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# An Efficient Guided Backpropagation Approach for Detection of Plant Diseases Using Deep Learning Models

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**Abstract:** Technology driven agriculture or precision agriculture is an important research area as there is need for significant changes in agriculture for productivity. Researchers are inspired by the emergence of deep learning techniques as they are suitable for computer vision applications like plant disease detection. There are many pre-trained deep learning models already being used for this purpose. However, they are applied to entire leaf images leading to time and space complexity. In this paper, we proposed a novel deep learning framework that exploits pre-trained deep learning models along with transfer learning towards faster convergence and higher level of accuracy. Besides our framework is enhanced with Region of Interest (ROI) computation to leverage detection accuracy and reduction of computational complexity. We proposed an algorithm known as Learning based Plant Disease Detection using Guided Backpropagation for ROI Computation (LbPDD-GBROIC). The proposed framework exploits pre-trained deep models such as AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet v1 and VGG19 along with transfer learning and ROI computation. Our empirical study using PlantVillege dataset revealed that ROI computation has significant impact on all models. Inception V3 model outperformed other models with 99.76% accuracy.

**Keywords –** Plant Disease Detection, Deep Learning, Pre-Trained Models, Transfer Learning, Region of Interest, Guided Backpropagation

## 1. Introduction

Agriculture is the backbone of the entire world either directly or indirectly. India is particularly an agriculture based country where technology usage for monitoring agriculture has made significant strides with the ResourceSat-2 and ResourceSat-2 A satellites developed by Indian Space Research Organization (ISRO). With multi-spectral imaging and data of these satellites coupled with geospatial tools available, there is possibility for working towards Precision Agriculture (PA), a technology driven approach to optimize farming inputs and produce optimal outcomes, covering different dimensions of agriculture. They include crop yield estimation, understanding variations in crops, obtaining soil conditions, finding health of crops, crop discrimination and so on. As found in the literature, it is understood that agricultural crop monitoring at the level of a government is always in different perspective. It is in the perspective of analysis of agricultural dimensions and dynamics in the country. However, there is need for reaching PA benefits to rural agricultural communities and farmers. This is the main problem for many reasons such as feasibility, monetary and issues pertaining to quality of satellite imagery. Poor spatial resolution has been the primary problem with satellite image processing. However, there has been significant improvement in the satellite usage strategies and technologies of late. Now it is possible to have multi-spectral images pertaining to agricultural crops with desired quality and process it. Unmanned Arial System (UAS) is an important alternative when satellite imagery does not serve due to poor lighting conditions or lack of conducive atmosphere. With improved spatial resolution that is sufficient for precision farming applications, multi-spectral remote sensing satellites are capable of serving immensely. With all these encouraging signs from one side and the farmers being away from technological innovations from other side, there is need for brining precision farming closer to the farmers. This is the motivation behind taking up this research which is aimed at building a precision farming system that is Artificial Intelligence (AI) enabled and meant for

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analysing multi-spectral images captured by satellites and UAS (if used) to detect crop diseases. This research is to leverage technological innovations and help farmers to reap its benefits. It can be used by any person or entity targeting particular crop in a given region to know health of the crop and make well informed decisions. Though there are plenty of possibilities in precision farming, this research initially limits its functions to crop disease detection early so that, it helps the stakeholders to make decisions in right time and act in right time in right way. With AI capabilities that involve in machine learning and deep learning techniques, there is possibility of considering any crop because there is sufficient training data to detect crop diseases of all crops in India. Therefore, this research is not limited to a particular crop as it can monitor any crop and detect diseases early with the help of deep learning based pre-trained models that grow in training samples from time to time. By exploiting transfer learning techniques, this research optimizes the training time and ensures faster detection of diseases.

## 2. Related Work

This section reviews literature on existing methods on automatic plant disease detection. There have been improvements in capturing satellite based multi-spectral imagery as explored in [1], [5], [14] and [15]. In [1] classification of forest species is made and the health condition is also analysed using multi-spectral imagery. In [5] monitoring wheat diseases and discriminating is performed using multi-spectral satellite images. In [14] UAV is used in order to capture multi-spectral images of crop and wheat crop is analysed to understand the growth conditions. In [15], land cover research carried out with semi-supervised learning for classification using adaptive kernel and multi-attention with multi-spectral satellite imagery.

There is an alternative approach found for capturing agricultural images using Unmanned Aerial Vehicle (UAV) as explored in [1], [3], [11], [14] and [19]. Wheat rust disease detection is studied in [2], [12] using high spatial resolution images acquired suing satellite technology. The concept of crop phenotyping is investigated with satellite imagery based applications in [4] and [13] while powdery mildew disease detection is studied in [6]. Grapevine leaf roll disease detection [7], purpose spot disease detection [8], crop yield prediction and estimation of nitrogen [9], using remote sensing for plant disease monitoring and pests [10] are some of the important international studies found in the literature.

