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PLANT DISEASE RECOGNIZANCE USING DEEP CONVOLUTIONAL-NEURAL-NETWORK

GEDDAM CHINNI[1], M CHIRANJEEVI[2]
[1]PG Scholar, Department of Computer Science and Engineering, Avanthi Institute of Engineering and Technology, Visakhapatnam, A.P, India
[2]Assistant Professor, Department of Computer Science and Engineering, Avanthi Institute of Engineering and Technology, Visakhapatnam, A.P, India

Abstract: *The timely identification and early prevention of crop diseases are essential for improving production. In this paper, deep convolutional-neural-network (CNN) models are implemented to identify and diagnose diseases in plants from their leaves, since CNNs have achieved impressive results in the field of machine vision. Standard CNN models require a large number of parameters and higher computation cost. In this paper, we replaced standard convolution with depth=separable convolution, which reduces the parameter number and computation cost. The implementedmodels were trained with an open dataset consisting of 14 different plant species, and 38 different categorical disease classes and healthy plant leaves. To evaluate the performance of the models, different parameters such as batch size, dropout, and different numbers of epochs were incorporated. The implemented models achieved disease-classification accuracy rates of 98.42%, 99.11%, 97.02%, and 99.56% using InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0, respectively, which were greater than that of traditional handcrafted-feature-based approaches. In comparison with other deep-learning models, the implemented model achieved better performance in terms of accuracy and it required less training time. Moreover, the MobileNetV2 architecture is compatible with mobile devices using the optimized parameter. The accuracy results in the identification of diseases showed that the deep CNN model is promising and can greatly impact the efficient identification of the diseases, and may have potential in the detection of diseases inreal-time agricultural systems.*

Keywords: *artificial intelligence; convolution neural network; deep learning; machine learning; transfer learning*

I. INTRODUCTION

The agricultural land mass is more than just being a feeding sourcing in today's world. Indian economy is highly dependent of agricultural productivity. Therefore in field of agriculture, detection of disease in plants plays an important role. To detect a plant disease in very initial stage, use of automatic disease detection technique is beneficial. For instance a disease named

little leaf disease is a hazardous disease found in pine trees in United States. The affected tree has a stunted growth and dies within 6 years. Its impact is found in Alabama, Georgia parts of Southern US. In such scenarios early detection could have been fruitful.

The existing method for plant disease detection is simply naked eye observation by experts through which identification and detection of plant diseases is done. For doing so, a large team of experts as well as continuous monitoring of plant is required, which costs very high when we do with large farms. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact to experts. Due to which consulting experts even cost high as well as time consuming too. In such conditions, the suggested technique proves to be beneficial in monitoring large fields of crops. Automatic detection of the diseases by just seeing the symptoms on the plant leaves makes it easier as well as cheaper. This also supports machine vision to provide image based automatic process control, inspection,and robot guidance. Plant disease identification by visual way is more laborious task and at the same time, less accurate and can be done only in limited areas. Whereas if automatic detection technique is used it will take less efforts, less time and become more accurate. In plants, some general diseases seen are brown and yellow spots, early and late scorch, and others are fungal, viral and bacterial diseases. Image processing is used for measuring affected area of disease and to determine the difference in the color of the affected area.

Image segmentation is the process of separating or grouping an image into different parts. There are currently many different ways of performing image segmentation, ranging from the simple thresholding method to advanced color image segmentation methods. These parts normally correspond to something that humans can easily separate and view as individual objects. Computers have no means of intelligently recognizing objects, and so many different methods have been developed in order to segment images. The segmentation process is based on various features found in the image. This might be color information, boundaries or segment of an image. We use Genetic algorithm for color image segmentation.

Evolutionary computing was first introduced in the 1960s by I. Rothenberg. His idea was then taken forward by other researchers. Sometimes evolutionary changes are small and appear insignificant at first glance, but they play a part in natural selection and the survival of the species. Examples of natural selections are

The warrior ants in Africa are probably one of the most impressive examples of adaptation. Within any single colony, ants emit a chemical signal that lets the others know they all belong to the same compound. Or, put more simply, a signal that says, “Don’t attack me, we’re all

family." However, warrior ants have learned how to imitate the signal from a different colony. So if a group of warrior ants attacks a colony, they will be able to imitate that colony's signal. As a result, the workers in the colony will continue on, nowunder the direction of new masters, without ever realizing an invasion has taken place.

