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# Analysis and Implementation of Fruit/Leave Disease Detection using Image Processing and Neural Approach

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## ABSTRACT

The latest generation of convolution neural networks (CNNs) has achieved impressive results in the field of image classification. This paper is concerned with a new approach to the development of fruit/plant disease detection model, based on leaf image processing and classification, by the use of ANN. Novel way of training and the methodology used facilitate a quick and easy system implementation in practice. The developed model is able to recognize 13 different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. According to our knowledge, this method for plant disease recognition has been proposed for the first time. All essential steps required for implementing this disease recognition model are fully described throughout the paper, starting from gathering images in order to create a database, assessed by agricultural experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training.

**KEYWORDS:** Fruit/Leaf diseases, SVM, segmentation, morphological processing, features extraction, clustering, fuzzy logic. Back Propagation Neural Network, CCV, K-means Clustering, LBP, SVM, CNN.

## INTRODUCTION

The problem of efficient plant disease protection is closelyrelated to the problems of sustainable agriculture and climatechange [1]. Research results indicate that climate change canalter stages and rates of pathogen development; it can alsomodify host resistance, which leads to physiological changes of host-pathogen interactions [2, 3]. The situation is furthercomplicated by the fact that, today, diseases are transferredglobally more easily than ever before. New diseases canoccur in places where they were previously unidentified and,inherently, where there is no local expertise to combat them[4–6]. Inexperienced pesticide usage can cause the developmentof long-term resistance of the pathogens, severely reducingthe ability to fight back. Timely and accurate diagnosis ofplant diseases is one of the pillars of precision agriculture[7]. It is crucial to prevent unnecessary waste of financial and other resources, thus achieving healthier production, byaddressing the long-term pathogen resistance developmentproblem and mitigating the negative effects of climate change.In this changing environment, appropriate and timelydisease identification including early prevention has never been more important. There are several ways to detect plantpathologies. Some diseases do not have any visible symptoms,or the effect becomes noticeable too late to act, and in thosesituations, a sophisticated analysis is obligatory.

However,most diseases generate some kind of manifestation in the visible spectrum, so the naked eye examination of a trained professional is the prime technique adopted in practice for plantdisease detection. In order to achieve accurate plant diseasediagnostics a plant pathologist should possess good observation skills so that one can identify characteristic symptoms[8]. Variations in symptoms indicated by diseased plants may lead to an improper diagnosis since amateur gardenersand hobbyists could have more difficulties determining itthan a professional plant pathologist. An automated systemdesigned to help identify plant diseases by the plant's appearance and visual symptoms could be of great help to amateursin the gardening process and also trained professionals as a verification system in disease diagnostics.Advances in computer vision present an opportunity toexpand and enhance the practice of precise plant protection and extend the market of computer vision applications in thefield of precision agriculture.

Exploiting common digital image processing techniquessuch as colour analysis and thresholding [9] were used withthe aim of detection and classification of plant diseases.Various different approaches are currently used fordetecting plant diseases and most common are artificialneural networks (ANNs) [10] and Support Vector Machines (SVMs) [11]. They are combined with different methods ofimage preprocessing in favour of better feature extraction.In machine learning and cognitive science, ANN is aninformation-processing paradigm that was inspired by theway biological nervous systems, such as the brain, processinformation. The brain is composed of a large number ofhighly interconnected neurons working together to solve specific problems.An artificial neuron is a processing element with manyinputs and one output. Although artificial neurons can havemany outputs, only those with exactly one output will be considered. Their inputs can also take on any value between 0 and1. Also, the neuron has weights for each input and an overallbias.The weights are real numbers expressing importance ofthe respective inputs to the output. The bias is used forcontrolling how easy the neuron is getting to output 1. For a neuron with really big bias it is easy to output 1, but when thebias is very negative then it is difficult to output 1.The output of the neuron is not 0 or 1. Instead, it is $\alpha\cdot(w\cdot x+b)$, where $\alpha$is called the transfer function. There aredifferent types of transfer function: step, linear, sigmoid, andso forth. The smoothness of $\alpha$means that small changes $\Delta wj$ in the weights and $\Delta b$in the bias will produce small change$\Delta$output in the output from the neuron. Small output changeis approximated by

$$\Delta output = \sum \frac{\partial output}{\partial w_j} \Delta w_j + \sum \frac{\partial output}{\partial b} \Delta b.$$

Basically, the small change in weight or bias causes the smallcorresponding change in the network output (Figure 1).Neural networks, with their outstanding ability to derivemeaning from complex or imperfect data, can be applied forextracting patterns and detecting trends that are too difficultto notice by humans or computer techniques. Other advantages of ANNs are adaptive learning, self-organization, real time operations, and so forth.There are two main categories of ANNs when speakingabout architecture: feed-forward ANNs where the output of any layer is unlikely to influence that same layer and feedbackANNs where signals travel in both directions by involvingloops in the network.

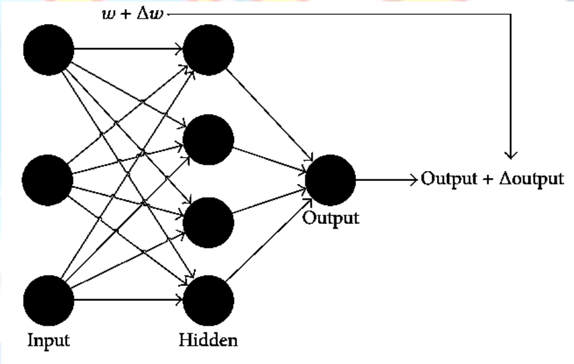



Figure 1: Simple model of ANN.

The method described in this paper is a new approach in detecting plant diseases using the deep convolutionalneural network trained and fine-tuned to fit accurately to thedatabase of a plant's leaves that was gathered independentlyfor diverse plant diseases. The advance and novelty of thedeveloped model lie in its simplicity; healthy leaves andbackground images are in line with other classes, enablingthe model to distinguish between diseased leaves and healthyones or from the environment by using deep CNN.

## 2. LITERATURE REVIEW

Implementing the appropriate management strategies likefungicide applications, disease-specific chemical applications, and vector control through pesticide applications couldlead to early information on crop health and disease detection. This could facilitate the control of diseases and improveproductivity. In [12], authors present, review, and recognizethe demand for developing a rapid, cost-effective, and reliable health-monitoring sensor that facilitates advancements inagriculture. They described the currently used technologiesthat include spectroscopic and imaging-based and volatile profiling-based plant disease detection methods for the purpose of developing ground-based sensor system to assist inmonitoring health and diseases in plants under field conditions.After analysis of their work and analysis presented bythe authors of [13–16], it was decided to use image processing disease recognition approach among other approaches commonly used for plant disease diagnostics, for instance,double-stranded ribonucleic acid (RNA) analysis, nucleicacid probes, and microscopy. Numerous procedures are currently in use for plant disease detection applying computer vision. One of them isdisease detection by extracting colour feature as authors in[17] have presented. In this paper YcbCr, HSI, and CIELBcolour models were used in the study; as a result, disease spotswere successfully detected and remained unaffected by thenoise from different sources, such as camera flash.In addition, plant disease detection could be achieved byextracting shape features method. Patil and Bodhe appliedthis technique for disease detection in sugarcane leaves wherethey have used threshold segmentation to determine leaf areaand triangle threshold for lesioning area, getting the average accuracy of 98.60% at the final experiments [18]. Furthermore, extracting texture feature could be used indetecting plant diseases. Patil and Kumar proposed a modelfor plant disease detection using texture features such asinertia, homogeneity, and correlation obtained by calculatingthe gray level cooccurrence matrix on image [19]. Combinedwith colour extraction, they experimented on detecting diseases on maize leaves.Combination of all these features provides a robustfeature set for image improvement and better classification.In [20], the authors have presented a survey of well-knownconventional methods of feature extraction. Due to the rapid progress of Artificial Intelligence (AI) science, work in thispaper is mainly focused on applying these methodologies andtechniques.There are some approaches which apply the feed-forwardback propagation of neural networks consisting of one input,one output, and one hidden layer for the needs of identifyingthe species of leaf, pest, or disease; this model was proposedby the authors in [21]. They developed a software model, tosuggest remedial measures for pest or disease managementin agricultural crops.Another technique proposed by the authors in [22]incorporates the features extracted by Particle Swarm Optimization (PSO) [23] and forward neural network in directionof determining the injured leaf spot of cotton and improvingthe accuracy of the system with the final overall accuracy of95%.Also, detection and differentiation of plant diseases canbe achieved using Support Vector Machine algorithms. Thistechnique was implemented for sugar beet diseases andpresented in [24], where, depending on the type and stageof disease, the classification accuracy was between 65% and90%. Likewise, there are methods that combine the feature extraction and Neural Network Ensemble (NNE) for plantdisease recognition. Through training a definite numberof neural networks and combining their results after that,NNE offers a better generalization of learning ability [25].Such method was implemented only for recognizing tea leaf diseases with final testing accuracy of 91% [26]. Another approach based on leaf images and using ANNsas a technique for an automatic detection and classificationof plant diseases was used in conjunction with *K*-means as aclustering procedure proposed by the authors in [27]. ANNconsisted of 10 hidden layers. The number of outputs was 6which was the number of classes representing five diseases along with the case of a healthy leaf. On average, the accuracyof classification using this approach was 94.67%.The authors in [28–31] presented the deep learningmethods for solving most complex tasks in different areas ofresearch in biology, bioinformatics, biomedicine, robotics,and 3D technologies.

## 3. BASIC SYSTEM MODEL

The entire procedure of developing the model for plantdisease recognition using deep CNN is described further indetail. The complete process is divided into several necessarystages in subsections below, starting with gathering imagesfor classification process using deep neural networks.

*3.1. Dataset.* Appropriate datasets are required at all stagesof object recognition research, starting from training phaseto evaluating the performance of recognition algorithms.All the images collected for the dataset were downloadedfrom the Internet, searched by disease and plant name onvarious sources in different languages, such as Latin, English, German, Serbian, and Hungarian. Images in the dataset weregrouped into fifteen different classes. Thirteen classes represented plant diseases which could be visually determinedfrom leaves.

In order to distinguish healthy leaves from diseased ones,one more class was added in the dataset. It contains onlyimages of healthy leaves. An extra class in the dataset withbackground images was beneficial to get more accurate classification. Thus, deep neural network could be trained to differentiate the leaves from the surrounding. The background images were taken from the Stanford background dataset[32]. In this stage, all duplicated images taken from differentsources were removed by developed python script applyingthe comparing procedure. The script removed the duplicatesby comparing the images' metadata: name, size, and the date.After the automated removal, images were assessed by human experts in much iteration.Next step was to enrich the dataset with augmentedimages. The main goal of the presented study is to train thenetwork to learn the features that distinguish one class fromthe others. Therefore, when using more augmented images, the chance for the network to learn the appropriate featureshas been increased. Finally, a database containing 30880images for training and 2589 images for validation has beencreated. The augmentation process is described in Section 3.3. all supported diseases together with thenumber of original images and number of augmented images for every class used as training and validation dataset for thedisease classification model.

*3.2. Image Preprocessing and Labelling.*

Images downloadedfrom the Internet were in various formats along with differentresolutions and quality. In order to get better feature extraction, final images intended to be used as dataset for deepneural network classifier were preprocessed in order to gain consistency. Furthermore, procedure of image preprocessinginvolved cropping of all the images manually, making thesquare around the leaves, in order to highlight the regionof interest (plant leaves). During the phase of collecting theimages for the dataset, images with smaller resolution and dimension less than 500 px were not considered as validimages for the dataset. In addition, only the images wherethe region of interest was in higher resolution were markedas eligible candidates for the dataset. In that way, it wasensured that images contain all the needed information forfeature learning. Images used for the dataset were image resized to 256 × 256 to reduce the time of training, which wasautomatically computed by written script in Python, using theOpenCV framework [33]. Many resources can be found by searching across the Internet, but their relevance is often unreliable. In the interestof confirming the accuracy of classes in the dataset, initiallygrouped by a keywords search, agricultural experts examinedleaf images and labelled all the images with appropriate disease acronym. As it is known, it is important to use accuratelyclassified images for the training and validation dataset. Onlyin that way may an appropriate and reliable detecting model be developed. In this stage, duplicated images that were leftafter the initial iteration of gathering and grouping imagesinto classes described in Section 3.1 were removed from thedataset.

*3.3. Augmentation Process.*

The main purpose of applyingaugmentation is to increase the dataset and introduce slightdistortion to the images which helps in reducing overfittingduring the training stage. In machine learning, as well asin statistics, overfitting appears when a statistical modeldescribes random noise or error rather than underlyingrelationship [34]. The image augmentation contained one of several transformation techniques including affine transformation, perspective transformation, and simple imagerotations. Affine transformations were applied to expresstranslations and rotations (linear transformations and vectoraddition, resp.) [35] where all parallel lines in the originalimage are still parallel in the output image. To find a transformation matrix, three points from the original image were needed as well as their corresponding locations in the outputimage. For perspective transformation, a 3×3 transformationmatrix was required. Straight lines would remain straighteven after the transformation. For the augmentation process,simple image rotations were applied, as well as rotations onthe different axis by various degrees.Transformations applied in augmentation process areillustrated in Figure 2, where the first row represents resultingimages obtained by applying affine transformation on the single image; the second row represents images obtainedfrom perspective transformation against the input image andthe last row visualizes the simple rotation of the input image.The process of augmentation was chosen to fit the needs; the leaves in a natural environment could vary in visual perspective.For this stage, in order to automate the augmentation process for numerous images from the dataset, particular application was developed in C++ using the OpenCV library [36],with possibility of changing the parameters of transformationduring the run-time, which improves flexibility.

*3.4. Neural Network Training.* Training the deep convolution neural network for making an image classificationmodel from a dataset described in Section 3.1 was proposed.

Each convolutional layer has $M$ maps of equal size, $M_x$ and $M_y$, and a kernel of size $K_x$ and $K_y$ is shifted over the certain region of the input image. The skipping factors $S_x$ and $S_y$ define how many pixels the filter/kernel skips in $x-$ and $y-$ direction between subsequent convolutions [46]. The size of the output map could be defined as

$$M_x^n = \frac{M_x^{n-1} - K_x^n}{S_x^n + 1} + 1,$$

$$M_y^n = \frac{M_y^{n-1} - K_y^n}{S_y^n + 1} + 1, \quad (2)$$

Where $n$ indicates the layer. Each map in layer $L^n$ is connected to most $M^{n-1}$ maps in layer $L^{n-1}$.

Rectified Linear Units (ReLU) are used as substitute for saturating nonlinearities. This activation function adaptively learns the parameters of rectifiers and improves accuracy at negligible extra computational cost [47]. It is defined as

$$f(z_i) = \max(0, z_i), \quad (3)$$

where $z_i$ represents the input of the nonlinear activation function $f$ on the $i$th channel.

Deep CNN with ReLUs trains several times faster. Thismethod is applied to the output of every convolutional andfully connected layer.Despite the output, the input normalization is notrequired; it is applied after ReLU nonlinearity after the firstand second convolutional layer because it reduces top-1 andtop-5 error rates. In CNN, neurons within a hidden layer aresegmented into “feature maps.” The neurons within a featuremap share the same weight and bias. The neurons within thefeature map search for the same feature. These neurons areunique since they are connected to different neurons in thelower layer. So for the first hidden layer, neurons within afeature map will be connected to different regions of the inputimage.The hidden layer is segmented into feature maps whereeach neuron in a feature map looks for the same feature butat different positions of the input image. Basically, the featuremap is the result of applying convolution across an image.

Each layer’s features are displayed in a different block, wherevisualization represents the strongest activation for the provided feature map, starting from the first convolutional layer,where features go from individual pixels to simple lines, to thefifth convolutional layer where learned features like shapesand certain parts of leaves are displayed (Figure 3).Another important layer of CNNs is the pooling layer,which is a form of nonlinear down sampling. Pooling operation gives the form of translation invariance [48]; it operatesindependently on every depth slice of the input and resizes itspatially. Overlapping pooling is beneficially applied to lessenoverfitting. Also in favour of reducing overfitting, a dropoutlayer [49] is used in the first two fully connected layers. Butthe shortcoming of dropout is that it increases training time2-3 times comparing to a standard neural network of the exactarchitecture [50]. Bayesian optimization experiments alsoproved that ReLUs and dropout have synergy effects, whichmeans that it is advantageous when they are used together.The advance of CNNs refer to their ability to learnrich mid-level image representations as opposed to hand designed low-level features used in other image classificationmethods.Figure 4 illustrates the filtered output images after everyconvolutional and pooling layer of the deep network. Outputimages are labelled with the name of corresponding layer atthe bottom right corner of every image.

*3.5. Performed Tests.*

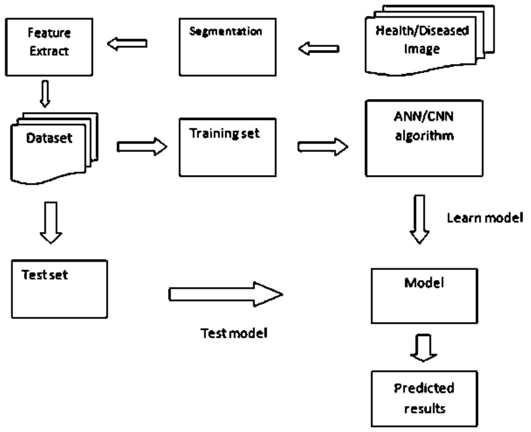
The common approach in measuringperformance of artificial neural networks is splitting data intothe training set and the test set and then training a neuralnetwork on the training set and using the test set for prediction. Thus, since the original outcomes for the testing setand our model predicted outcomes are known, the accuracyof our prediction can be calculated. Different tests were performed with 2589 original images, when trained with 30880images from database.For the accuracy test, 10-fold cross validation techniquewas used to evaluate a predictive model. The cross validationprocedure was repeated after every thousand training iteration. Overall estimated result of the test is graphically represented as top-1, to test if the top class (the one having the highest probability) is the same as the target label. The top-5 errorrate is there to test if the target label is one of the top 5 predictions, the ones with 5 of the highest probabilities. The numberof images used for the validation test from each labelled classis given in Table 1. Test results are presented in Section 4, for both complete dataset and each class separately.

*3.6. Fine-Tuning.*

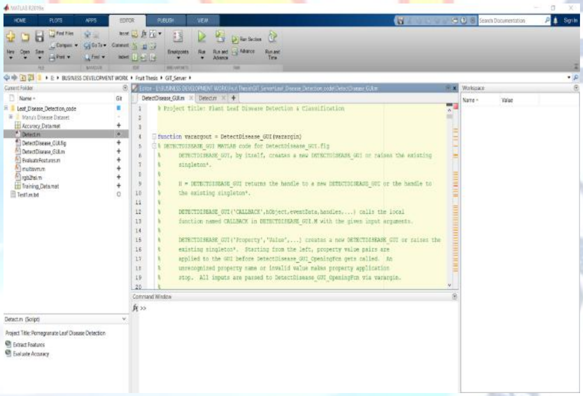
Fine-tuning seeks to increase the effectiveness or efficiency of a process or function by making smallmodifications to improve or optimize the outcome. The classification function in the original CaffeNet model is Softmaxclassifier that computes probability of 1,000 classes of the ImageNet dataset. Fine-tuned learning experiments require a bitof learning, but they are still much faster than learning fromscratch [43]. To start the fine-tuning procedure, this softmax classifier was removed, as mentioned and illustrated in Section 3.4 and the new one was initialized with random values.The new softmax classifier was trained from scratch usingthe back-propagation algorithm with data from the datasetdescribed in Section 3.1. This dataset has 15 different categories. Due to the smaller size of the dataset used for thisresearch when compared to ImageNet, ILSVRC-2012,overfitting was constrained by using lower initial learningrates for the fine-tuned hidden layers. The learning rateof the top layer was set to 10, while the learning rate of all theother seven learning layers was 0.1. The back-propagationalgorithm ran for 100,000 iterations. The process of finetuning was repeated changing parameters of hidden layers and hyperparameters.

## 4. RESULTS AND DISCUSSION

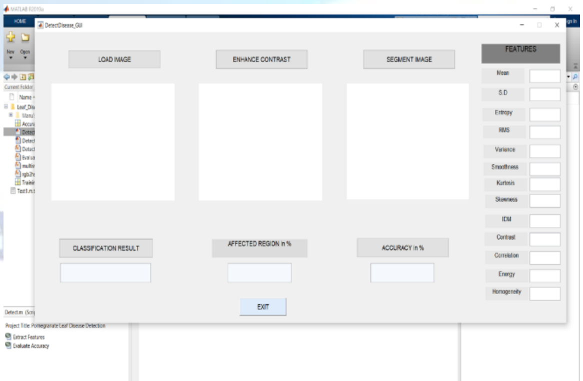
### 4.1 System Architecture for Fruit/Leaf Disease Detection

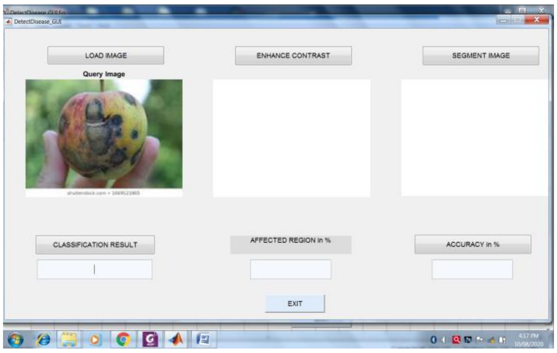



**Step 1.**

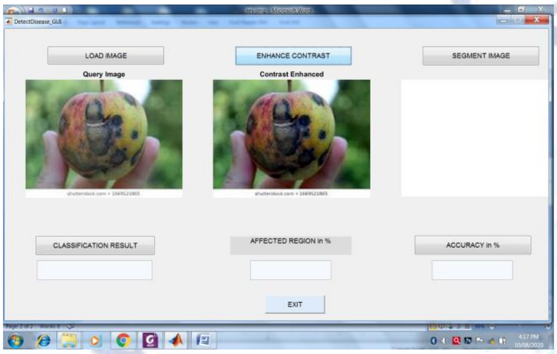


**Step 2.**

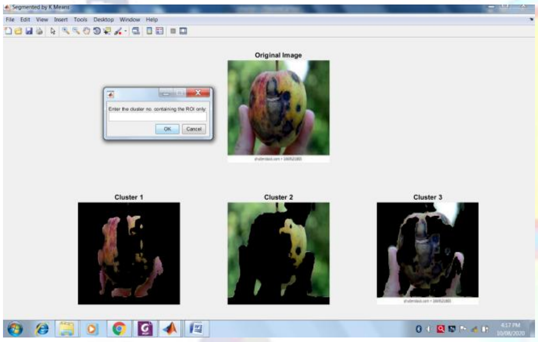




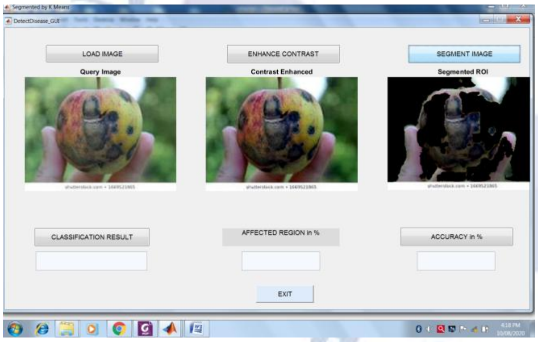

**(a)** selection of image(fruit/leaves)



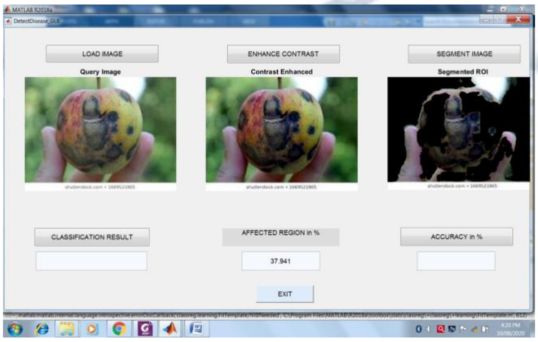

**(b)** image with enhanced contrast




**(c)** various cluster images for selection

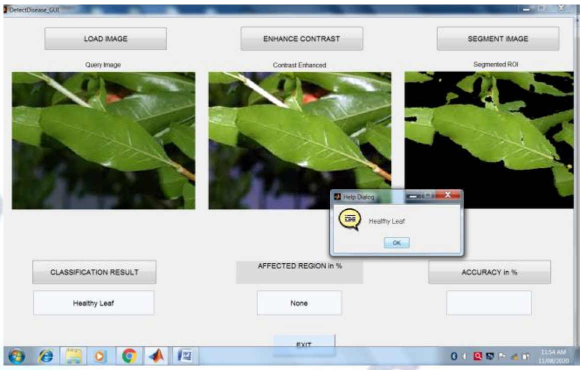



**(d)** segmented image with Region of Infection

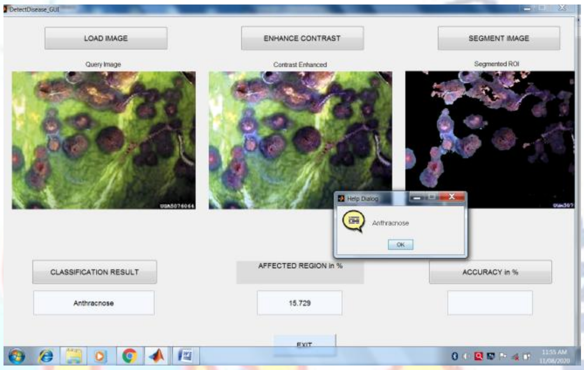



**(e)** final results of affected region [37% affected]

In this section we have shown different results obtained from simulation, Results includes various infected images identification,recognition andshowing the amount of infected area using MATLAB simulation.




**(f)**images of healthy leaves

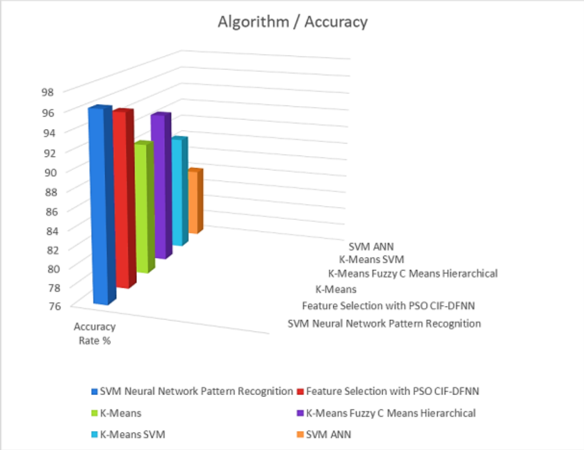



**(g)**final image of infected leave [15%]

### 4.2 A comparative study of algorithms and their advantages

| S No. | Algorithm Used | Accuracy Rate % | Advantages |
|---|---|---|---|
| 1. | SVM<br>Neural Network Pattern Recognition | 70.21<br>96.27 | Larger datasets are used<br>More Features are Extracted. |
| 2. | Feature Selection with PSO<br>CIF-DFNN | 95 | Accurate<br>Diminishes Error Rate High Performance |
| 3. | K-Means | 90.50 | Complexity Decreases |
| 4. | K-Means Fuzzy C Means<br>Hierarchical | 75.86<br>80.05<br>92.72 | K- Valuable Less Effort Accuracy |
| 5. | K-Means SVM | 88.89 | Normal & abnormal leaves are studied<br>Confusion matrix is plotted |
| 6. | SVM ANN | 83.83<br>77.75 | Comparison results shows SVM is better |

### 4.3 Comparison of most frequently used algorithm's overall accuracy rate in percentage




## 5. CONCLUSION

In this paper, it is proposed to find how much percent the fruit/plants are affected and recognize the defected fruit in the given image. This feature is very useful for the farmers and useful for different purposes. To get better results in the classification and identification of fruit diseases ANN model and image processing are used. We have added this feature to model so that the fusion of image processing and deep neural network not only useful for the fruit disease detection but also it is useful detecting diseases in vegetables and plants and completely helpful for the agricultural industry.

- Since currently the system is trained using Fruit/Plant Leave dataset, the model is trained to detect ROI and diseases.
- We propose to train the system with much more data of various other Fruits & plants and diseases to further increase the scope of the system.
- By adding images of many other Fruits & plants, it will help in extracting many more features of the plants which certainly help in improving the accuracy of the system.
- The users using the system may also contribute to the system by capturing different types of Fruits/plant Leave images which can be added to the dataset.
- This dataset can be further used to build better models Also they may be improved in terms of accuracy by implementation of better algorithms in the coming future.
- We also propose to provide certain remedies for the crop diseases to the user by analyzing the diseases.
- This will certainly help the users to avoid such diseases in the future. Also, the remedies will help the user to get rid of the diseases hence, improving their yield.

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