Land cover classification is explored in [15] with different machine learning techniques. The usage of hyperspectral images with high resolution is found essential as found in the literature. Such images are available with the innovations in satellite technologies and they are helping in precision agriculture research [16]. The usage of satellite data with different kinds of analysis on the data available is studied in [17] using imagery captured from China satellite known as GF-1. Early detection of plant disease and plant stress detection is studied in [18] by using multi-spectral imagery. It is understood from the literature that there is significant increase in the quality of multi-spectral imagery like never before and that has led to the progress in the research of precision farming. In [20] feasibility of the precision farming is explored with satellite imagery.

Khalil et al. [21] observed that the Crop yield prediction is crucial for agriculture management. Satellite and deep learning techniques enhance accurate yield estimation. Kala et al. [22] found that the Plantain cultivation faces diseases; deep learning techniques like G-RecConNN aid disease classification and early detection for farmers. Maillet et al. [23] discussed about Crop disease detection by using weather and satellite data with transformer-based multimodal fusion architecture yields promising results. Sharma et al. [24] automated plant disease detection using ML and DL techniques is pivotal for agriculture. Challenges and improvement strategies outlined. Nerkar et al. [25] described Quality crop production relies on timely fertilization and effective disease detection. A novel GAN-based model improves cross-dataset accuracy. Hirani et al. [26] explored CNNs which are widely used in plant disease detection, but transformers show potential with a 97.98% validation accuracy. Saleem et al. [27] found that agriculture's automation is by AI and robotics thrives with advancements in ML and DL, outperforming traditional methods in efficiency. Thakar et al. [28] enabled the digitization of agriculture by technological advancements. Machine learning aids efficient farming practices and economic growth.

Lakshmi et al. [29] proposed DPD-DS that employs an efficient CNN framework for precise plant disease detection and segmentation, exhibiting improved accuracy and speed. Ang et al. [30] stated that the Hyper spectral and multispectral technologies aid agriculture. Review explores big data, ML, and deep learning applications, proposing EML-SPDA solution. Shin et al. [31] employed DL to identify strawberry powdery mildew, evaluating popular models. ResNet-50 shows highest accuracy. Joshi et al. [32] introduced a robust deep-learning system for plant disease identification achieving 99.58% cross-validation accuracy. Jain et al. [33] introduced an advanced disease detection system for crops using image processing and mimetic salp swarm optimization. Liu et al. [34] reviewed the progress and challenges of deep learning techniques in hyper spectral image analysis in agriculture. Srinidhi et al. [35]

presented a solution for swift paddy classification into healthy or diseased plants using CNN and contour detection. From the review of literature, it is observed that there is need for improving plant disease detection process by considering region of interest.

## 3. Proposed System

This section presents the proposed system, shown in Figure 1, based on pre-trained deep learning models. It also throws light on our novel approach defined for ROI computation besides the proposed algorithm. Besides, it provides details of transfer learning used with the pre-trained deep learning models.

### 3.1 Problem Definition

Provided a leaf image collected from agricultural crop, detecting whether the crop is affected with a disease and classifying the disease is the important problem considered. Moreover, the solution should consider ROI in the given leaf so as to improve detection accuracy.

### 3.2 Proposed Architecture

The proposed system has two phases known as offline phase and online phase as part of supervised learning. In the offline process, continuous improvements are made with respect to training and increasing samples in the crop leaf disease database. In the offline process there is provision for taking new training samples and update crop disease prediction model from time to time. After taking new training samples, features are extracted (using filter model) and then features are optimized (using wrapper method). The optimized features are given to train an advanced Convolutional Neural Network (CNN) model (one of the pre-trained deep models like AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet1_1 and VGG19) such as that is best used to build a prediction model. It can also take knowledge from pre-trained deep learning models that get updated from time to time to leverage training accuracy. The online approach is initiated on demand by the user or the system automatically. When user provides a test sample or set of samples, it is subjected to noise removal which is essential for quality improvement. After removing noise, Region of Interest (ROI) is computed and identified. For the ROI region feature selection is carried out with filter and wrapper methods. Then the optimized features are given to the crop disease prediction model which identifies the disease. Thus the trained samples are stored back to crop leaf disease database in order to increase training samples from time to time. As training samples are increased, the detection accuracy will be improved further.

