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RECOGNITION MODEL FOR CROP DISEASES AND PESTICIDE RECOMMENDATIONS IN IOT-DRIVEN E-AGRICULTURE SOLUTIONS

S. Sreenath Kashyap[1], G. Vamshi[2], S. Vijender reddy[2], V. Vishnu Vardhan Reddy[2]
[1,2]Department of Electronics and Communication Engineering, Kommuri Pratap Reddy Institute of Technology, Ghatkesar, Hyderabad.

ABSTRACT
A country's inventive growth is dependent on the agricultural sector. Agriculture, the foundation of all nations, offers food and raw resources. Agriculture is hugely important to humans as a food source. As a result, plant diseases detection has become a major concern. Traditional methods for identifying plant disease are available. However, agriculture professionals or plant pathologists have traditionally employed empty eye inspection to detect leaf disease. This approach of detecting plant leaf disease traditionally can be subjective, time-consuming, as well as expensive, and requires a lot of people and a lot of information about plant diseases. It is also possible to detect plant leaf diseases using an experimentally evaluated software solution. Currently, machine learning and deep learning are being used in recent years. This work is focused on implementation of Plant disease detection and classification (PDDC-Net) using deep learning models. The preprocessing operation was also performed to remove the different types of noises, which also normalizes the dataset images. Further, the PDDC-Net implements the operation using residual network based convolutional neural network (ResNet-CNN) for feature extraction and classification. Experimental results have shown that the proposed PDDC-Net model achieved a good accuracy rate for plant leaf disease detection and classification.

Keywords:
Disease detection, Deep learning, ResNet-CNN.

1. Introduction
1.1 Overview
Plant diseases and pests are important factors determining the yield and quality of plants. The identification can be carried out by means of digital image processing. In recent years, deep learning has made breakthroughs in the field of digital image processing, far superior to traditional methods. How to use deep learning technology to study plant diseases and pests identification has become a research issue of great concern to researchers. This review provides a definition of plant diseases and pests detection problem, puts forward a comparison with traditional plant diseases and pests detection methods. According to the difference of network structure, this study outlines the research on plant diseases and pests detection based on deep learning in recent years from three aspects of classification network, detection network and segmentation network, and the advantages and disadvantages of each method are summarized.
Mobile applications with inbuilt deep learning models are helping farmers to detect and classify the disease throughout the world. It consists of disparate techniques like ANN and CNN to diagnose the disease in plant leaves. It uses key features of images to detect and diagnose the type of diseases present in leaves. Some pre-trained models like Alex Net, Google Net, LeNet, ResNet, VGGNET and Inception with a huge number of learnable parameters had shown classification or detection of disease in leaves. This paper focused on different architecture like predefined and user defined models that were used for detection of diseases in plant leaves.
It reviews various classification techniques exclusively used for plant disease identification. Early stage plant disease identification is extremely important as that can adversely affect both quality and