All rat snakes have similar diets, are excellent climbers and kill by constriction. They all have the same reaction when startled (they remain motionless), and will avoid confrontation whenever possible. Some will bite if threatened, although they are non-venomous. However, rat snakes come in a wide variety of colors, from yellow striped to black to orange to greenish. This is because rat snakes are found all over the Eastern and Midwestern states, and are subjected to all types of weather and terrain. Rat snakes are common in urban areas, but they can also be found in wooded areas, mountains orcoastal regions. As a result, rat snakes have had to adapt to their local environments in an effort to avoid detection and hunt more effectively.

Genetic algorithms belong to the evolutionary algorithms which generate solutions for optimization problems. Algorithm begins with a set of solutions called population. Solutions from one population are chosen and then used to form a new population. This is done with the anticipation, that the new population will be enhanced than the old one. Solutions which are selected to form new solutions (offspring) are chosen according to their fitness – the more appropriate they are, the more probability they have to reproduce.

Fig 1 Leaf Minor disease

Some advantages of genetic algorithm are
Genetic algorithm optimizes both variables efficiently, continuous or discrete.
It searches from a large sampling of the cost surface.
Large number of variables can be processed at the same time.
It can optimize variables with highly complex cost surfaces.
Gives a number of optimum solutions, not a single solution.

Fig 2 Leaf Minor Second Stage disease

The basic steps of genetic algorithm are as follows:

[Start] Generate random population of n chromosomes (suitable solutions for the problem).

[Fitness] Evaluate the fitness $f(x)$ of each chromosome x in the population.

[New population] Create a new population by repeating following steps until the new population is complete.

[Selection] Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected).

[Crossover] With a crossover probability cross over the parents to form a new offspring (children). If no crossover was performed, offspring is an exact copy of parents.

[Mutation] With a mutation probability mutate new offspring at each locus (position in chromosome).

[Accepting] Place new offspring in a new population.

[Replace] Use new generated population for a further run of algorithm.

[Test] If the end condition is satisfied, stop, and return the best solution in current population.

[Loop] Go to step 2.

II. RELATED WORK

The implementation of proper techniques to identify healthy and diseased leaves helps in controlling crop loss and increasing productivity. This section comprises different existing machine-learning techniques for the identification of plant diseases.

Shape- and Texture-Based Identification

In this, the authors identified diseases using tomato-leaf images. They used different geometric and histogram-based features from segmented diseased portions and applied an SVM classifier with different kernels for classification. S.Kaur et al. identified three different soybean diseases using different color and texturefeatures. In P Babu et al. used a feed- forward neural network and back propagation to identify plant leaves and their diseases. S. S. Chouhan et al. used a bacterial-foraging-optimization-based dial- basis function neural network (BRBFNN) for the identification of leaves and fungal diseases in plants. In their approaches, they used a region-growing algorithm to extract features from a leaf on the basis of seed points having similar attributes. The bacterial-foraging optimization technique is used to speed up a network and improve classification accuracy.

Deep-Learning-Based Identification

Mohanty et al. used Alex Net and Google Net CNN architectures in the identification of 26 different plant diseases. Ferentinos et al. [used different CNN architectures to identify 58 different plant diseases, achieving high levels of classification accuracy. In their approach, they also tested the CNN architecture with real-time images. Sladojevic et al. designed a DL architecture to identify 13 different plant diseases. They used the Caffe DL framework to perform CNN training. Kamilaris et al. exhaustively researched different DL approaches and their drawbacks in the field of agriculture. In this, the authors proposed a nine-layer CNN model to identify plant diseases. For experimentation purposes, they used the Plant Village dataset and data-augmentation techniques to increase the data size, and analyzed performance. The authors reported better accuracy than that of a traditional machine-learning-based approach.

