, and other areas of endeavour.

Fig. 2. Res Net-CNN

Table.1. Layers description.

Name of the layer	Filter	Size of the Kernel	Size of the Feature
Convl 2D's + ReLU	32	3x3	62 x 62 x 32

Max Pooling 2D	NA	3x3	31 x 31 x 32
Convl 2D's + ReLU	32	3x3	29 x 29 x 32
Max Pooling 2D	NA	3x3	14 x 14 x 32
Flatten	NA	1 x 6272	1 x 6272
Dense + ReLU	NA	1x256	1X256
Dense + SoftMax	NA	1 x 15	1X15

In most cases, convolution neural networks are made up of three distinct components. Convolution layer, used for separating out features. Feature selection is the primary use of the convergence layer, which is often referred to as the pooling layer. By lowering the total number of features, the number of parameters may be brought down. The attributes are summarized and output by the entire connection layer, which is responsible for this function. A convolution process makes up one part of a convolution layer, while ReLU, a nonlinear activation function, is the other. An illustration of a typical CNN model design for crop disease identification may be found in Figure 2.The issue that occurs due to the fact that there are far too many parameters: The dimensions of the image that is being read in are presumed to be 350 pixels on each side. When it is put inside of a feedforward network that has all of its links created, there are 7500 connections to the hidden layer that are completely independent from one another. In addition to this, each connection has a one-of-a-kind weight parameter that is coupled with it. This parameter is unique to that link. When more layers are added to the model then there is rise in the parameters . The reason for this is because every parameter represents a different layer in the model. On the one hand, there's a good chance that it will make the over-fitting problem more frequent. This is one of the potential outcomes. On the other hand, the neural network is too complicated, which will have a significant impact, both positively and negatively, on how well the training is carried out. The process of sharing parameters in convolutional neural networks is a technique that makes it possible to apply the exact same parameters to several functions of a model. In addition, the operations that are carried out by each individual component that constitutes Each local input will have a specific place where the convolutional kernel operates. The neural network does not have to optimize its learning for every single parameter at each location; all it has to do is learn a collection of parameters and pass them on to the next stage.

IV. RESULTS

The details of the projected simulation results, which were obtained by using the Python programming environment and Spyder software, are provided in this section. Also covered are the modules utilized in this work. Additionally, the suggested PDDC-net's performance is contrasted with the most advanced methods.

A. Modules

- ❖ Upload Crop Disease Dataset: The dataset is chosen using this module.
- ❖ Image Processing & Normalization: This module does the pre-processing of images and dataset normalization.
- ❖ Develop Model for Disease Recognition: This module either selects trained model or retrains exiting model.
- ❖ Upload Test Image & Predict Disease: This module uses the test image for identifying the disease class.
- ❖ Accuracy & Loss Graph: Accuracy - loss comparison graph over epochs can be visualized using this module.

B. Results and Discussions

Figure 3 has a list of various photo representations from dataset sample. Figure 4 has the classification of outcome of test images and the potato healthy is recognized by classified class name. Figure 5 has the recognized potato with early blight as class name. Here disease names and plant names are predicted. In Figure 6 Accuracy-losses per epochs. Loss is indicated by blue line and Green line indicates accuracy. Table 2 has performance comparisons. Proposed Res Net - CNN has produced results encouraging results when compared with current NB, RF SVM in terms of accuracy, precision, recall, and f1-SCOREs. In conclusion, the results of the performance achieved by the suggested Res Net - CNN was encouraging to that achieved by SVM, naive bayes, and random forest.

Fig. 3.Sample dataset

.

Fig. 4. Healthy Potato Leaf

.

Fig. 5. Recognized Potato early blight Leaf

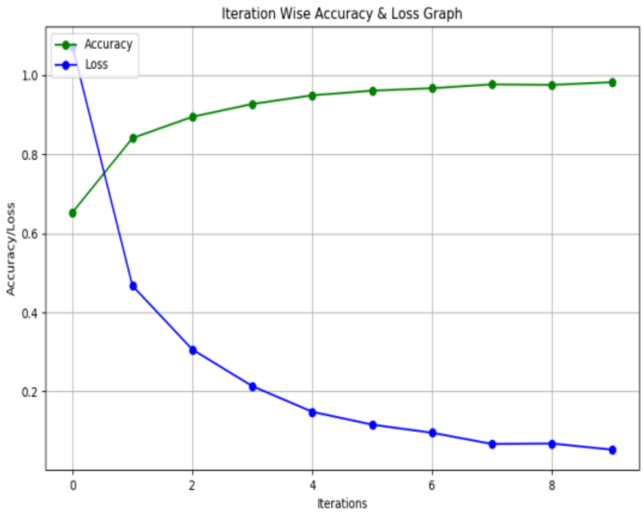


Fig. 6. Accuracy - loss graph Per iteration Epoh

Table 2: Performance comparison.