quantity of crops in agriculture. For identification of plant diseases, different approaches like image processing, machine learning, artificial neural networks, and deep learning are in use. This review focusses on an in-depth analysis on recently emerging deep learning-based methods starting from machine learning techniques. The paper highlights the crop diseases they focus on, the models employed, sources of data used and overall performance according to the performance metrics employed by each paper for plant disease identification.
Review findings indicate that Deep Learning provides the highest accuracy, outperforming existing commonly used disease identification techniques and the main factors that affect the performance of deep learning-based tools. this paper is an attempt to document all such approaches for increasing performance accuracy and minimizing response time in the identification of plant diseases. The authors also present the attempts for disease diagnosis in Indian conditions using real dataset.
Image processing algorithms are developed to detect the plant infection or disease by identifying the colour feature of the leaf area. K mean algorithm is used for colour segmentation and GLCM is used for diseases classification. Vision based plant infection showed efficient result and promising performance.
ML is the technology that allows machines to communicate with human beings and understand their needs. It also makes machines act like human beings and make the decision on behalf of humans. It is one of the areas that have grown fast over the past few years. ML helps in classifying plant diseases. The use of this technology is seen as a significant beginning and achievement in dealing with plant diseases. It has also increased productivity in the field of cultivation. Visualization techniques have also been included in this technology, and it has been improved over the last three years to the current improved levels. The challenges that face the world today, related to the diseases affecting plants.
The images of the plants have three key features, namely, color, shape, and texture. Compared to color and texture, the shape feature cannot help find the plant's diseases. Ex:- Hlaing and Zaw classified tomato plant disease using a combination of texture and color features. They used the Scale Invariant Feature Transform (SIFT) to find the texture information, containing details about the shape, location, and scale. Similarly, they gathered the color details from the RGB channel.
Automatic detection techniques can enhance the quality of food production and minimize economic losses. In recent years, deep learning has brought tremendous improvements in the recognition accuracy of image classification and object detection systems. Thus, the main objectives are: 1) To design such system that can detect crop disease and pest accurately. 2) Create database of insecticides for respective pest and disease. 3) To provide remedy for the disease that is detected. The main advantages of our solution include high processing speed and high classification accuracy. A plant disease recognition system can work as a universal detector, recognizing general abnormalities on the leaves, such as scorching or mold. The goal of plant disease management is to reduce the economic and aesthetic damage caused by plant diseases. Traditionally, this has been called plant disease control, but current social and environmental values deem "control" as being absolute and the term too rigid.

1.2 Motivation
Recognition models of crop diseases with pesticides suggestion using convolutional neural networks are motivated by several factors:
- Increasing prevalence of crop diseases: Crop diseases are a major threat to global food security, and the increasing prevalence of these diseases is a major concern for farmers.
- Timely disease detection: Timely detection and management of crop diseases are critical to ensuring healthy crops and preventing losses. However, manual disease detection is time-consuming and often inaccurate, making it difficult to manage diseases effectively.

- Need for sustainable agriculture practices: Excessive use of pesticides can have negative environmental and health effects, and reducing their use is important for promoting sustainable agriculture practices.
- Advancements in deep learning: The recent advancements in deep learning, particularly the development of convolutional neural networks, have shown promise in automating the detection and recognition of complex patterns in images, including those of diseased crops.

By using recognition models of crop diseases with pesticides suggestion using convolutional neural networks, farmers can detect and manage crop diseases more effectively, reduce the use of pesticides, and increase the efficiency and sustainability of agriculture practices. These models have the potential to improve food security and promote more sustainable agriculture practices in the face of increasing global challenges.

2. LITERATURE SURVEY

Akulwar, Pooja (2020) described the case study on “Crop Disease Detection and Yield prediction”. The study included identification of crop condition, disease detection, prediction about specific crop and recommendation using machine learning algorithms. It gives an idea about how recommender system is used in agriculture for disease detection and prediction.

Kumar, Ajay, Vikram Bali, and Shubhangi Pandey (2022) proposed Convolutional neural networks (CNNs), IT have shown to be effective in the field of machine learning, (CNN) Adam optimization model is being used in this paper to detect and determine illnesses in plants based on their leaves The performance of the models was evaluated using various factors such as batch size, dropout, and the number of epochs. The accuracy of implemented model is 96.77% which is higher than the accuracy achieved from other models like SVM (Support Vector Machine) and basic CNN.

Devi, V. Brindha, et al (2022) studied for productive crop organization in large areas using the key variables namely, texture, phenology, soil moisture, topographic vegetation, different satellite, and climatic data (precipitation and temperature). Since machine learning methodology in the sector of leaf-based image organization has displayed magnificent outcomes, an efficient Learning algorithm to find the impending disorder existing in plants on a massive scale, is used. In this system topographic and climate variables associated with spectral responses are compared and the near-infrared band is used with high spectral range (0.85 to 0.88m). The characteristic feature in image is obtained using Histogram of an Oriented Gradient (HOG). To evaluate RF models, a 20% independent dataset of training samples is used in addition to OOB data. The mean drop in accuracy and mean drop in Gini score are calculated. A comparative analysis is done on different Machine learning algorithms. The proposed RF model is efficient and robust algorithm obtaining an accuracy of 97.2% in detecting the disease to provide nourishment security.