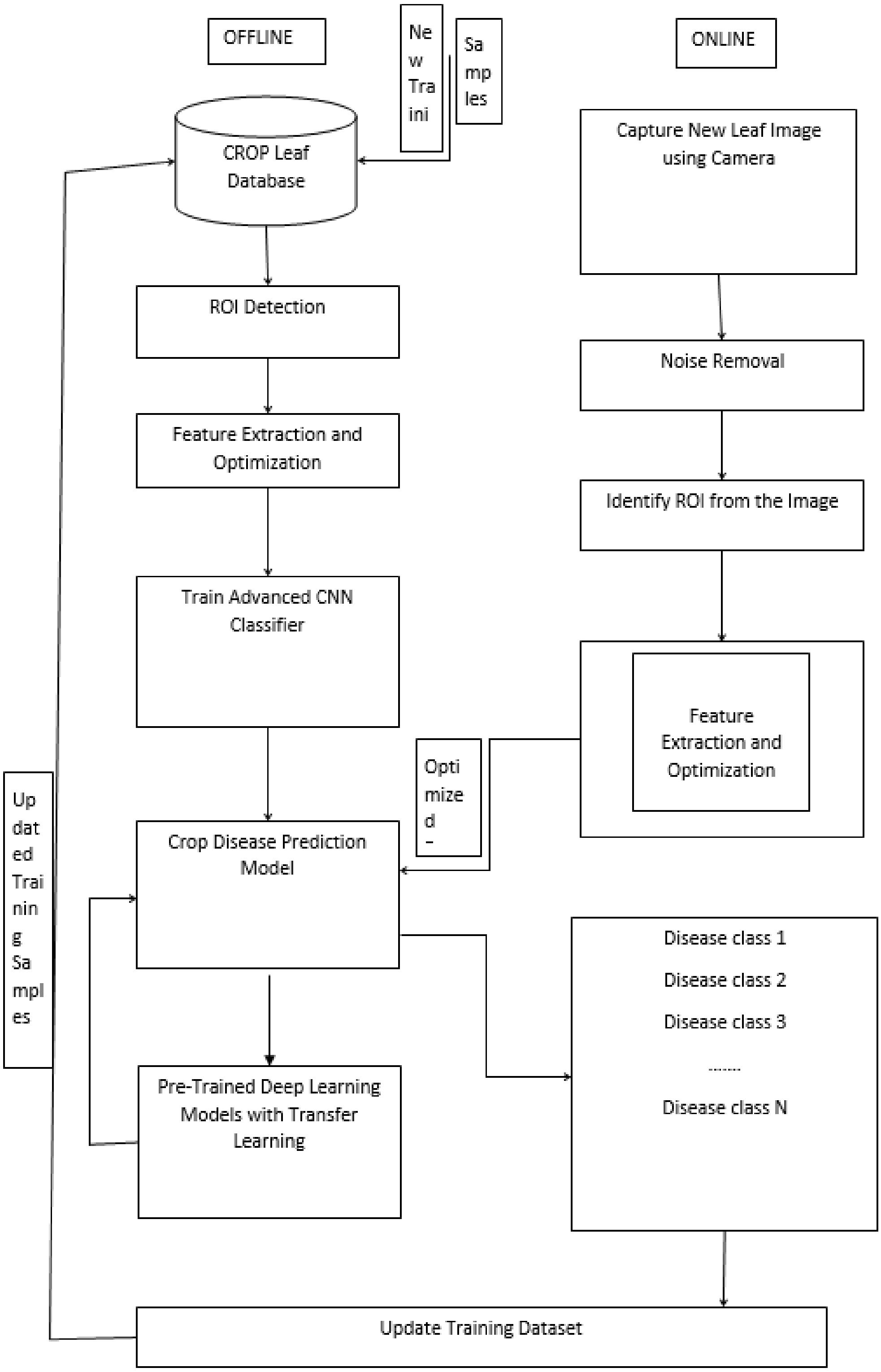


**Fig 1:** Proposed system for AI enabled plant disease detection

As the processing of entire image is costly in terms of computations and execution time, we proposed a novel methodology for ROI computation which finds the region which is affected by some disease. ROI computation method analytically estimates significance of each pixel. This method is based on the intuition that, considering ground truth denoted as *y*, the pixels that are significant can impact on the training process and resultant accuracy in prediction. A pixel is considered important if its value of gradient is a bigger absolute value. In the same fashion, if the value of gradient is close to zero or nearer to it, its importance is less. With aggregation, the overall importance of a region on leaf is computed. Computing a gradient and finding whether a pixel is important is not computationally expensive. This is the novel approach used for plant disease detection. It enables the proposed system to leverage detection accuracy.