Method	Accuracy (%)
Navie Bayes [8]	89.239
Random Forest [5]	78.384
Decision Tree [17]	72.495
Support Vector Machine [11]	87.4585
XGBoost [3]	99.485

V. CONCLUSION

For the dataset acquired , 27 variants of diseases were investigated in this paper. Res Net - CNN technologies are used in construction of the mode. The built model has high accuracy in identifying the diseases for the acquired dataset, overall accuracy is up to 98.23%.overall the built model has very good performance when compared with conventional models. Future scope of this reach is increasing data set and fine tuning the model

REFERENCES

[1] A. Krizhevsky, et al, ''ImageNet classification with deep convolutional neural networks,'' in Proc. Int. Conf. Neural Inf. Process. Syst. Red Hook, NY, USA: Curran Associates, 2012, pp. 1097–1105.
[2] C. Szegedy, et al ''Going deeper with convolutions,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2015, pp. 1409–1414.
[3] C. Szegedy, et al, ''Rethinking the inception architecture for computer vision,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 2818–2826.
[4] E. C. Too, et al ''A comparative study of fine-tuning deep learning models for plant disease identification,'' Comput. Electron. Agricult., vol. 161, pp. 272–279, Jun. 2019.
[5] Ahmed, et al " Identification of Crop Diseases and Insect Pests Based on Deep Learning", https://doi.org/10.1155/2022/9179998, 2022.
[6] I. Sa, et al, ''DeepFruits: A fruit detection system using deep neural networks,'' Sensors, vol. 16, p. 1222, Aug. 2016.
[7] K. He, et al, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput.Vis. Pattern Recognit., Jun. 2016, pp.770–778.
[8] K. He, et al, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 770–779.
[9] M. Dyrmann, et al, ''species classification using deep convolution neural network,'' Bio systems Eng., vol. 151, pp. 72– 80, Nov. 2016.
[10] M. Keiichiro, et al, "Factors leading insect pest outbreaks and preventive pest management " Japanese Journal of Applied Entomology and Zoology, vol. 62, no. 3, pp. 171–187, 2018.
[11] Ranjith, M., et al," Biodiversity of insect pests and natural enemies" Indian Journal of Agricultural Sciences, 2018, 88(1), 157-158.
[12] Mr.P.SrinivasaRao et at "Research on Recognition of crop Disease and insect Pests Based on Deep Learning in Harsh Environment " International Journal for Modern Trends in Science and Technology 2023ISSN: 2455-3778 online
[13] S. P. Mohanty, et al, ''Using deep learning for image-based plant disease detection,'' Frontiers Plant Sci., vol. 7, p. 1419, Sep. 2016.
[14] S. Sladojevic, et al, ''Deep neural networks-based recognition of plant diseases by leaf image classification,'' in Proc. Comput. Intell.Neurosci., May 2016, Art. no. 3289801.
[15] S. Ren, K. et al, ''Faster R-CNN: Towards real time object detection with region proposal networks,'' Neural Inf. Process. Syst., 2015, pp. 91–99.
[16] Chitteti, Chengamma, and K. Reddy Madhavi. "Taylor African vulture optimization algorithm with hybrid deep convolution neural network for image captioning system." Multimedia Tools and Applications (2024): 1-19.
[17] Srinivasan, et al, Development and validation of an integrated pest management strategy for the control of major insect pests on yard-long bean in Cambodia. Crop Protection, 116, 82-91.
[18] Tao, Y., &et al," Recognition system for leaf diseases of Ophiopogonjaponicus based on PCA-SVM. Plant Diseases & Pests
[19 5. R. Suhasini, B. Ratnamala, G. Sravanthi, K. P. Kumari and S. R. Polamuri, "Detecting Fake News on Twitter by Using Artificial Intelligence," 2023 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE), GHAZIABAD, India, 2023, pp. 594-598, doi: 10.1109/AECE59614.2023.10428322.
[20] Y. Lecun, et al, ''Gradient-based learning applied to document recognition,'' Proc.IEEE, vol.86, Nov. 1998.
[21] Z. Alom, et al, ''The history began from AlexNet: A comprehensive survey on deep learning approaches,'' in Proc.Comput. Vis. Pattern Recognition., 2018,