Pre trained Alex Net and Google Net were used in to detect 3 different soybean diseases from healthy-leaf images with modified hyper parameters such as mini batch size, max epoch, and bias learning rate. Six different pre-trained network(Alex Net, VGG16, VGG19, Google Net, ResNet101 and DenseNet201) used by KR Aravind et al. to identify 10 different diseases in plants, and they achieved the highest accuracy rate of 97.3% using Google Net. A pre trained VGG16 as the feature extractor and multiclass SVM were used in to classify different eggplant diseases. Different color spaces (RGB, HSV, YCbCr, and grayscale) were used to evaluate performance; using RGB images, the highest classification accuracy of 99.4% was achieved. In , the authors classified maize leaf diseases from healthy leaves using deep-forest techniques. In their approach, they varied the deep-forest hyper parameters regarding number of trees, forests, and grains, and compared their results with those of traditional machine-learning models such as SVM, RF, LR, and KNN. Lee et al. compared different deep- learning architectures in the identification of plant diseases. To improve the accuracy of the model, Ghazi et al. used a transfer- learning-based approach on pre trained deep-learning models [40]. In [41], the authors used a shallow CNN with SVM and RF classifiers to classify three different types of plant diseases. In their work, they mainly compared their results with those of deep-learning methods and showed that classification using SVM and RF classifiers with extracted features from the shallow CNN outperformed pre trained deep learning models. A self-attention convolutional neural network (SACNN) was used in to identify several crop diseases. To examine the robustness of the model, the authors added different noise levels in the test-image set. Oye wola et al. identified 5 different cassava-plant diseases using plain convolutional neural network

(PCNN) and deep residual network (DRNN), and found that DRNN outperformed PCNN by a margin of 9.25%. Ramacharan et al. [4] used a transfer-learning approach in the identification of three diseases and two pest-damage types in cassava plants. The authors then extended their work on the identification of cassava plant diseases using a smart phone- based CNN model and achieved accuracy of 80.6% . A NASNet-based deep CNN architecture was used in to identify leaf diseases in plants, and an accuracy rate of 93.82% was achieved. Rice- and maize-leaf diseases were identified by Chen et al. using the INC-VGGN method. In their approach, they replaced the last convolutional layer of VGG19 with two inception layers and one global average pooling layer. A shallow CNN (SCNN) was used by Yang Li et al. in the identification of maize, apple, and grape diseases. First, they extracted CNN features and classified them using SVM and RF classifiers. Sethy et al. used different deep-learning models to extract features and classify them using an SVM classifier. Using ResNet50 with SVM, they achieved the highest performance accuracy.

III. PROPOSED SYSTEM

The proposed work aims in making the automated system easily available forthe farmer's using the device for early detection of the diseases in plants.. The means engaged with malady identification are Digital picture securing, Image pre- handling (commotion expulsion, Color change, and histogram adjustment), K-implies Segmentation, Feature extraction, and characterization utilizing the help vector the handling that is finished by utilizing these parts is isolated into two stages. The principal handling stage is the disconnected stage or Training Phase. In this stage, a lot of information pictures of leaves (sick and typical) were handled by picture analyzer and certain highlights were extricated. At that point these highlights were given as contribution to the classifier, and alongside it, the data whether the picture is that of a sick or an ordinary leaf. The classifier then learns the relation among the features extracted and the possible conclusion about the presence of the disease. Thus the system is trained.

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IV. BACKGROUND WORK

Convolutional-Neural-Network Models Interest in CNNs has recently surged, and DL is the most popular architecture because DL models can learn

relevant features from input images at different convolutional levels similar, to the function of the human brain. DL can solve complex problems particularly well and quickly with high classification accuracy and a lower error rate. The DL model is composed of different components (convolutional, pooling layer, and fully connected layers, and activation functions). Table 2 shows the number of layers and parameter sizes of different CNN architectures. Alex Net has a layer size of 8 and 60 millions parameters, whereas VGGNet-16 and Google Net have parameter sizes of 138 and 7 million, respectively. The layers in those two models are 16 and 27. The layers in ResNet-152 are 152, and the parameter size is 50 million. InceptionV3, MobileNetV1, and MobileNetV2 have a parameter size of 27, 4.2, and 3.37 million, respectively. In our work, we used the InceptionV3, InceptionResNetV2, MobileNetV2, and EfficientNetB0 architectures to identify different plant diseases using the leaves of different disease-affected plants. We used these models because their parameter size is optimal in comparison with that of other architectures. During implementation, we used a pre trained weight based on the Image Net Large-Scale Visual Recognition (ILSVRC) dataset.