Kumar, Raj, and Neha Shukla (2022) proposed a system that has the ability to detect diseases in plants using CNN as well as recommend various crops based on the quality of the soil by performing analysis on its various parameters using ML. The dataset for disease prediction training and test is obtained from the Plant Village Dataset and correctly separated and therefore various species of plants are recognized and re-named to make an accurate database. The next step is to obtain a test database that will be consisting of different diseases in plants that are used to check the accuracy and confidence level of the proposed module. Then the classifier is trained using training data and after that, the output is going to be detected with the best accuracy. And for the crop recommendation system, the Support vector classifier (SVC) algorithm is used as it outperforms compared to other classifiers like KNN, Logistic Regression, Random Forest, and Decision Trees, in the system to improve the efficiency rate of our model. The developed model also maps the soil and crop database and suggests suitable crops based on the available nutrients level of the soil and thus allows formers to make better decisions regarding the type of crops that can be sown-in in the field. This study also compared the performance of various classifiers on the available dataset for study and chose the one with the highest accuracy.

Liu, Dongmei, et al (2022) proposes a crop pest image recognition method based on transfer learning and convolution neural network. Firstly, the crop pest image is geometrically operated to expand the crop pest image data set, and then the expanded data set is divided into training set and test set. Then, Alex net, VGG-16, and ResNet-50 models are pretrained on ImageNet large image data set. Based on the theory of transfer learning, the learned model parameters are transferred to the small sample image data set of crop diseases and insect pests in this paper, so as to train the crop diseases and insect pests recognition model. This method is tested on Image Database for Agricultural Diseases and Pests (IDADP). The experimental results show that the convolution neural network plant leaf image recognition method based on transfer learning has better effect. It can quickly and accurately diagnose crop diseases, reduce the use of pesticides and fertilizers, and improve the yield and quality of crops.

Shoaib, Muhammad, et al (2022) proposed a solution to detect tomato plant disease using a deep leaning-based system utilizing the plant leaves image data. We utilized an architecture for deep learning based on a recently developed convolutional neural network that is trained over 18,161 segmented and non-segmented tomato leaf images—using a supervised learning approach to detect and recognize various tomato diseases using the Inception Net model in the research work. For the detection and segmentation of disease-affected regions, two state-of-the-art semantic segmentation models, i.e., U-Net and Modified U-Net, are utilized in this work. The plant leaf pixels are binary and classified by the model as Region of Interest (ROI) and background. There is also an examination of the presentation of binary arrangement (healthy and diseased leaves), six-level classification (healthy and other ailing leaf groups), and ten-level classification (healthy and other types of ailing leaves) models. The Modified U-net segmentation model outperforms the simple U-net segmentation model by 98.66 percent, 98.5 IoU score, and 98.73 percent on the dice. InceptionNet1 achieves 99.95% accuracy for binary classification problems and 99.12% for classifying six segmented class images; Inception Net outperformed the Modified U-net model to achieve higher accuracy. The experimental results of our proposed method for classifying plant diseases demonstrate that it outperforms the methods currently available in the literature.

I **Rezk, Nermeen Gamal, et al (2022)** proposes an efficient IoT-based plant disease recognition system using semantic segmentation methods such as FCN-8 s, CED-Net, SegNet, DeepLabv3, and U-Net with the CRF method to allocate disease parts in leaf crops. Evaluation of this network and comparison with other networks of the state art. The experimental results and their comparisons proclaim over F1-score, sensitivity, and intersection over union (IoU). The proposed system with SegNet and CRFs gives high results compared with other methods. The superiority and effectiveness of the mentioned improvement method, as well as its range of implementation, are confirmed through experiments.

