Image-Based Plant Disease Detection Using Convolutional Neural Network

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Abstract- *Rapid human population growth requires corresponding increase in food production. Easily spreadable diseases can have a strong negative impact on plant yields and even destroy whole crops. That is why early disease diagnosis and prevention are of very high importance. Traditional methods rely on lab analysis and human expertise which are usually expensive and unavailable in a large part of the undeveloped world. Here, image segmentation using Rough Set based Fuzzy K-Means Algorithm. Rough sets offer an effective approach of managing uncertainties and also used for image segmentation, feature identification, dimensionality reduction, and pattern classification. The proposed algorithm is based on a modified K-means clustering using rough set theory (RFKM) for image segmentation, which is further divided into two parts. Primarily the cluster centers are determined and then in the next phase they are reduced using Rough set theory (RST). K-means clustering algorithm is then applied on the reduced and optimized set of cluster centers with the purpose of segmentation of the images. For feature extraction used texture features obtained by analysing the grey level co-occurrence matrix and general colour statistical features obtained by histogram analysis of the full image. The GLCM is used to describe a spatial relationship of neighbouring pixels. This project presents the most recent results in this field, and find the early disease diagnosis and prevention using CNN.*

Keywords- K-means clustering, CNN, Rough set theory

I. INTRODUCTION

Human population steadily continues to grow, and along with it the need for food production increases. According to the UN projections, human population is expected to reach 9.7 billion in 2050, 2 billion more than today. Considering that most of the population growth is to occur in the least developed countries (around 80% increase in the next 30 years), where the food scarcity is the main problem, it is easy to conclude that minimizing food loss in those countries is a primary concern. It is estimated that the yield loss worldwide is between 20 and 40 percent, with many farms suffering a total loss.

Traditional methods for detecting diseases require manual inspection of plants by experts. This process needs to be continuous, and can be very expensive in large farms, or even completely unavailable to many small farm holders living in rural areas. This is why many attempts to automate disease detection have been made in the last few decades. One of the notable approaches is the use of hyperspectral imaging. Hyperspectral images are usually taken by satellites or airborne imaging devices and used for monitoring large areas. A downside of this approach is extremely high equipment cost, as well as high dimensionality and small number of samples which make them unsuitable for machine learning (ML) analysis. Because of the recent breakthroughs in computer vision and the availability of cheap hardware, currently the most popular approach is the analysis of RGB images. The other motive for analysing RGB images is that with the current smartphone ubiquitousness these solutions have potential to reach even the most rural areas. RGB images can be analysed by classical ML algorithms or the deep learning (DL) approach.

There are different types of plant disease exist, but majority of these disease can be categorize into the three different categories which are bacterial disease viral disease and the fungal disease. The most ideal way to detect the disease is the classification followed by detection. Classification is done on the basis of shape and texture features.

This is also known as bacterial leaf spot. Bacterial leaf spot is majorly detected in stone fruits such cherry, plum etc. In this disease black spots or dark spots occur on the different part of leafs. Yellow halos is also symptom of this disease. Spot size is of irregular nature. Bacterial spots occur on the different part on the top and bottom start occurring and if these spots cluster together in any section of the leaf then this results in killing of that section by this disease. Wet and cool formation also contribute to the formation of the bacterial disease in the plant leaves. In these formations bacterial leaf spot can spread very quickly. Mostly bacterial leaf spot occur on the aged leaves but it can destroys the tissues of the new leaves too.

Viral disease are caused by viruses and as virus are intercellular, so these diseases attacks inside out. Viral disease are sometime very difficult to identify. Virus can affect any region of the plants such leafs, roots, stem and others. Abnormal patterns are observed on the affected area green and yellow coloration is seen in leaves affected with the virus. The life span of the plant or its parts affected with the viral disease is very less. It directly affects the productivity and other factors. Wrinkles on the different part of the leaves is also primary symptom of these disease. Every virus life span is very high as compared to the other types of the disease, because each virus if not properly cured give rise to new type of the virus so it is important for timely prevention of these disease.

Fungal disease occur because of the fungi or fungal organism. One of the property of the fungi is that it spread with wind and the water. Gray green spots on the leaf of the plants are observed and if not properly cured they start getting spread toward the outer region of the leaf. Wilting, scabs are the primary symptoms fungal disease. Fungal disease attack on the plant leafs result in the yellowness of leaves at end.