Convolutional neural networks became familiar in machine vision since the AlexNet model was popularized in DL architecture. The development of the Inception model was important in the field of machine vision. Inception is a simple and more powerful DL network with sparsely connected filters, which can replace fully connected network architectures, especially inside convolutional layers, as shown in Figure 1b. The Inception model's computational efficiency and number of used parameters are much lower in comparison with those of other models such as Alex Net and VGG Net. An inceptionlayer consists of differently dazed convolutional layers (e.g., 1 × 1, 3 × 3, and n × n convolutional layers) and pooling layers with all outputs integrated together and propagating to the input of the next layer. Instead of using standard convolution in the inception block, we used depth wise separable convolution. The number of parameters required in depth wise separable convolution is much less than that of standard convolution.

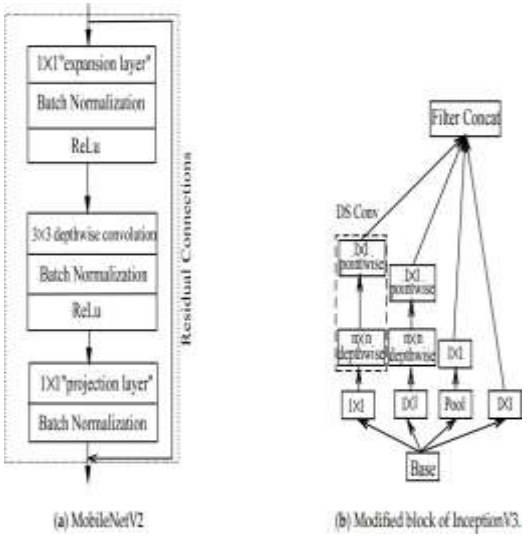

Fig 3 Basic Architecture of implemented model

VI. RESULTS ANALYSIS

The diseased leaf image is acquired using the camera; the image is acquired from a certain uniform distance with sufficient lighting for learning and classification. The example pictures of the ailing leaves are gathered and are utilized in preparing the framework. To prepare and to test the framework, ailing leaf pictures and less sound pictures are taken. The pictures will be put away in some standard configuration. The picture foundation ought to give an appropriate difference to the leaf shading. Leaf sickness dataset is set up with both highly contrasting foundations, in view of the similar investigation dark foundation picture gives better outcomes and subsequently it is utilized.