Shi, Tingting, et al (2023) discussed the major challenges faced by CNN-based plant disease severity assessment methods in practical applications and provided feasible research ideas and possible solutions to address these challenges.

Musa, Aminu, et al (2021) proposed automation of hydroponic systems to improve efficiency and minimize manpower requirements. Thus, increasing profit and farm produce. However, a fully automated hydroponic system should be able to identify cases such as plant diseases, lack of nutrients, and inadequate water supply. Failure to detect these issues can lead to damage of crops and loss of capital. This paper presents an Internet of Things-based machine learning system for plant disease detection using Deep Convolutional Neural Network (DCNN). The model was trained on a data set of 54,309 instances containing 38 different classes of plant disease. The images were retrieved from a plant village database. The system achieved an Accuracy of 98.0% and AUC precision score of 88.0%.

Kosamkar, Pranali K., et al (2018) proposed the system which works on pre-processing, feature extraction of leaf images from plant village dataset followed by convolution neural network for classification of disease and recommending Pesticides using Tensor flow technology. The main two processes that we use in our system is android application with Java Web Services and Deep Learning. We have use Convolution Neural Network with different layers five, four & three to train our model and android application as a user interface with JWS for interaction between these systems. Our results show that the highest accuracy achieved for 5-layer model with 95.05% for 15 epochs and highest validation accuracy achieved is for Slayer model with 89.67% for 20 epochs using tensor flow.

3. PROPOSED SYSTEM

3.1 Crop Disease Recognition Model

Agriculture is one of the most important sources for human sustenance on Earth. Not only does it provide the necessary food for human existence and consumption but also plays a major vital role in the economy of the country. But Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products. Nowadays farmers are facing many crucial problems for getting better yield cause of rapid change in climate and unexpected level of insects, in order to get better yield, need to reduce the level of pest insect. Several millions of dollars are spent worldwide for the safety of crops, agricultural produce and good, healthy yield. It is a matter of concern to safeguard crops from Bio-aggressors such as pests and insects, which otherwise lead to widespread damage and loss of crops. In a country such as India, approximately 18% of crop yield is lost due to pest attacks every year which is valued around 90,000 million rupees. Conventionally, manual pest monitoring techniques, sticky traps, black light traps are being utilized for pest monitoring and detection in farms.

Manual pest monitoring techniques are time consuming and subjective to the availability of a human expert to detect the same. Disease is caused by pathogen which is any agent causing disease. In most of the cases pests or diseases are seen on the leaves or stems of the plant. Therefore, identification of plants, leaves, stems and finding out the pest or diseases, percentage of the pest or disease incidence, symptoms of the pest or disease attack, plays a key role in successful cultivation of crops. In general, there are two types of factors which can bring death and destruction to plants; living(biotic) and nonliving (abiotic) agents. Living agent's including insects, bacteria, fungi and viruses. Nonliving agents include extremes of temperature, excess moisture, poor light, insufficient nutrients, and poor soil pH and air pollutants.

In recent years, deep learning has made breakthroughs in the field of digital image processing, far superior to traditional methods. How to use deep learning technology to study plant diseases and pests' identification has become a research issue of great concern to researchers.

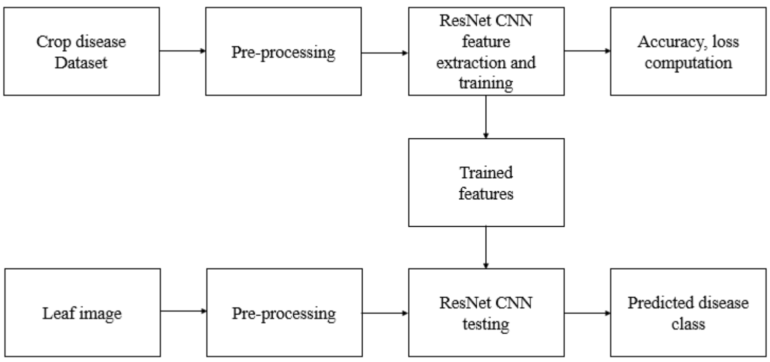

Fig. 1: Block diagram of proposed system.

Crop disease datasets are pre-processed and uploaded to Residual Network-CNN (ResNet-CNN) for feature extraction. On the other hand, leaf images are also pre-processed and uploaded to ResNet CNN

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for testing. The leaf images and the crop disease datasets are compared to the trained features which are already trained with the plant diseases. The extracted features have some loss computation and accuracy. The comparison graph could predict the classes of plant disease.

3.2 Crop disease dataset

The dataset totally contains 15 classes of crop diseases, such as pepper__bell___Bacterial_spot', 'Pepper__bell___healthy', 'Potato___Early_blight', 'Potato___healthy', 'Potato___Late_blight', 'Tomato__Target_Spot', 'Tomato__Tomato_mosaic_virus', 'Tomato__Tomato_YellowLeaf__Curl_Virus', 'Tomato_Bacterial_spot', 'Tomato_Early_blight', 'Tomato_healthy', 'Tomato_Late_blight', 'Tomato_Leaf_Mold','Tomato_Septoria_leaf_spot','Tomato_Spider_mites_Two_spotted_spider_mite . Here, Pepper, Potato, and Tomato are the major crop classes with different disease sub-types.

3.3 Image pre-processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data — the aim of digital image processing is to improve the image data (features) by suppressing unwanted distortions and/or enhancement of some important image features so that our AI-Computer Vision models can benefit from this improved data to work on. To train a network and make predictions on new data, our images must match the input size of the network. If we need to adjust the size of images to match the network, then we can rescale or crop data to the required size.

we can effectively increase the amount of training data by applying randomized augmentation to data. Augmentation also enables to train networks to be invariant to distortions in image data. For example, we can add randomized rotations to input images so that a network is invariant to the presence of rotation in input images. An augmented Image Datastore provides a convenient way to apply a limited set of augmentations to 2-D images for classification problems.

we can store image data as a numeric array, an ImageDatastore object, or a table. An ImageDatastore enables to import data in batches from image collections that are too large to fit in memory. we can use an augmented image datastore or a resized 4-D array for training, prediction, and classification. We can use a resized 3-D array for prediction and classification only.

There are two ways to resize image data to match the input size of a network. Rescaling multiplies the height and width of the image by a scaling factor. If the scaling factor is not identical in the vertical and horizontal directions, then rescaling changes the spatial extents of the pixels and the aspect ratio.

Cropping extracts a subregion of the image and preserves the spatial extent of each pixel. We can crop images from the center or from random positions in the image. An image is nothing more than a two-dimensional array of numbers (or pixels) ranging between 0 and 255. It is defined by the mathematical function f(x,y) where x and y are the two co-ordinates horizontally and vertically.

Resize image: In this step-in order to visualize the change, we are going to create two functions to display the images the first being a one to display one image and the second for two images. After that, we then create a function called processing that just receives the images as a parameter.

Need of resize image during the pre-processing phase, some images captured by a camera and fed to our AI algorithm vary in size, therefore, we should establish a base size for all images fed into our AI algorithms.

3.4 Proposed ResNet-CNN

Deep neural network is gradually applied to the identification of crop diseases and insect pests. Deep neural network is designed by imitating the structure of biological neural.

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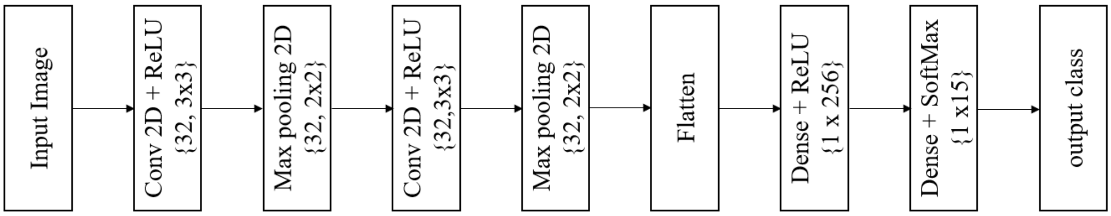

Fig. 2: Proposed ResNet-CNN.

Table. 1: Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32
Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 15	1 x 15

network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network. The success of AlexNet network model also confirms the importance of convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis, and other fields.

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for crop disease recognition is shown in Fig. 2.

The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Convolutional neural networks mainly solve the following two problems.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the

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parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Image stability: Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation, and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

3.5 ResNet-CNN

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from.

Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$..

4. RESULTS AND DISCUSSION

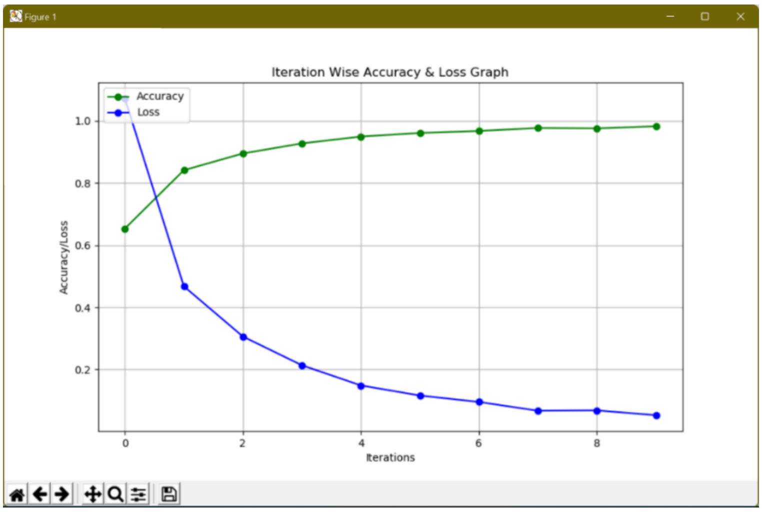
4.1 Modules

1) Upload Crop Disease Dataset: This module is used to select the dataset.
2) Image Processing & Normalization: The image preprocessing and normalization of dataset is achieved by this module.
3) Build Crop Disease Recognition Model: Either selection of trained model or retraining of module is achieved by this module.
4) Upload Test Image & Predict Disease: This module is used to identify the disease class from the test image.
5) Accuracy & Loss Graph: This module is used to plot the accuracy and loss comparison graph various iterations (epochs).

4.2 Screenshots

In below screen potato leaf predicted as healthy and pesticide suggested as no pesticide is required now try with other images.

Now click on ‘Accuracy & Loss Graph’ button to get below graph.



In above graph x-axis represents epoch/iterations and y-axis represents accuracy/loss and green line represents accuracy and blue line represents loss and from above graph we can see with each increasing iteration accuracy is getting better and better and loss getting decrease.

5. CONCLUSION AND FUTURE SCOPE

In this work 15 kinds of crop diseases were studied. The model is constructed by using deep learning theory and ResNet-CNN technology. Experiments show that the model can effectively identify the data set, and the overall recognition accuracy is as high as 98.23%. The results show that the recognition accuracy of this hybrid network model is relatively higher than the traditional model, and it can be effectively applied to the identification and detection of plant diseases.

In the future work, there are two directions should be improved, they are extended data set and optimized model. There are 27 diseases with 10 crop species dataset is available, and other species and diseases were not involved, such as rice and wheat, and their related diseases. Therefore, the next step is to obtain more crop species and disease images for research. This model has achieved good recognition accuracy and is worthy of further study and optimization. At the same time, we should design a network model which can classify crop images with higher accuracy.

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