II. LITERATURE SURVEY

Features are the vital factor for image classification in the field of machine learning. The advancement of deep convolutional neural network (CNN) shows the way for identification of rice diseases using deep features with the expectation of high returns. This paper introduced 5932 on-field images of four types of rice leaf diseases, namely bacterial blight, blast, brown spot and tungro. In addition, the performance evaluation of 11 CNN models in transfer learning approach and deep feature plus support vector machine (SVM) was carried out. The simulation results show the deep feature plus SVM perform better classification compared to transfer learning counterpart. Also, the performance of small CNN models such as mobilenetv2 and shufflenet was examined. The performance evaluation was carried out in terms of accuracy, sensitivity, specificity, false positive rate (FPR), F1 Score and training time. Again, the statistical analysis was performed to choose the better classification model. The deep feature of ResNet50 plus SVM performs better with F1 score of 0.9838. The fc6 layer of vgg16, vgg19 and AlexNet have better contribution towards classification compared to fc7 and fc8. Further, the F1 score of CNN classification models was compared with other traditional image classification models such as bag-of-feature, local binary patterns (LBP) plus SVM, histogram of oriented gradients (HOG) plus SVM and Gray Level Co-occurrence Matrix (GLCM) plus SVM.

Plant diseases have a disastrous impact on the safety of food production, and they can cause a significant reduction in both the quality and quantity of agricultural products. In severe cases, plant diseases may even cause no grain harvest entirely. Thus, the automatic identification and diagnosis of plant diseases are highly desired in the field of agricultural information. Many methods have been proposed for solving this task, where deep learning is becoming the preferred method due to the impressive performance. In this work, we study transfer learning of the deep convolutional neural networks for the identification of plant leaf diseases and consider using the pre-trained model learned from the typical massive datasets, and then transfer to the specific task trained by our own data. The VGGNet pre-trained on ImageNet and Inception module are selected in our approach. Instead of starting the training from scratch by randomly initializing the weights, we initialize the weights using the pre-trained networks on the large labeled dataset, ImageNet. The proposed approach presents a substantial performance improvement with respect to other state-of-the-art methods; it achieves a validation accuracy of no less than 91.83% on the public dataset. Even under complex background conditions, the average accuracy of the proposed approach reaches 92.00% for the class prediction of rice plant images. Experimental results demonstrate the validity of the proposed approach, and it is accomplished efficiently for plant disease detection.

The rice heading stage is an essential phase of rice production as it directly affects the rice yield. This paper transforms the issue of rice heading stage automatic observation into the problem of rice spike detection and proposes a new method for automatic observation of the rice heading stage. Rice spike detection is achieved using a new multi-classifier cascade method comprised of the following steps: First, SVM with color feature as input is utilized to distinguish the rice spike image patches from the background patches (leaf, soil, water, etc.); Second, a gradient histogram method is applied to remove the yellow leaf patches from consideration; Third, a convolutional neural network (CNN) is utilized to further reduce the false positive rate. The arrival of the rice heading stage is determined by the number of the detected spike patches. To evaluate the proposed method, it was applied to the automatic rice heading stage observation of six image sequences collected by the designed observation device between 2011 and 2013. In the experiment, the proposed method produced similar results to the conventional manual observation method in determining the arrival of the rice heading stage. The differences between the proposed method and manual way were within two days. Experiments demonstrated that the proposed method is an effective approach of automatic observation of the rice heading stage in paddy fields and can be utilized to replace the manual observation.

Cassava is the third largest source of carbohydrates for human food in the world but is vulnerable to virus diseases, which threaten to destabilize food security in sub-Saharan Africa. Novel methods of cassava disease detection are needed to support improved control which will prevent this crisis. Image recognition offers both a cost effective and scalable technology for disease detection. New deep learning models offer an avenue for this technology to be easily deployed on mobile devices. Using a dataset of cassava disease images taken in the field in Tanzania, we applied transfer learning to train a deep convolutional neural network to identify three diseases and two types of pest damage (or lack thereof). The best trained model accuracies were 98% for brown leaf spot (BLS), 96% for red mite damage (RMD), 95% for green mite damage (GMD), 98% for cassava brown streak disease (CBSD), and 96% for cassava mosaic disease (CMD). The best model achieved an overall accuracy of 93% for data not used in the training process. Our results show that the transfer learning approach for image recognition of field images offers a fast, affordable, and easily deployable strategy for digital plant disease detection.

Agricultural area is the only area through which the food requirements of complete human race are being served. In India, around 70% of the total population relies on agriculture and grow several kinds of fruits and vegetable crops within their fields. However, there is a need for high technicality while cultivating crops that are of optimum yield and quality. The plant disease detection is the technique which can detect disease from the plant leaves. The plant disease detection has various steps which are textural feature analysis, segmentation, and classification. This research paper is based on the plant disease detection using the KNN classifier with GLCM algorithm. In the proposed method, the image is taken as input which is preprocessed, GLCM algorithm is applied for the textural feature analysis, k-means clustering is applied for the regionbased segmentation, and KNN classifier is applied for the disease prediction. The proposed technique is implemented in MATLAB and simulation results show up to 97% accuracy.

Automatic pest detection is a useful method for greenhouse monitoring against pest attacks. One of the more harmful pests that threaten strawberry greenhouses is thrips (Thysanoptera). Therefore, the main objective of this study is to detect of thrips on the crop canopy images using SVM classification method. A new image processing technique was utilized to detect parasites that may be found on strawberry plants. SVM method with difference kernel function was used for classification of parasites and detection of thrips. The ratio of major diameter to minor diameter as region index as well as Hue, Saturation and Intensify as color indexes were utilized to design the SVM structure. Also, mean square error (MSE), root of mean square error (RMSE), mean absolute error (MAE) and mean percent error (MPE) were used for evaluation of the classification. Results show that using SVM method with region index and intensify as color index make the best classification with mean percent error of less than 2.25%.

Modern phenotyping and plant disease detection provide promising step towards food security and sustainable agriculture. In particular, imaging and computer vision based phenotyping offers the ability to study quantitative plant physiology. On the contrary, manual interpretation requires tremendous amount of work, expertise in plant diseases, and also requires excessive processing time. In this work, we present an approach that integrates image processing and machine learning to allow diagnosing diseases from leaf images. This automated method classifies diseases (or absence thereof) on potato plants from a publicly available plant image database called ‘Plant Village’. Our segmentation approach and utilization of support vector machine demonstrate disease classification over 300 images with an accuracy of 95%. Thus, the proposed approach presents a path toward automated plant diseases diagnosis on a massive scale.

An automated plant species identification system could help botanists and layman in identifying plant species rapidly. Deep learning is robust for feature extraction as it is superior in providing deeper information of images. In this research, a new CNN-based method named D-Leaf was proposed. The leaf images were pre-processed and the features were extracted by using three different Convolutional Neural Network (CNN) models namely pre-trained AlexNet, fine-tuned AlexNet, and D-Leaf. These features were then classified by using five machine learning techniques, namely, Support Vector Machine (SVM), Artificial Neural Network (ANN), k-Nearest-Neighbor (k-NN), Naïve-Bayes (NB), and CNN. A conventional morphometric method computed the morphological measurements based on the Sobel segmented veins was employed for benchmarking purposes. The D-Leaf model achieved a comparable testing accuracy of 94.88 percent as compared to AlexNet (93.26 percent) and fine-tuned AlexNet (95.54 percent) models. In addition, CNN models performed better than the traditional morphometric measurements (66.55 percent). The features extracted from the CNN are found to be fitted well with the ANN classifier.

Xinjiang is the major cotton-producing area in China, also well known in the world for its high-quality cotton. The growth and quality of cotton are closely related to the pest attack, but it is difficult for farmers to manually recognize all the types of pests because of the similar appearance. To solve this problem, we propose a few-shot cotton pest recognition method, which only needs few raw training data, quite different from the typical deep learning methods. We use two datasets to verify the effectiveness and feasibility of the few-shot model, one is the National Bureau of Agricultural Insect Resources (NBAIR), the other is a dataset with the natural scenes. The convolutional neural network (CNN) is adopted to extract feature vectors of images. The CNN feature extractor is trained by the triplet loss to distinguish different pest species to ensure the system robustness. Furthermore, the few-shot recognition model is finally running in an embedded terminal, based on the compiled convolutional and max-pooling circuit in the FPGA and the control program in the ARM. The running speed reaches 2 frames per second and can be faster by the further parallelism in hardware. The testing accuracy for the two datasets is 95.4% and 96.2% respectively, shown the generalization ability of the proposed few-shot model. Moreover, this work can also be regarded as a positive attempt to combine the software and hardware for the landing of intelligent algorithms in the agricultural applications.

Plant Diseases and Pests are a major challenge in the agriculture sector. An accurate and a faster detection of diseases and pests in plants could help to develop an early treatment technique while substantially reducing economic losses. Recent developments in Deep Neural Networks have allowed researchers to drastically improve the accuracy of object detection and recognition systems. In this paper, we present a deep-learning-based approach to detect diseases and pests in tomato plants using images captured in-place by camera devices with various resolutions. Our goal is to find the more suitable deep-learning architecture for our task. Therefore, we consider three main families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD), which for the purpose of this work are called “deep learning meta-architectures”. We combine each of these meta-architectures with “deep feature extractors” such as VGG net and Residual Network (ResNet). We demonstrate the performance of deep meta-architectures and feature extractors, and additionally propose a method for local and global class annotation and data augmentation to increase the accuracy and reduce the number of false positives during training. We train and test our systems end-to-end on our large Tomato Diseases and Pests Dataset, which contains challenging images with diseases and pests, including several inter- and extra-class variations, such as infection status and location in the plant. Experimental results show that our proposed system can effectively recognize nine different types of diseases and pests, with the ability to deal with complex scenarios from a plant’s surrounding area.

III. PROPOSED SYSTEM

Images were taken with a standard digital camera, outside, under different weather conditions, and were collected from multiple sources, making the dataset more diverse. Large number of samples and different diseases make this dataset suitable for applying ML algorithms, especially DL ones. The downside of this dataset is that individual leaves were cropped and put against a uniform background to be photographed, making conditions substantially different than those in the field.

The distribution of images is not uniform, and the number of samples per class varies from 150 to 5500, which can be seen in Fig 1 Also, reports about significant number of mislabelled samples were made. The dataset offers colour images, grayscale images, and segmented images where the background is masked. When using classical algorithms, certain pre-processing steps need to be taken.

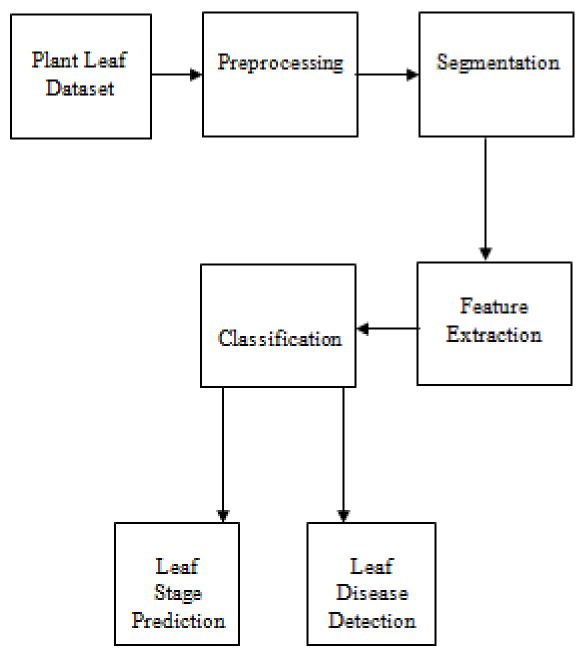


Fig 1 Proposed Block Diagram

Proposed System

When working on image classification, the usual preprocessing steps include scaling images to the same dimensions, removal of the background and artifacts.Since the plant village dataset includes already segmented and scaled images, these steps were not needed in our case.

In this work, we have used texture features obtained by analysing the grey level co-occurrence matrix (GLCM). The GLCM is used to describe a spatial relationship of neighbouring pixels. CNN is the simplest type of artificial neural networks. It is a supervised learning algorithm able to model highly non-linear functions.

Advantages of Proposed System

Good classification in large number of samples
Test time is efficient
It is high and accurate and handle many feature

MODULES

Segmentation
Feature extraction
Convolutional Neural Network

MODULES DESCRIPTION

Region segmentation

When working on image classification, the usual preprocessing steps include scaling images to the same dimensions, removal of the background and artifacts. Since the PlantVillage dataset includes already segmented and scaled images, these steps were not needed in our case. We preprocessed these images by futher segmenting them in order to extract potentionally infected leaf areas, which has been done by removing all pixels whose green channel value exceeded those of red and blue channels.

Feature extraction

Feature selection is arguably the hardest and the most important part in the implementation of ML algorithms. Selecting appropriate features requires detailed analysis and expertise in the domain of interest. In this work, we have used texture features (on both full images and images with removed green pixels) obtained by analysing the grey level co-occurrence matrix (GLCM) and general colour statistical features obtained by histogram analysis of the full image.

The GLCM is used to describe a spatial relationship of neighbouring pixels, i.e. it describes a probability of two pixel values, i and j, being on a distance d and at angle θ from one another. It is defined as a matrix of dimension N×N (N is the number of distinct pixel values), where value G(i,j) represents a number of times when pixel of value j occurred at a distance d and at angle θ from a pixel of value i. From the GLCM, texture features like correlation, contrast, energy, homogeneity and dissimilarity can be obtained. Colour features are obtained by extracting statistical features from image histograms.

They are used to provide a general description of colour statistics in the image. In this paper, we have used 120 features obtained by texture analysis and 96 features obtained by colour analysis, 216 in total. We have calculated 12 GLCMs for both a full image and image with removed green pixels. We have used 4 distances (1, 3, 10 and 20 pixels), and 3 angles (0, π/4, π/2). For each GLCM we have calculated 5 features (correlation, contrast, energy, homogeneity and dissimilarity). Colour features were calculated only for full images. We used 6 features per colour channel (mean, standard deviation, kurtosis, skew, entropy and RMS), 18 features in total. We also calculated a histogram with 26 buckets per channel and used pixel count per bucket as features, which multiplied with 3 channels gave us 78 features.

CNN Algorithm

CNN is a subclass of neural network which is inspired by the working principle of using the human visual cortex for object recognition. CNNs were designed for identifying objects, as well as their classes, in an image. CNN differs from conventional machine learning algorithms in the context of feature extraction, where CNN extracts features globally through a number of stacked layers. The working principle of using the human visual cortex for object recognition. CNNs were designed for identifying objects, as well as their classes, in an image. CNN differs from conventional machine learning algorithms in the context of feature extraction, where CNN extracts features globally through a number of stacked layers. Generally, CNN architecture consists of several convolution layers and pooling layers. These layers are followed by one or more fully connected (FC) layers. The convolutional layer is the Generally, CNN architecture consists of several convolution layers and pooling layers. These principal building block of a CNN. Convolution is a mathematical operation that acts upon two sets of information. The operation can be addition, multiplication, or a derivative such as

$$y = x \times \mathcal{F} \rightarrow [i] = \sum_{j=-\alpha}^{+\alpha} x[i-j]\,\mathcal{F}[j]$$

In the case of CNNs, the two sets of information are the input data and a convolution filter, which is also called the kernel. The convolutional operation is performed by sliding the kernel over the entire input, which produces a feature map. In practice, different filters are utilized to perform multiple convolutions to produce distinct feature maps. These feature maps are finally integrated to formulate the final output from the convolution layer. Activation functions are used after the convolution operation to introduce non-linearity to the model. Different activation functions such as linear function, sigmoid, and tanh are used, but the rectified linear unit (ReLU) was used in the proposed CNN since it can train the model faster and ensure near-global weight optimization. The ReLU activation function is defined as follows:

$$f(x_i) = max(0, x_i)$$

The pooling layer appears next to the convolution layer. This layer down-samples each feature map to reduce their dimensions, which in turn reduces over fitting and training time. The max pooling is widely used in CNNs which just selects the maximum value in the pooling window. The FC layer is essentially a fully connected artificial neural network. In a nutshell, in a CNN, the convolution and pooling layers extract low-level features such as edges, lines, ears, eyes, and legs, and the fully connected layer performs the classification task based on these low-level features. The activation function used in this final classification layer is typically a SoftMax function, which assigns a probability value to each class which adds up to 1. The SoftMax function is defined as

$$P\left(y = j \mid \varphi^{(i)}\right) = \frac{\neg\varphi^{(i)}}{\sum_{j=0}^{k} \neg\varphi_k^{(i)}}$$

If the weight matrix is denoted as W and the feature matrix by X, then φin the above equation is generalized as

$$\varphi = \sum_{i=0}^{k} W_i X_i = W^T X$$

NEURAL NETWORK TRAINING

In AI, a convolutional neural organization is a sort of feed-forward fake neural organization in which the network design between its neurons is roused by the association of the creature visual cortex. Individual cortical neurons react to improvements in a limited district of room known as the responsive field. The responsive fields of various neurons incompletely cover with the end goal that they tile the visual field. The reaction of an individual neuron to boosts inside its open field can be approximated numerically by a convolution activity. Convolutional networks were propelled by natural cycles and are varieties of multilayer perceptron intended to utilize negligible measures of pre-handling. They have wide applications in picture and video acknowledgment, recommender frameworks and regular language preparing. Convolutional neural organizations (CNNs) comprise of various layers of responsive fields. These are little neuron assortments which cycle parts of the info picture. The yields of these assortments are then tiled so their info districts cover, to get a higher-goal portrayal of the first picture; this is rehashed for each such layer. Tiling permits CNNs to endure interpretation of the information picture. Convolutional organizations may incorporate neighborhood or worldwide pooling layers, which consolidate the yields of neuron bunches. They too comprise of different mixes of convolutional and completely associated layers, with point savvy nonlinearity applied toward the finish of or after each layer. A convolution procedure on little locales of info is acquainted with lessen the quantity of free boundaries and improve speculation. One significant bit of leeway of convolutional networks is the utilization of shared weight in convolutional layers, which implies that a similar channel (loads bank) is utilized for every pixel in the layer; this both lessens memory impression furthermore, improves execution. The layer's boundaries are involved a set of learnable portions which have a little open field yet stretch out through the full profundity of the info volume. Amended Linear Units (Re LU) are utilized an alternative for soaking nonlinearities. This initiation work adaptively learns the boundaries of rectifiers and improves precision at unimportant extra computational expense. In the unique situation of fake neural organizations, the rectifier is an enactment work characterized as:f(x)=max (0, x).

Where x is the contribution to a neuron. This is otherwise called an incline work what is more, is like half-wave correction in electrical designing. This enactment work was first acquainted with a dynamical organization by Hahn failure et al. in a 2000 paper in Nature with solid organic inspirations what is more, numerical avocations. It has been utilized in convolutional networks more successfully than the generally utilized strategic sigmoid (which is roused by likelihood hypothesis; see strategic relapse) and its more down to earth partner, the exaggerated digression. The rectifier is, starting at 2015, the most famous actuation work for profound neural organizations. Profound CNN with ReLU's trains a few times quicker. This technique is applied to the yield of each convolutional and completely associated layer. Despite the yield, the information standardization is not needed; it is applied after ReLU nonlinearity after the first and second convolutional layer since it lessens top-1 and top-5 mistake rates. In CNN, neurons inside a covered-up layer are fragmented into "include maps." The neurons inside an element map share a similar weight and inclination. The neurons inside the component map look for a similar component. These neurons are exceptional since they are associated with various neurons in the lower layer. So, for the first concealed layer, neurons inside an element guide will be associated with various districts of the info picture. The shrouded layer is portioned into highlight maps where every neuron in an element map searches for a similar component in any case, at various places of the information picture. Essentially, the component map is the aftereffect of applying convolution over a picture. The convolutional layer is the center structure square of a CNN. The layer's boundaries comprise of a lot of learnable channels (or pieces), which have a little open field, yet reach out through the full profundity of the information volume. During the forward pass, each channel is convolved over the width and tallness of the input volume, registering the speck item between the sections of the channel also, the info and creating a 2-dimensional actuation guide of that channel. Therefore, the organization learns channels that initiate when it recognizes some sort of highlight at some spatial situation in the info. Stacking the actuation maps for all channels along the profundity measurement structures the full yield volume of the convolution layer. Three hyper parameters control the size of the output volume of the convolutional layer: the depth, stride, and zero-padding.

Depth

Depth of the yield volume controls the quantity of neurons in the layer that interface with a similar district of the information volume. These neurons will figure out how to initiate for various highlights in the information. For model, if the primary Convolutional Layer accepts the crude picture as info, at that point various neurons along the profundity measurement may initiate in the presence of different arranged edges, or masses of shading.

Stride

It controls how depth columns around the spatial dimensions (width and height) are allocated. When the stride is 1, a new depth column of neurons is allocated to spatial positions only 1 spatial unit apart. This leads to heavily overlapping receptive fields between the columns, and to large output volumes. Conversely, if higher strides are used then the receptive fields will overlap less and the resulting output volume will have smaller dimensions spatially.

Zero Padding

Zero padding happens as we include a border of pixels each with value zero across the boundaries of the input pictures. This adds sort of a padding of zeros across the outside of the picture, hence the name zero padding.

CNN MODEL STEPS

Conv2D: It is a 2D Convolution Layer, this layer creates a convolution kernel that's wind with layers input which helps produce a tensor of outputs.

```
keras.layers.Conv2D(filters, kernel_size, strides=(1, 1),
padding='valid', data_format=None, dilation_rate=(1, 1),
activation=None, use_bias=True,
kernel_initializer='glorot_uniform',
bias_initializer='zeros', kernel_regularizer=None,
bias_regularizer=None, activity_regularizer=None,
kernel_constraint=None, bias_constraint=None
```

Maxpooling

Max pooling may be a pooling process that choose the very best element from the region of the feature map covered by the filter. Thus, the output after max-pooling level would be a feature map comprising the foremost important features of the previous feature ma.

Flatten

In between the convolutional layer and therefore the fully connected layer, there is a ‘Flatten’ layer. Flattening transforms a two-dimensional matrix of features into a vector which will be fed into a totally connected neural network classifier. Image Data

Generator

Image Data Generator quickly found out Python generators which will automatically turn image files on disk into batches of preprocessed tensors.

Training Process

Effective training begins well before a trainer delivers a private training session and continues then training session is complete. Training are often viewed as a process comprised of 5 related stages or activities: assessment, motivation, design, delivery, and evaluation.

Epochs

An epoch may be a term utilized in machine learning and indicates the amount of passes of the whole training dataset the machine learning algorithm has completed. Datasets are usually grouped into batches (especially when the quantity of knowledge is extremely large).

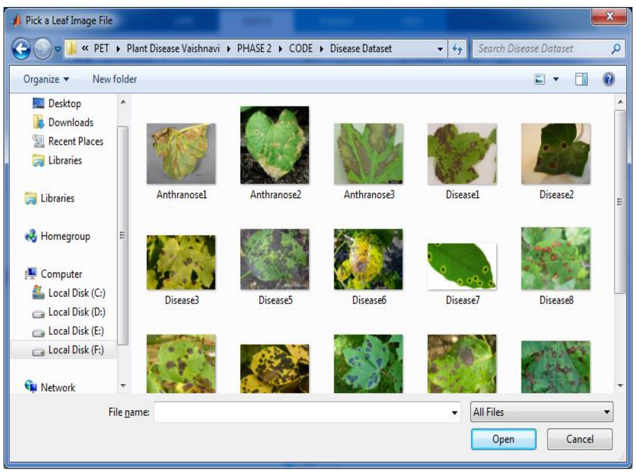
Validation Process

Validation is mentioned because the process where a trained model is evaluated with a testing data set. The testing data set may be a separate portion of an equivalent data set from which the training set springs . the most purpose of using the testing data set is to check the generalization ability of a trained model.

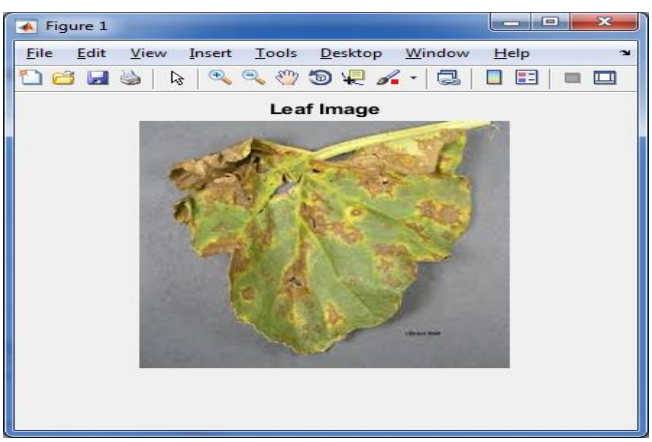
Training and Testing Model

The dataset is preprocessed like Image reshaping, resizing and conversion to an array form. Similar processing is additionally done on the test image. A dataset consisting of about 38 different plant leaf diseases is obtained, out of which any image is often used as a test image for the software.

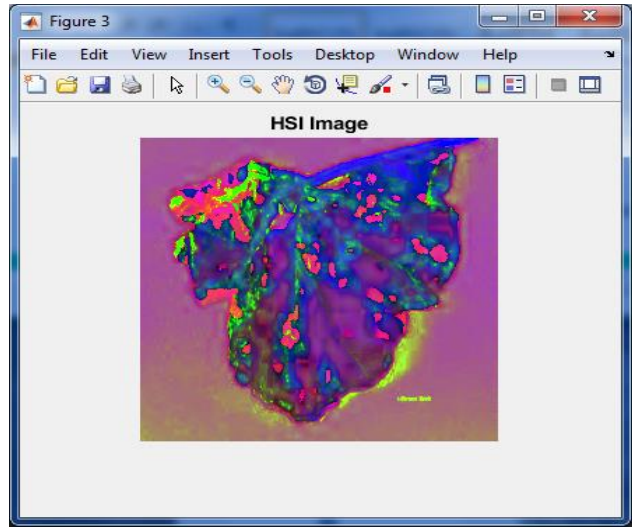
IV. SCREEN SHOTS



Input File Path



Leaf Image



HSI Image

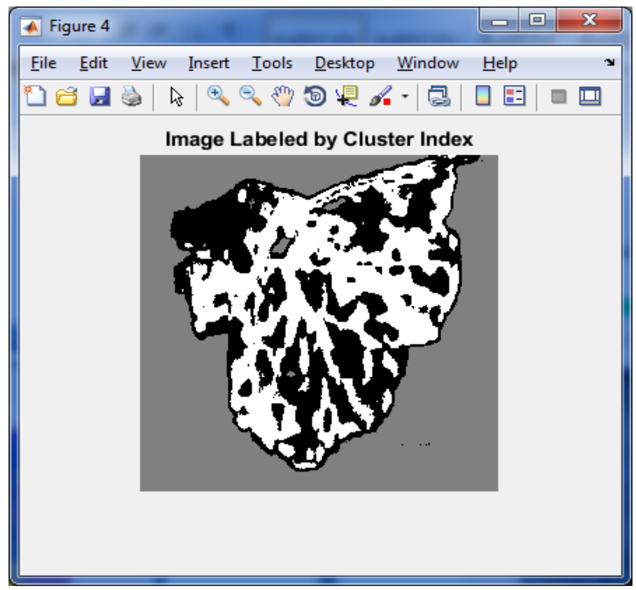
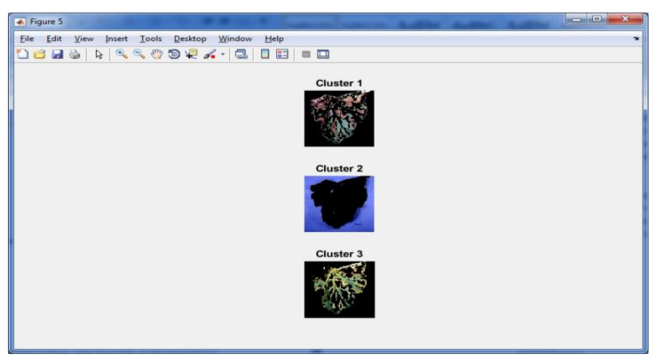
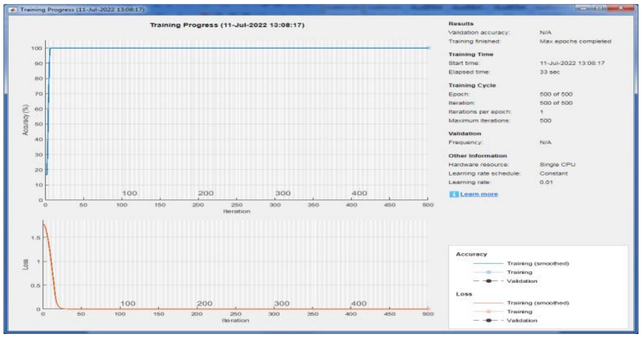


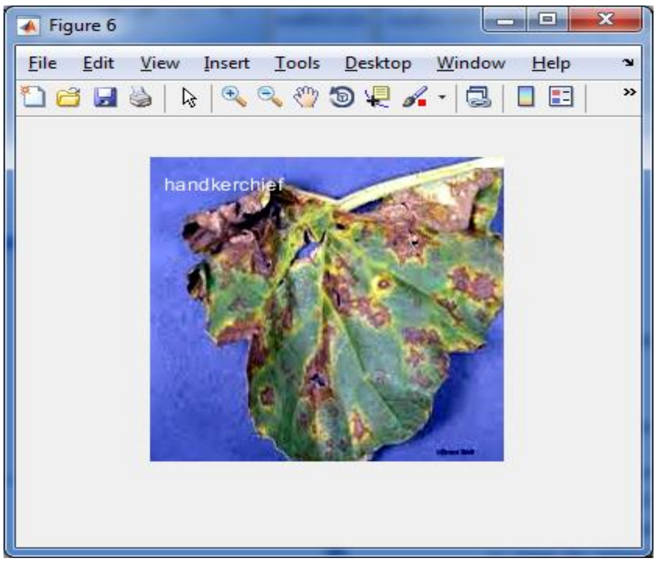
Image Labeled by cluster index



Cluster Selection



Convolutional neural network trainer tool



Leaf Type

```
species_disease =

  1×1 cell array

    {'ANTHRANOSE'}
```

Disease Detection

V. CONCLUSION

Thus, the rapid human population growth requires corresponding increase in food production. Here, image segmentation using Rough Set based Fuzzy K-Means Algorithm. Rough sets offer an effective approach of managing uncertainties and also used for image segmentation, feature identification, dimensionality reduction, and pattern classification. The proposed algorithm is based on a modified K-means clustering using rough set theory (RFKM) for image segmentation, which is further divided into two parts. Primarily the cluster centers are determined and then in the next phase they are reduced using Rough set theory (RST). K-means clustering algorithm is then applied on the reduced and optimized set of cluster centers with the purpose of segmentation of the images. For feature extraction used texture features obtained by analysing the grey level co-occurrence matrix and general colour statistical features obtained by histogram analysis of the full image. The GLCM is used to describe a spatial relationship of neighbouring pixels. This project presents the most recent results in this field, and finds the early disease diagnosis and prevention using CNN.

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