Fig 4 Basic Output window

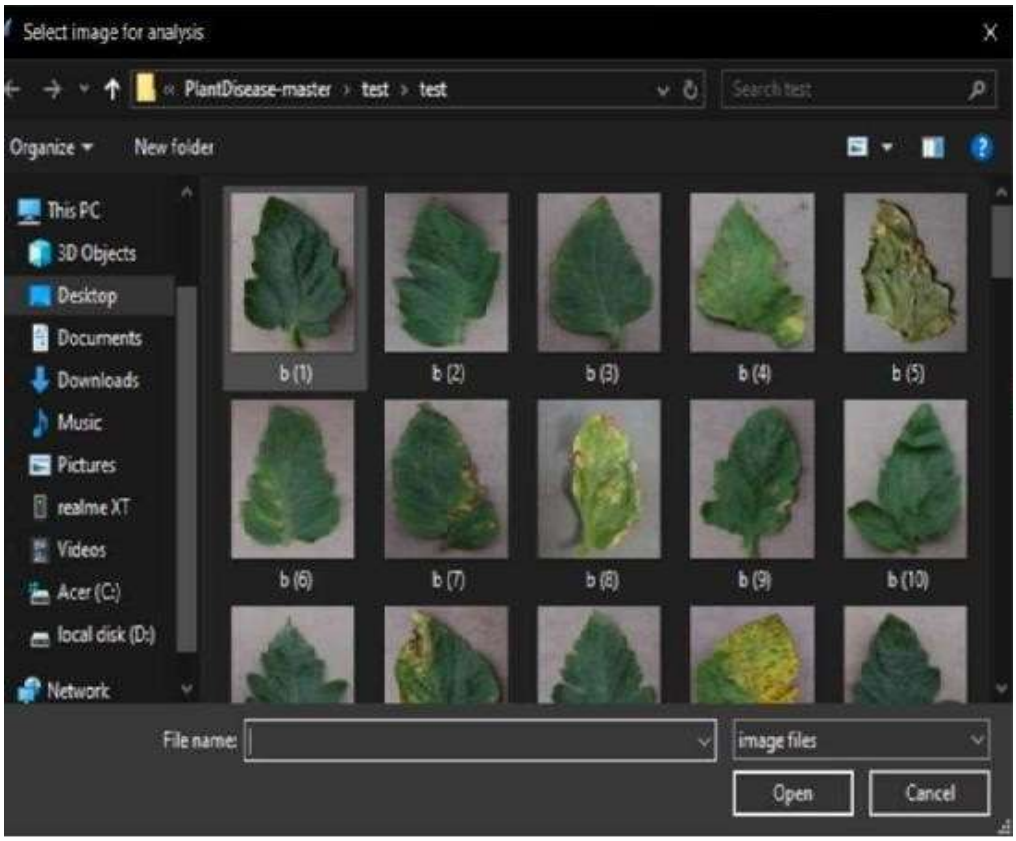

Fig 5 Image Selection for output analysis

Fig 6 Image Analyzing

Fig 7 Leaf Results

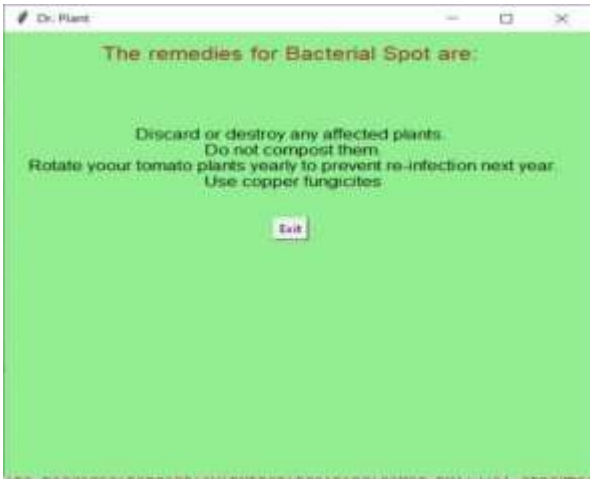

Fig 8 output

VII. CONCLUSION

There are many developed methods in the detection and classification of plant diseases using diseased leaves of plants. However, there is still no efficient and effective commercial solution that can be used to identify the diseases. In our work, we used four different DL models (InceptionV3, InceptionResnetV2, MobileNetV2, EfficientNetB0) for the detection of plant diseases using healthy-and diseased-leaf images of plants. To train and test the model, we used the standard Plant Village dataset with 53,407 images, which were all captured in laboratory conditions. This dataset consists of 38 different classes of different healthy- and diseased-leaf images of 14 different species. After splitting the dataset into 80–20 (80% of whole data for training, 20% whole images for testing), we achieved the best accuracy rate of 99.56% in EfficientNetB0 model. On average, less time was required to train the images in the MobileNetV2 and EfficientNetB0 architectures, and it took 565 and 545 s/epoch, respectively, on colored images. In comparison with other deep- learning approaches, the implemented deep-learning model has better predictiveability in terms of both accuracy and loss. The required time to train the model was much less than that of other machine- learning approaches. Moreover, the MobileNetV2 architecture is an optimized deep convolutional neural network that limits the parameter number and operations

as much as possible, and can easily run on mobile devices.

Future Scope:

In future works, we are intending to utilize provincial pictures and improved CNN models so as to improve the arrangement execution. Furthermore, we will assemble pictures of various sicknesses so as to enhance the database. The principle objective for ensuing exploration will build up a savvy cell phone application that can recognize different plant sicknesses. This application, which will furnishprogrammed plant ailment conclusion with visual examination, could be of extraordinary advantage to clients with next to zero information on the plants that they are developing. The proposed framework might be actualized by including additional administrations like close by government stores, value list for the pesticides, close by open market and some more.

Future work ought to be centered on recognizing illnesses in different areas of the plant and various periods of the sickness. The created model could be a piece of a choice emotionally supportive network and all things considered give reasonable conditions to ideal choices. It canlikewise be incorporated into a versatile application and give a cheap answer for recognizing plant maladies by just snapping a picture of the plant leaf.

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Author's Profile:

GEDDAM CHINNI completed B.Tech in Computer Science and Engineering from Avanthi Institute of Engineering and Technology. Now she is Pursuing M. Tech in Department of Computer Science and Engineering in Avanthi Institute of Engineering and Technology, Visakhapatnam, A.P, India.

M. CHIRANJEEVI received M.tech from Berhampur University, Rayagada . Currently he is working as Assistant Professor in the Department of Computer Science and Engineering in Avanthi Institute of Engineering and Technology, Visakhapatnam, A.P, India