| Notation | Meaning |
|---|---|
| $x$ | Denotes input image |
| $f(x)$ | Denotes output of network |
| $G(x)$ | Denotes the gradient |
| $W$ | Denotes width |
| $H$ | Denotes height |
| $i$ | Denotes indexing channels |
| $j, k$ | Denotes indexing channels for pixels |
| $W * H$ | Denote height and width dimensions |
| TP | True positive |
| TN | True negative |
| FP | False positive |
| FN | False negative |

**Table 1:** Notations used in this paper

In order to compute ROI, given input image *x* is propagated through the network and compute output of the network denoted as $f(x)$. Then, with respect to *x*, gradient of $f(x)y$ is computed considering the ground truth of *x*. Computation of the gradient, denoted as $G(x)$, is done as in Eq. 1. This will help in finding the significance of each pixel in *x*. A tensor, $G(x)$, has dimension which is same as that of *x*. Therefore tensor's dimension is $3 * W * H$ which has indices such as *i*, *j* and *k*, representing channels and pixels respectively.

$$G(x) = \frac{df(x)y}{dx} \quad (1)$$

To know significance of pixel $x(i,j)$, across the channels maximum absolute values are computed. The resultant matrix known as M is computed as in Eq. 2.

$$M(i,j) = Max\{|G(0,i,j)|, |G(1,i,j)|, |G(2,i,j)|\} \quad (2)$$

Thus the ROI computation process has provision to localize the important region with considerable precision in the given input image. It is achieved with guided backpropagation. With the computation of ROI, the rest of the process such as training will be done based on ROI to reduce space and time complexity besides making it computational inexpensive. Table -1 has notations used in this paper.

### 3.3 Pre-Trained Models Used

In this paper we used many pre-trained deep learning models and exploited transfer learning for improving their plant disease detection performance. The models include AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet v1 and VGG19. AlexNet [36] is a CNN variant widely used in computer vision applications. DenseNet169 [37] is another pre-trained model used in the proposed system. Inception V3 [38] is another CNN variant used to solve different real world problems such as sentiment analysis and computer vision based applications. ResNet50 [39] is the CNN based model that has identity and convolutional blocks designed to improve prediction performance. Sqeezenet v1 [40] and VGG19 [41] are the other two CNN[42] variants used in computer vision applications. In this paper, all these models are used along with transfer learning for leveraging plant disease detection performance.

### 3.4 Transfer Learning

Transfer learning is the process of reusing pre-trained deep learning models to solve new kinds of problems. With transfer learning, the pre-trained deep learning models mentioned in Section 3.3 are reused to exploit their knowledge gained from training ImageNet and train them with new samples to leverage their performance.

### 3.5 Algorithm Design

Learning based Plant Disease Detection using Guided Backpropagation for ROI Computation (LbPDD-GBROIC)

**Input:** Learning based Plant Disease Detection using Guided Backpropagation for ROI Computation

**Inputs**

PlantVillege dataset D

Pre-trained deep learning models pipeline P

(P includes AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet v1 and VGG19)

**Output**

Plant disease classification results R

1. Begin
2. (T1, T2)🡠DataSplit(D)
3. For each model p in P
4. For each instance t1 in T1
5. roi🡠ComputeROI(t1)
6. F🡠ExtractFeatures(F)
7. Train p using F (transfer learning)
8. End For
9. End For
10. For each trained model p in P
11. R🡠TestModel(T2)
12. Display R
13. End For
14. End

**Algorithm 1:** Learning based Plant Disease Detection using Guided Backpropagation for ROI Computation

As presented in Algorithm 1, it takes PlantVillege dataset D and pre-trained deep learning models pipeline P as inputs and perform disease detection. It results in disease detection and classification. The given dataset is divided into training set (T1) and test set (T2) before the algorithm uses guided backpropagation approach towards ROI computation and training pre-trained models through transfer learning. There is an iterative process involved in step 3 through step 9 where each training data instance is subjected to ROI computation followed by feature extraction. Then in step 7 a model is trained using the features. All the trained models are persisted for reuse of models in future. This could help in prevention of reinventing wheel and reuse same models every time for testing phase. Each trained model is used to perform plant disease detection and classification using T2. Finally, the algorithm returns classification results.

### 3.6 Evaluation Methodology

Confusion matrix is conceptually illustrated in Figure 2. It reflects four different cases possible when the proposed system detects given test sample. When there is a disease in the given sample and if the proposed algorithm detects it as such, this case is known as True Positive (TP). When there is no disease in the given sample and if the proposed algorithm detects it as healthy, this case is known as True Negative (TN). When there is no disease in the given sample and if the proposed algorithm detects it as having disease, this case is known as False Positive (FP). When there is actual disease in the given sample and if the proposed algorithm detects it as healthy, this case is known as False Negative (FN).

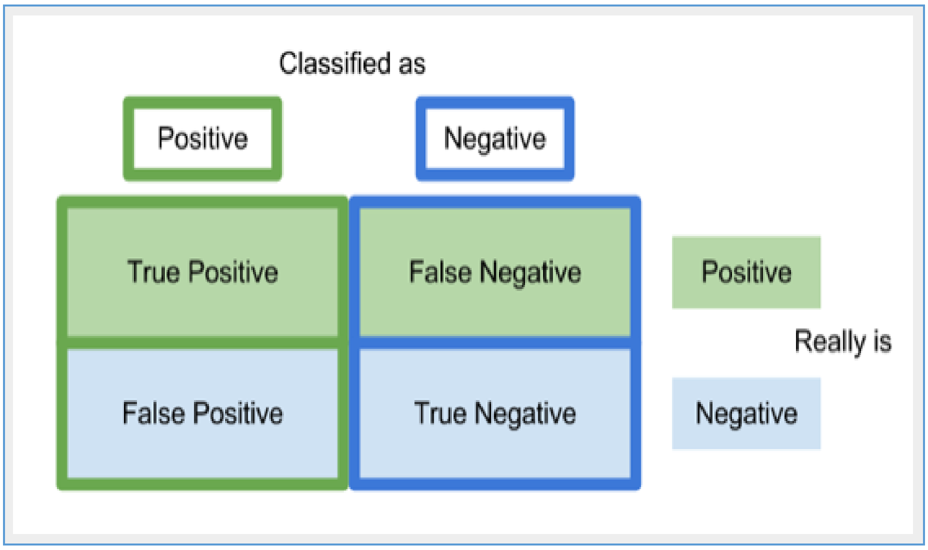


**Fig 2:** Confusion matrix

Based on the confusion matrix and the four cases described above, different performance metrics are derived and used for evaluation of the proposed system. Accuracy is a widely used metric for performance evaluation. This metric is as expressed in Eq. 3.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

Accuracy reflects the number of correct predictions against all the predictions made by an anomalous detection model. This metric results in a value between 0.0 and 1.0 reflecting least and highest performance respectively.

## 4. EXPERIMENTAL RESULTS

This section presents experimental results of the proposed framework. In other words, all pre-trained deep models are evaluated with and without guided backpropagation or ROI approach. The models used by the framework include AlexNet [36], DenseNet169 [37], Inception V3 [38], ResNet50 [39], Sqeezenet v1 [40] and VGG19 [41]. The models are evaluated with different kinds of test images. Their performance is analysed in terms of training time and accuracy.

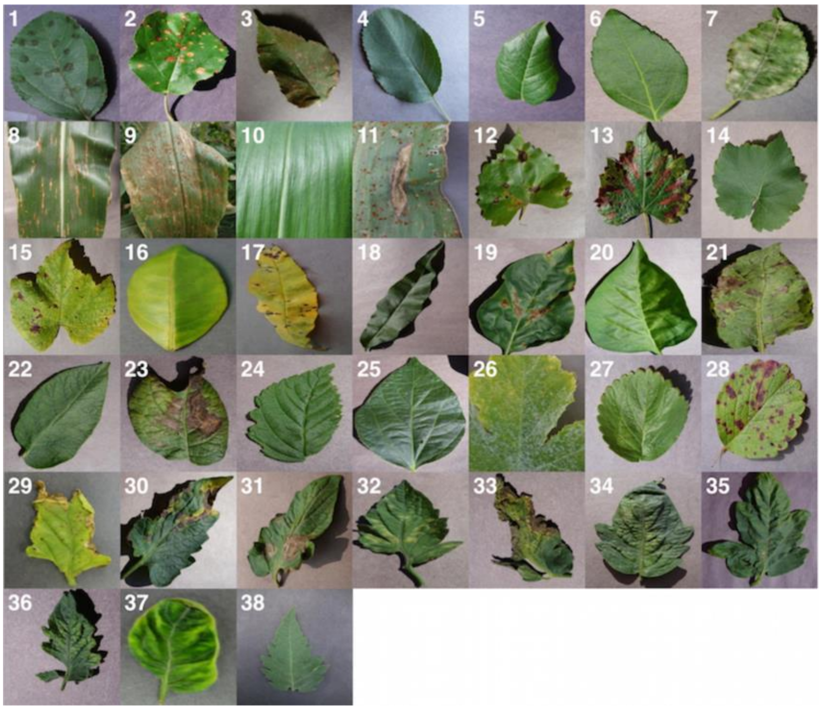


**Fig 3:**An excerpt from Plant Village dataset reflecting various crops and diseases

As presented in Figure 3, an excerpt from PlantVillege data is provided with visualization of all representative crops and diseases.

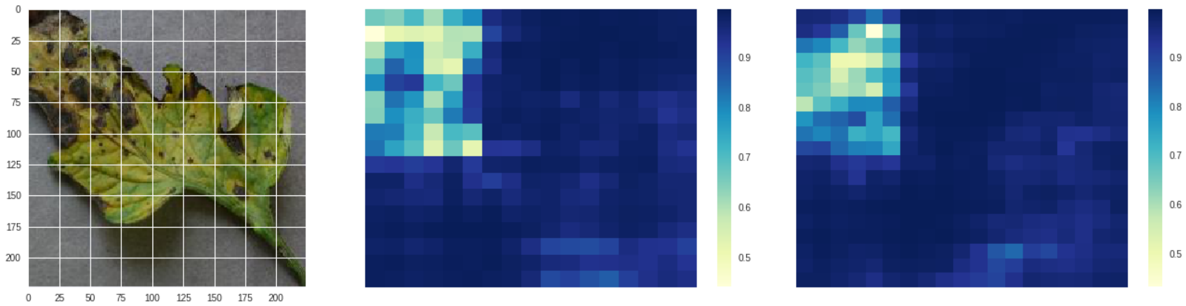


**Fig 4:** Early blight disease detection in Tomato crop

As presented in Figure 4, the given test sample is correctly detected and classified as early blight disease in Tomato crop. The input image and its heatmaps are visualized.

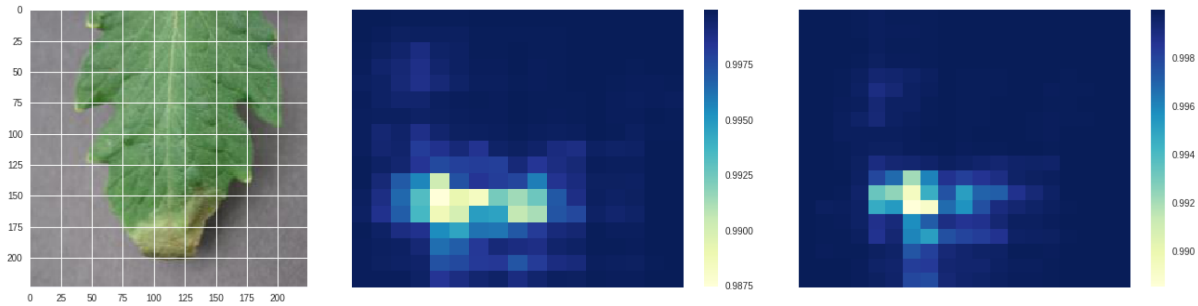


**Fig 5:** Late blight disease detection in Tomato crop

As presented in Figure 5, the given test sample is correctly detected and classified as late blight disease in Tomato crop. The input image and its heatmaps are visualized.

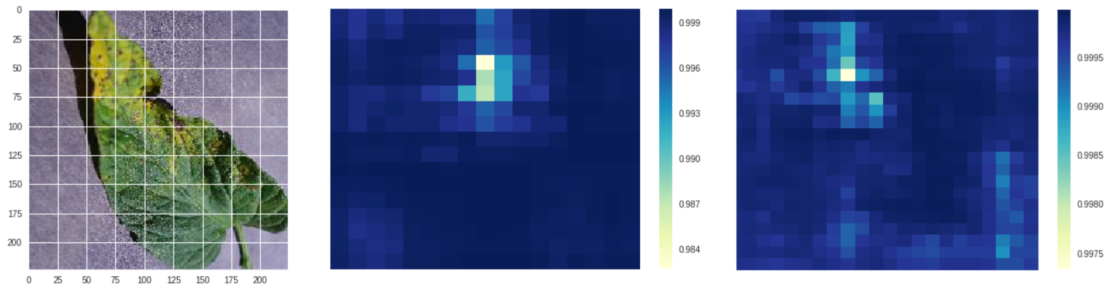


**Fig 6:**Septorial leaf spot disease detection in Tomato crop

As presented in Figure 6, the given test sample is correctly detected and classified as septorial leaf spot disease in Tomato crop. The input image and its heatmaps are visualized.

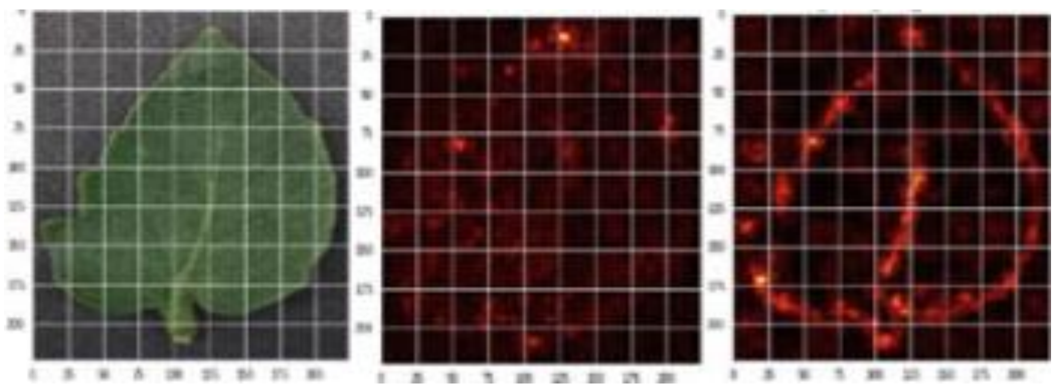

**Fig 7:** Healthy Tomato leaf and its ROI without guided backpropagation and with guided backpropagation

As presented in Figure 7, given test sample (left) is correctly classified as healthy Tomato leaf and its ROI without guided backpropagation (middle) and ROI with guided back propagation (right) are visualized.

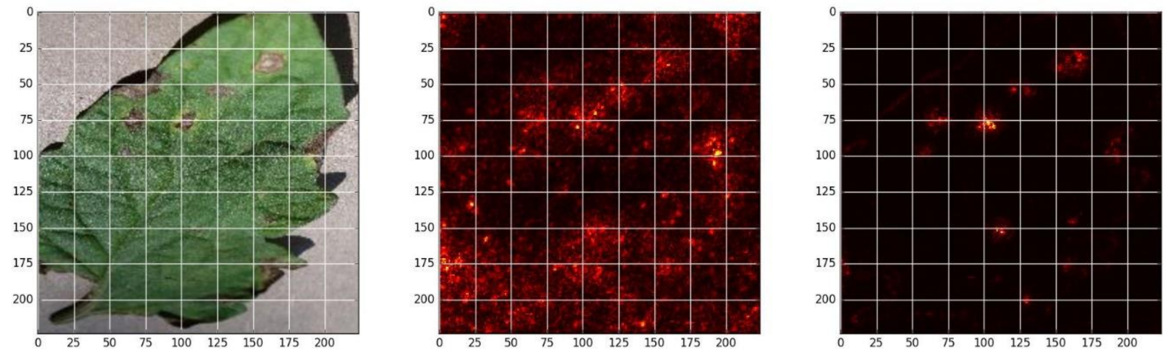

**Fig 8:** Tomato early blight disease detection and ROI without guided backpropagation and with guided backpropagation

As presented in Figure 8, given test sample (left) is correctly classified as early blight disease in Tomato crop and its ROI without guided backpropagation (middle) and ROI with guided back propagation (right) are visualized.

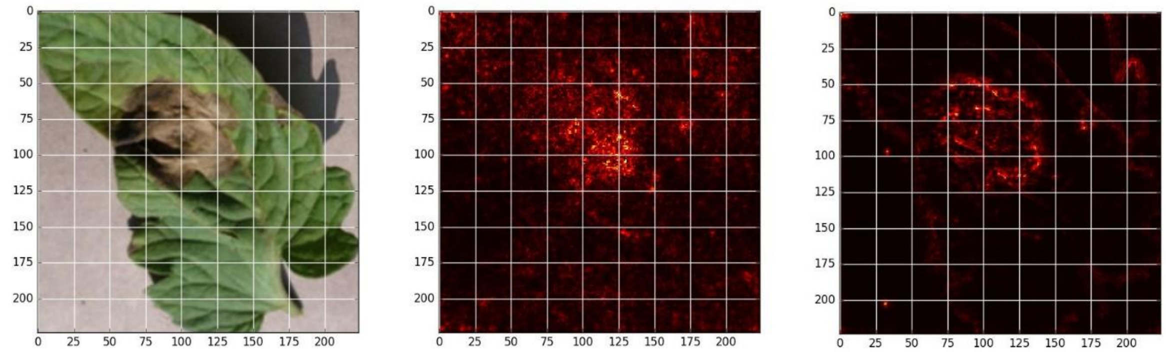

**Fig 9:** Tomato late blight disease detection and ROI without guided backpropagation and with guided backpropagation

As presented in Figure 9, given test sample (left) is correctly classified as late blight disease in Tomato crop and its ROI without guided backpropagation (middle) and ROI with guided back propagation (right) are visualized.

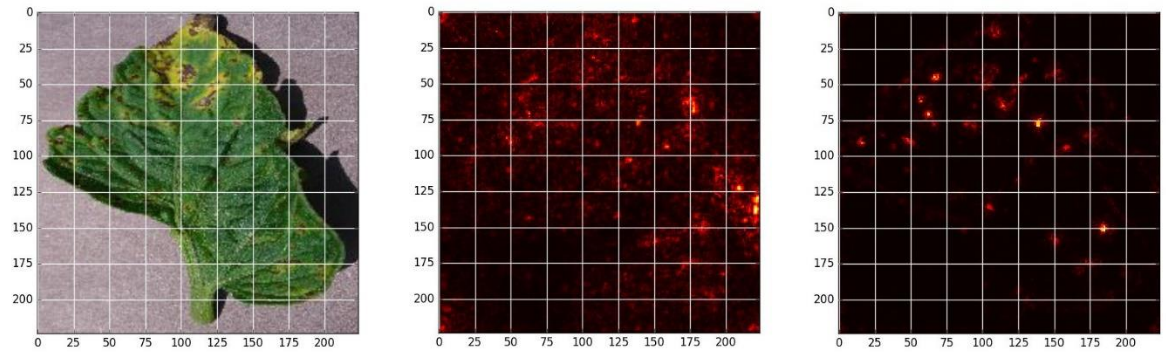

**Fig 10:** Tomato septorial leaf spot disease detection and ROI without guided backpropagation and with guided backpropagation

As presented in Figure 10, given test sample (left) is correctly classified as septrorial leaf spot disease in Tomato crop and its ROI without guided backpropagation (middle) and ROI with guided back propagation (right) are visualized.

| **Model** | **Training time(h)** | **Accuracy without (ROI)** | **Accuracy with (ROI)** |
|---|---|---|---|
| AlexNet | 1.5 | 0.8926 | 0.9924 |
| DenseNet169 | 3.16 | 0.9193 | 0.9972 |
| Inception V3 | 5.64 | 0.8909 | 0.9976 |
| ResNet50 | 1.88 | 0.8777 | 0.9967 |
| Squeezenet v1 | 2.1 | 0.881 | 0.992 |
| VGG19 | 3.55 | 0.8076 | 0.9949 |

**Table 2:** Performance comparison among all models

As presented in Table 2, performance of each model is observed in terms of training time and accuracy of the model.

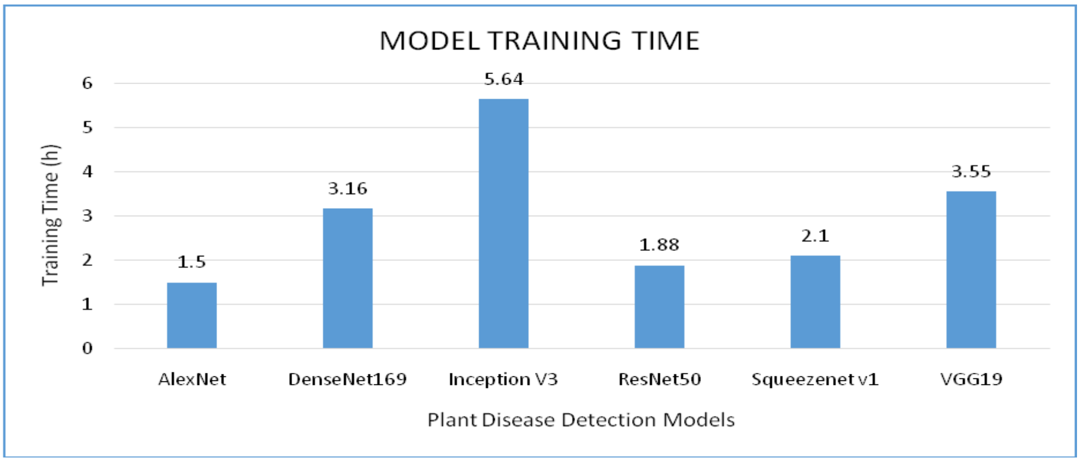


**Fig 11:** Training time comparison for all models

As presented in Figure 11, training time of each deep learning model is provided in hours. AlexNet model needed 1.5 hours, DenseNet169 3.16, Inception V3 5.64, ResNet50 1.88, Squeezenet v1 2.1 and VGG19 needed 3.55 hours. AlexNet took least time for training while ResNet50 required highest time for training.


**Fig 12:** Accuracy of deep learning models with and without ROI computation

As presented in Figure 12, all deep learning models used in the proposed framework for automatic detection of plant diseases are evaluated in terms of accuracy. Higher in accuracy indicates better prediction performance for the models. All models are pre-trained models with ImageNet. