An Investigation Study on Extracting and Segmenting Region of Interest For Plant Leaf Disease Deteciton

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ABSTRACT

Plants become the indispensable origin of food, fuel for human beings. So, the researchers and agriculture associated industries with significant endeavors are presuming in research, to carry on with agriculture for an elongated period without any violation. An identification and recognition of fruit leaf diseases in the early stage is said to be the prevailing ultimatum in Computer Vision (CV) due to their predominant applications in agriculture. As far as agriculture is concerned, different types of fruit diseases is said to be exist that in turn has a negative impact influencing the fabrication and fruit quality. On the basis of the indications, most of these diseases are inferred by the nude eyes of a specialist in this domain. Despite the observed indications, due to the dearth of specialists and cost involved, yet plant leaf disease identification is said to be a major domain in agriculture. Several methods have been designed to increase the classification accuracy by introducing better classifier, ensure performance accuracy by removing noise, improve the prediction accuracy and enhance the classification performance. In this estimates, the computing researchers in cooperation with agriculture specialists have put forward several materials and methods for automated plant disease detection

Keywords
Computer Vision, Plant Leaf Disease Identification, Agriculture, Fruit Quality, Prediction Accuracy

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Introduction

Present-day technologies have given human confraternity the potentiality to generate abundant food to link up with the insistence of greater than 7 billion people. However, food security remains engender by a number of factors, to name a few being, change in climatic conditions, pollinator decline, disease in plant and so on. Globally speaking, disease found in plant is not only a menace to food security, but can also result in catastrophic effects for small and mid level farmers whose income hang on fine crops. As far as the developing world is concerned, it is found that greater than 80 percent of the agricultural production is produced by smallholder farmers and reports of capitulate loss of greater than 50% due to diseases are prevalent. Many feature extraction and segmentation methods are developed to detect the plant leaf disease at an early stage with higher detection speed and sensitivity.

The paper is structured as given below. Section 2 reviews the plant leaf disease identification methods in agriculture domain. Section 3 explains the existing plant leaf disease identification methods. Section 4 illustrates experimental settings with possible comparison between the four methods. Section 5 renders the disadvantages of segmentation and classification methods on plant leaf disease identification. Section 6 concludes paper.

Literature Review

Productivity in agriculture is something on which economy is said to be heavily depended on. Due to this reasons that plant disease detection plays a pivotal role in the field of agriculture because the presence of disease is found to be quite instinctive. Upon improper attention in this are results in significant influences on plants and due to which quality and quantity of production is said to be affected to a greater extent. Plant disease detection through segmentation and feature extraction methods is found to be more advantageous as it minimizes great deal of monitoring and therefore detecting the disease symptoms at an early stage itself.

The VGGNet connection layers implemented with a global pooling layer and two Inception modules namely, INC-VGGN was proposed in [1] to enhance feature extraction for plant leaf disease detection. Despite improvements observed in feature extraction accuracy, the plant disease detection time consumed was not said to be minimized. In [2], an optimized dense convolutional neural network (DenseNet) framework was proposed with the objective of identifying corn leaf disease. With optimization being achieved, however, disease detection accuracy was not said to be concentrated with the lack of proper image segmentation mechanism.

In [3], a new apple leaf disease detection method using data augmentation and image annotation was proposed using laboratory images and complex images. The method utilized deep convolutional neural network to detect common disease occurring in apple therefore contributing to higher accuracy and faster detection speed. A strong correlation model with feature selection using genetic algorithm was designed in [4] for apple disease detection based on the prominent features with significant classification accuracy. Moreover in order to take quick and efficient decision making, decision support features were obtained in [5] and with it disease effects were minimized and therefore contributing to fault detection.

Plant disease detection via certain automatic mechanism is said to be advantageous as it minimizes enormous monitoring task involved in big farms of crops. In addition, with this, early stage detection is also said to be ensured with the detection of disease symptoms upon appearance on plant leaves. An algorithm was presented in [6] for automatic detection and classification of disease involved in plant leaf. A significant method for leaf region extraction in digital plant images based on segmentation by applying Circular Hough Transform was presented in [7] resulting in segmentation accuracy.

Convolutional neural network model was employed in [8] for plant disease detection with the aid of healthy and diseased plants via deep learning methodologies. A structured assessment of plant disease detection using deep learning techniques was proposed in [9]. The foremost cause influencing occurrence of apple leaf disease that results in enormous loss is the economical aspect every year to great extent. Hence, it is of appreciable to analyze the recognition of apple leaf diseases. On the basis of DenseNet-121 deep convolution network [10], regression, multi-label classification and focus loss function were employed for apple leaf disease identification.

With the growth in the quantity of data being generated by agricultural machinery, more advanced methods are requisite to get full edge of those data. In [11], a Convolutional Neural Network (CNN) was employed with the purpose of extracting pertinent spatial structures of disparate attributes and integrated them to design yield feedback to nutrient and management of the corresponding seed rate. Yet another automated image segmentation model was designed in [12] by utilizing Heaviside function for accurate diagnosis and identification of diseases occurring in cotton.

Efficient feature extraction and classification for early plant leaf disease identification

Plant leaf diseases are accountable for considerable economic forfeitures in the agricultural industry globally. Keeping an eye on plant well-being and recognizing microorganism in an early stage is crucial to minimize the spread of disease and ease efficient management exercises. Many techniques were introduced in the literature on feature extraction and segmentation for plant leaf disease detection at an early stage.

Deep Transfer Convolutional Neural Learning for Plant Disease Identification

Plant diseases are the principal harms to the agricultural development and they have a catastrophic influence on the food production safety. In acute occurrences, plant diseases may results in no harvest entirely. Hence, the plant disease identification in an automatic manner is highly wanted in agricultural information. A plant disease identification model using INC-VGGN was proposed using deep transfer learning. Here, initially the plan disease image samples were obtained and were then labeled on the basis of domain expert knowledge in the corresponding field. Then with the obtained images, certain image processing techniques like, grey transformation, image filtering, image sharpening and resizing were applied with which new sample images were produced with the aid of data augmentation methods. Next, the resultant images were provided as input for model training. Finally, the trained images were applied for class prediction and the results were obtained. With this, both plant disease identification accuracy was improved and also minimized the false positive rate.

Optimized Dense Convolutional Neural Network for Disease Recognition

One of the most cultivated grains globally is corn. With corn crops being tremendously prone to certain leaf diseases, an optimized dense convolutional neural network (CNN) architecture, called, Optimized DenseNet was designed to detect common rust, corn gray leaf spot, and northern corn leaf blight. With the indications of leaf disease not variant in their developing phases, a solution using deep learning was designed with the objective of monitoring the crop in a continuous manner. Here, multi-channeled images in a batch of 32 was provided as input and was then passes via first convolution layer that in turn extracted pertinent features and outputs a feature map. The feature map was then passed as input to the first dense block of 5 convolution layers. This first convolution layer in turn generated 4 feature maps that were further integrated to the input, where the second convolution layer were added as input to generate another 4 feature maps, that were then concatenated to the prevailing obtained feature maps, and therefore resulting in increase in both the quality and quantity of crop production.

Improved Convolutional Neural Networks for Real Time Apple Leaf Disease Detection

Different types of apple leaf diseases have negative impact on the apple yield, therefore destroying the entire crop yield to a greater extent. However, the existing research works in the area of apple leaf disease shortfalls a precise and fast apple disease detection and therefore compromising the fine development of the apple industry. A deep learning model based on enhanced convolutional neural networks (CNNs), called Inception module and Rainbow concatenation with Single Shot multi-box Detector (INAR-SSD) was designed with the objective of detection of apple leaf diseases in a real time manner. Here initially data augmentation was employed by means of GoogLeNet Inception structure and Rainbow concatenation. Next, pooling and deconvolution were used in a simultaneous manner to combine both context and integrated features of the feature pyramid with which larger diseased object were detected in an efficient manner. Also, a deep convolutional neural network was utilized that in turn obtained the pertinent features in an automatic manner with which automatic detection of discriminative features were done for both the diseased and normal apple images. Here, five types of habitual apple diseases were detected with high accuracy. Moreover, the proposed method not only detected different diseases in the same diseased apple image but also detected the same disease of different sizes in the diseased image obtained under real conditions, therefore contributing to accuracy.

Strong Correlated and Genetic Algorithm based Segmentation and Classification of Apple Disease

Agriculture forms the major portion of the entire part of the world economy as it bestows food safety to a greater extent. Despite this, in the recent years, it has been identified that plants are considerably contaminated by several diseases. This results in boundless losses in agriculture industry globally. On the other hand, the laboring examination of fruit diseases is a laborious procedure that can be reduced by utilizing mechanized models for plan disease detection at an earlier stage itself. A new method called, Multi Support Vector Machine (M-SVM) was designed for identifying and recognizing apple diseases to a greater extent.

In M-SVM, three channels course of actions called, preprocessing, spot segmentation and features extraction, and classification was presented. Initially, apple leaf spots were improved by means of a hybrid method that remained the coexistence of filtering and correlation techniques. Followed by which the lesion spots were segmented by means of strong correlation on the basis of optimization by integrating with the Expectation Maximization (EM) segmentation. Next, fusion of color, color histogram, and Local Binary Pattern (LBP) features were performed in a parallel manner. Finally, the extracted features were optimized via genetic algorithm for further classification and detection of disease, therefore improving the sensitivity or true positive rate.

Existing Technologies and Accuracy Rate

Junde Chen, Jinxiu Chen, Defu Zhang,Yuandong Sun, Y.A. Nanehkaran, Mar 2020, proposed Deep transfer learning for plant disease detection, Accuracy achieved 92.00%, drawbacks: Despite improvements observed in feature extraction accuracy, the plant disease detection time consumed was not said to be minimized.

Abdul Waheed, Muskan Goyal, Deepak, Ashish Khanna, Aboul Ella Hassanien, Hari Mohan Pandey, Apr 2020, Computers and Electronics in Agriculture, Elsevier, proposed Optimized dense convolutional neural network for disease recognition, , Accuracy achieved 98.06%, drawbacks: With optimization being achieved, however, classification accuracy was not concentrated.

Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang, May 2019, IEEE Access, proposed Real-Time Detection Using Deep Learning Approach, Accuracy achieved 90%, drawbacks: Region of interest part was not focused.

Muhammad Attique Khan, Mikramulllah Lali, Muhammad Sharif, Kashif Javed, Khursheed Aurangzeb, Syed Irtaza Haider, Abdulaziz Saud Altamrah and Talha Akram, Jul 2019, IEEE Access, proposed Segmentation and Classification of Apple Diseases based on Strong Correlation and Genetic Algorithm, Accuracy Achieved 99.9% , drawbacks: Less focus on feature extraction.

X.E. Pantazi, D. Moshou, A.A. Tamouridou, Nov 2018, Computers and Electronics in Agriculture, Elsevier, proposed automated leaf disease detection through one class classifiers, Accuracy achieved 85.7%, drawbacks: gap in performance accuracy.

Aditya Karlekara, Ayan Sealb, , Mar 2020, Soybean leaf disease classification, proposed SoyNet, PDDB database, Open database, Accuracy achieved 98.14%, problem statement Overhead was not concentrated.

Konstantinos P. Ferentinos, Jan 2018, Semi automatic leaf disease detection, proposed Rule-based semi-automatic system, Plant Village Dataset, Accuracy achieved 85.65%, problem statement Disease categorization was not made.

Mohammad Reza Larijani1 | Ezzatollah Askari Asli-Ardeh1 | Ehsan Kozegar2 |Reyhaneh Loni3, Sep 2019, Rice blast disease based on KNN algorithm, KNN Machine Learning, Rice leaf dataset Accuracy achieved 94%, problem statement Less concentration on prediction accuracy.

Prabira Kumar Sethy, May 2020, Deep feature-based rice leaf disease identification, proposed Time involved in disease identification was not focused with 97.37% Accuracy rate

Guiling Sun , Xinglong Jia , and Tianyu Geng, May 2018, Hindawi, proposed Plant disease recognition with 93.33% Accuracy rate, the research problem statement is Less focus on classifier performance.

Chen Jun-De, Yin Huayi, Zhang De-Fu, Nov 2019, proposed Self adaptive classification for plant disease detection with 90.91% Accuracy rate and the research problem statement is Computational time involved in classification was less focused.

Gittaly Dhingra, Vinay Kumar, Hem Dutt Joshi, Jan 2019, proposed Neutrosophic approach for leaf disease identification, with Accuracy rate 98.4%, and the problem statement is paid less concentration on enhancing efficacy of disease detection.

Geetharamani G. , Arun Pandian J., Apr 2019, proposed Plant leaf disease identification using nine-layer deep CNN with 96.46% Accuracy, and the problem statement is Plant disease diagnosis was not focused.

Mingjie L V, Guoxiong Zhou, Mingfang He, Aibin Chen, Wenzhuo Zhang, Yahui Hu, Mar 2020, proposed Maize leaf disease based on feature enhancement with 91.83% Accuracy and the problem statement is Not facilitated a rapid and reasonable judgement for crop disease information.

Peng Jiang, Yuehan Chen, Bin Liu, Dongjian He, Chunquan Liang, May 2019, proposed Apple leaf disease using deep learning with 97.14% Accuracy.

Bin Liu, Cheng Tan, Shuqin Li, Jinrong He, Hongyan Wang, Jun 2020, proposed Data augmentation for grape leaf disease identification, with 98.70% Accuracy and the problem statement is With lack of feature extraction, generates large number of identical images are generated.

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Weihui Zenga, Miao Lib, Mar 2020, proposed Crop leaf disease recognition based on self-attention CNN with 94.81% Accuracy.

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S. Ramesh, D. Vydeki, Sep 2019, proposed Recognition of paddy leaf disease using Jaya algorithm with 98.9% Accuracy.
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Alexandre Barbosa, Rodrigo Trevisan, Naira Hovakimyana, Nicolas F. Martin, Feb 2020, proposed Crop management using CNNs with 82% Accuracy.
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Ning Yang, Junjie Yu, Aiying Wang, Jian Tang, Rongbiao Zhang, Liangliang Xie, Fangyu Shuc Oppong Paul Kwabenaa, Apr 2020, proposed Rice blast detection using fingerprint texture with 97.18% Accuracy.
Muhammad Sharifa, Muhammad Attique Khana, Zahid Iqbal, Muhammad Faisal Azam, M. Ikram Ullah Lali, Muhammad Younus Javed, Apr 2018, proposed Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation with 90.4% Accuracy.
Yan Guo, Jin Zhang, Chengxin Yin, Xiaonan Hu, Yu Zou, Zhipeng Xue, and Wei Wang, Aug 2020, proposed Plant disease identification based on deep learning with 83.57% Accuracy.
Feng Qin, Dongxia Liu, Bingda Sun, Liu Ruan, Zhanhong Ma, Haiguang Wang, Dec 2016, proposed Identification of Alfalfa Leaf Diseases Using Image Recognition with 97.64%.
Koushik Nagasubramanian, Sarah Jones, Asheesh K. Singh,, Soumik Sarkar, Arti Singh and Baskar Ganapathysubramanian, Jul 2019, proposed Plant disease identification using deep learning with 95.73% Accuracy.
Vibhor Kumar Vishnoi, Krishan Kumar, Brajesh Kumar, Apr 2020, proposed Plant disease detection using computational intelligence with 83.25% Accuracy.
Sachin B. Jadhav, Vishwanath R. Udupi, Sanjay B. Patil, Jan 2020, proposed Plant disease identification using convolutional neural network with 98.75% Accuracy.
M.A. Ebrahimi, M.H. Khoshtaghaza, S. Minaei, B. Jamshidi, Mar 2017, proposed Pest detection based on SVM with 84.55 Accuracy.

Performance analysis of plant leaf disease identification

Experimental results of four existing methods, namely, three existing protocols, namely INC-VGGN, optimized dense convolutional neural network (CNN) architecture (Optimized DenseNet), Inception module and Rainbow concatenation with Single Shot multi-box detector (INAR-SSD) and Multi Support Vector Machine (M-SVM) are implemented in MATLAB. For conducting the experiments plant village dataset https://www.kaggle.com/emmarex/plantdisease/discussion is used from kaggle is taken for performing plant leaf disease identiifcaiton. Four parameters are employed to compute the performance, namely

- Disease identification accuracy,
- False positive rate
- Detection speed and
- Sensitivity

The performance of four existing methods is analyzed with the aid of table value and graphical analysis.

Performance analysis of disease identification accuracy

Disease identification accuracy is defined as the number of input plant images provided as input that are correctly classified as normal or diseased to the total number of pant leaf images. The disease identification accuracy is mathematically evalauted as given below.

$$Acc = \left[\frac{n_{cc}}{n}\right] * 100 \qquad (1)$$

From the above equation (1), accuracy 'Acc' is obtained based on the number of plant leaf images provided as input 'n' and number of images correctly classified 'n_{cc}'. It is measured in terms of percentage (%).

Table 1 Tabulation for disease identification accuracy

Number of images	**Disease identification accuracy (%)**			
	INC-VGGN	**Optimized DenseNet**	**INAR-SSD**	**M-SVM**
20	75	70	68.25	65.25
40	83	80	75.35	73.45
60	87	85	78.45	74.15
80	88	84	75.15	70.25
100	84	82	73.25	72.15
120	85	83	71.45	69.45
140	84	82	70	68.35
160	88	86	74.15	72.55
180	86	84	73.15	71.45
200	85	83	71.45	70.85

Table 1 given above shows the performance results of disease identification accuracy for different numbers of images. From the above table values it is inferred that the disease identification accuracy performance of INC-VGGN is comparatively higher than Optimized DenseNet, INAR-SSD and M-SVM. The graphical results of disease identification accuracy are illustrated in figure 1.

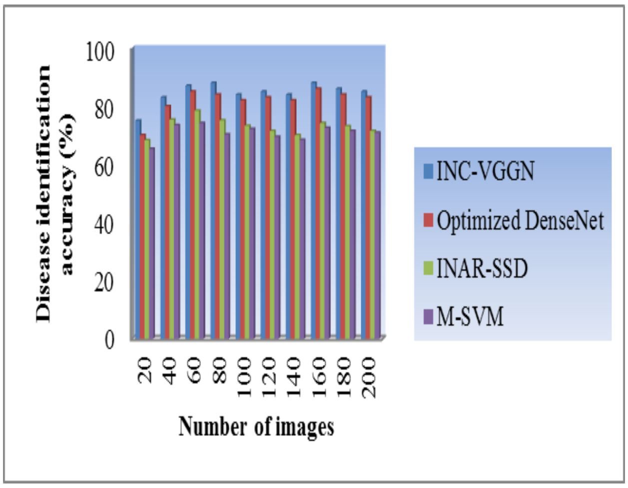

Figure 1 Graphical representation of disease identification accuracy

Figure 1 given above shows the graphical representation of disease identification accuracy with respect to 200 different numbers of images. From the figure, it is clear that the disease identification accuracy using INC-VGGN method is greater than Optimized DenseNet, INAR-SSD and M-SVM. This is due to the application of Transfer Learning of the Deep Convolutional Neural Networks for plant leaf disease identification. Instead of initiating the training from the starting point in a random manner by assigning the weights, pre-trained networks were utilized to initialize the weights, therefore resulting in the improvement of disease identification accuracy of INC-VGGN by 3% compared to Optimized DenseNet, 16% compared to INAR-SSD and 19% compared to M-SVM respectively.

Performance analysis of false positive rate

False positive rate is defined as the percentage ratio of number of input plant leaf images inaccurately classified to the total number of plant leaf images considered as input for experimentation. The false positive rate is analyzed is expressed as given below.

$$FPR = \left[\frac{n_{ic}}{n}\right] * 100 \quad (2)$$

From the above equation (2), false positive rate 'FPR' is obtained based on the number of images provided as input 'n' and number of images incorrectly classified 'n_{ic}' and is expressed in terms of percentage (%).

Table 2 Tabulation for false positive rate

Number of images	False Positive Rate (%)			
	INC-VGGN	Optimized DenseNet	INAR-SSD	M-SVM
20	25	30	34	35
40	17	20	22	24
60	13	15	18	21
80	12	16	19	22
100	16	18	21	23
120	15	17	20	19
140	16	18	22	20
160	12	14	17	18
180	14	16	19	20
200	15	17	20	21

Table 2 given above provides the simulations results of false positive rate versus different numbers of input images provided as input. The table values shows that performance of false positive rate is comparatively reduced by INC-VGGN when compared to Optimized DenseNet, INAR-SSD and M-SVM. The graphical results of false positive rate are shown in figure 2.

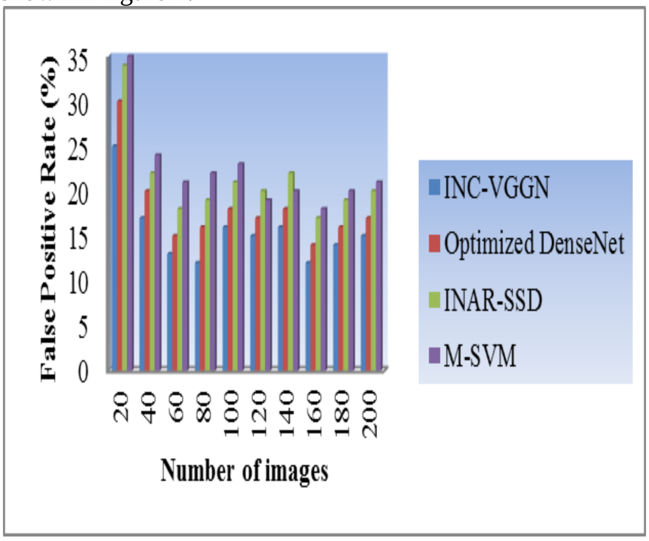

Figure 2 Graphical representation of false positive rate

Figure 2 given above shows the graphical representation of false positive rate for different numbers of input images. From the figure it is inferred that the false positive rate using INC-VGGN is lesser than Optimized DenseNet, INAR-SSD and M-SVM. The reason behind the improvement is due to the application of the deep learning approach using the tanh activation function at the output layer. With this activation function, features are analyzed in an effective manner and classified accordingly. Followed by classification, out-of-sample error is measured, upon occurrence of minimal error, the process is said to be stopped or else, the weights between the layers are adjusted and similar processes is said to be repeated, therefore contributing to false positive rate. With this, the INC-VGGN reduced the false positive rate by 14% compared to Optimized DenseNet, 27% compared to INAR-SSD and 30% compared to M-SVM respectively.

Performance analysis of detection speed

Detection speed refers to the speed with which the plant disease are said to be detected. Higher the detection speed more efficient the method is said to be. This is mathematically evaluated as given below.

$$DS = \sum_{i=1}^{n} n_i * Time\ [PLDD] \quad (3)$$

From the above equation (3), the detection speed 'DS' is measured based on the samples or number of images considered for simulation 'n' and the time consumed in plant leaf disease detection '$Time\ [PLDD]$'. It is measured in terms of frames per second (FPS). Table 3 given below shows the simulation results of detection speed versus number of data packets. The table values illustrate the packet delivery ratio performance of Scalable and energy efficient routing protocol (SEEP) is comparatively higher than Cluster-Tree based Energy Efficient Data Gathering (CTEEDG) protocol and Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol (FBCFP). The graphical results of packet delivery ratio are shown in figure 3.

Table 3 Tabulation for detection speed

Number of images	Detection speed (FPS)			
	INC-VGGN	Optimized DenseNet	INAR-SSD	M-SVM
20	15.25	16.15	17.55	16.55
40	16.15	17.85	19.35	18.25
60	18.25	20	21.25	20.45
80	14.35	15	16.45	15.85
100	15.25	17	18.35	17.45
120	19.35	20.15	20.25	20.20
140	21.25	22.15	22.45	22.30
160	18.45	20.25	21.15	20.85
180	19.35	20.85	21.35	21
200	17.25	19.35	23.13	20.45

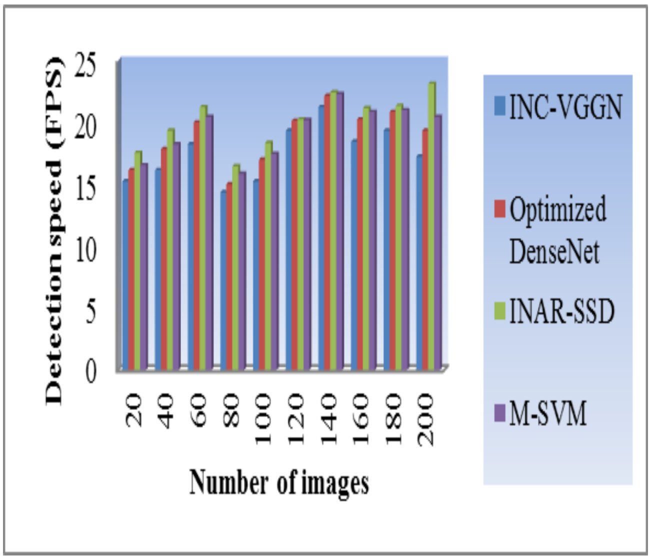

Figure 3 Graphical representation of detection speed

Figure 3 given above shows the detection speed for four different methods, INC-VGGN, Optimized DenseNet, INAR-SSD and M-SVM respectively with respect to 200 different numbers of images. From the figure it is inferred that the detection speed is high using INAR-SSD when compared with three other different methods. The improvement in detection speed using INAR-SSD is due to the application of deep learning-based approach. With this deep learning-based approach, discriminative features are extracted automatically. Moreover, by introducing GooGleNet Inception model and combining Rainbow concatenation, multi-scale disease object detection is enhanced therefore improving disease detection performance. With this, the detection speed is said to be improved using INAR-SSD by 16% compared to INC-VGGN, 7% compared to Optimized DenseNet and 4% compared to M-SVM respectively.

Performance analysis of sensitivity

Sensitivity refers to the potentiality of a test (i.e., plant leaf disease identification) to correctly identify sample plants with a disease. In other words, it measures the ratio of positives (i.e., diseased plant leaf) that are correctly identified (e.g., the percentage of diseased plant leaf which is correctly identified as having some disease). This is mathematically expressed as given below.

$$S = \frac{TP}{TP + FN} * 100 \quad (4)$$

From the above equation (4), the sensitivity rate 'S' is measured based on the number of true positives 'TP' and the summation of true positive and false negative '$TP + FN$' respectively. It is measured in terms of percentage (%).

Table 4 Tabulation for detection speed

Number of images	Sensitivity (%) – TPR			
	INC-VGGN	Optimized DenseNet	INAR-SSD	M-SVM
20	84.25	85	86.35	89.45
40	85.55	86.25	87.55	91.35
60	87.35	88.25	88.95	92.45
80	88.15	89	90.35	94.15
100	86.35	87.45	89.25	90.25
120	87.35	88	89.45	92.55
140	90.25	91.35	92	97.15
160	88.15	89.35	90	95.25
180	86.15	87.35	88	94.15
200	87	88.45	89	95

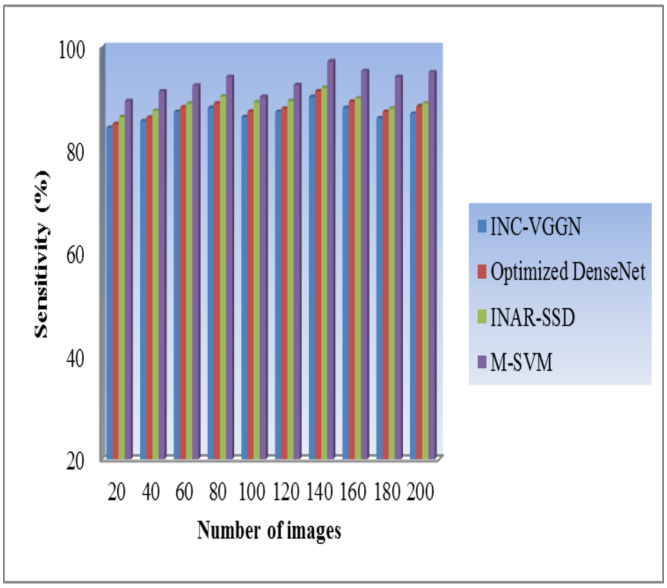

Figure 4 Graphical representation of sensitivity

Figure 4 given above shows the graphical representation of sensitivity with respect to 200 numbers of images. From the figure it is inferred that the sensitivity rate is better using M-SVM when compared to three other methods. The reason behind the improvement of sensitivity is due to the application of three procedures separate for preprocessing, segmentation and feature extraction and classification. Here, a hybrid contrast stretching strategy was utilized where a 3D-Box filter was applied that in a start blurred the boundary of a lesion spot, followed by an application of de-correlation function that in turn minimized the image distortion. Then a strong correlation using expectation maximization was utilized upon detection of smaller infected region and finally, with the application of genetic algorithm for feature selection via parallel approach in turn improved the sensitivity of M-SVM by 7% compared to Optimized DenseNet, 6% compared to INAR-SSD and 5% compared to M-SVM respectively.

Discussion and Limitation on plant leaf disease detection

INC-VGGN was proposed to improve the feature extraction rate involved in plant leaf disease detection. Though improvements here were found to be in terms of accuracy, the time consumed in detecting the plant leaf disease was not concentrated. Optimized DenseNet with the aid of modified depth Convolution was utilized. In addition, the loads of the weights were stored and via best fit model classification was performed that in turn resulted in optimization of identifying corn leaf disease. Despite improvement observed in optimization, the disease detection accuracy was not concentrated. INAR-SSD method was designed using data augmentation and image annotation with the aid of laboratory and complex images. Here, deep convolutional neural network was used with the objective of detecting the common disease in apple plant leaf. With this not only the accuracy was said to be attained but also the detection speed was said to be faster. M-SVM utilized a correlation model and feature selection was performed using genetic algorithm for apple disease detection based on the pertinent features. With this, the classification accuracy was said to be effective. However, the time consumed in disease detection was less focused.

Major Research Gap

A comparison of different plant leaf disease detection methods are analyzed and inspected. From the study, it is comprehensible that the disease detection accuracy was improved using INC-VGGN. INC-VGGN was proposed to improve the feature extraction rate involved in plant leaf disease detection. Though improvements here were found to be in terms of accuracy, the time consumed in detecting the plant leaf disease was not concentrated. Moreover, the false positive rate was also reduced by means of INC-VGG. However, the detection speed and sensitivity rate was not concentrated. Optimized DenseNet with the aid of modified depth Convolution was utilized. In addition, the loads of the weights were stored and via best fit model classification was performed that in turn resulted in optimization of identifying corn leaf disease. Despite improvement observed in optimization, the disease detection accuracy was not concentrated. INAR-SSD method was designed using data augmentation and image annotation with the aid of laboratory and complex images. Here, deep convolutional neural network was used with the objective of detecting the common disease in apple plant leaf. With this not only the accuracy was said to be attained but also the detection speed was said to be faster. M-SVM utilized a correlation model and feature selection was performed using genetic algorithm for apple disease detection based on the pertinent features. With this, the classification accuracy was said to be effective. However, the time consumed in disease detection was less focused.

Research Questions

Based on the above research gap leads to the following research questions

- What if the affected leaf area is concentrated by means of a better classifier model?
- Whether noise present in the image being removed makes a different in the performance accuracy?
- Does concentration on region of interest plays a major role in prediction accuracy?
- Does feature extraction play a pivotal role in improving the classifier performance?

Conclusion

A comparison of different plant leaf disease detection methods are analyzed and inspected. From the study, it is comprehensible that the disease detection accuracy was improved using INC-VGGN. Moreover, the false positive rate was also reduced by means of INC-VGG. However, the detection speed and sensitivity rate was not concentrated. On the other hand, the detection speed was found to be faster with the aid of INAR-SSD. However, the false positive rate and detection accuracy was not focused. In addition, the sensitivity rate was found to be higher using M-SVM, but less focus was made on detection speed and detection accuracy. The wide range of experiments on existing method computes the performance of the plant leaf disease detection with its own drawbacks. Finally in future, the research work can be carried out using deep learning technique for concentrating on the computational cost and classifier performance involved in plant leaf disease detection.

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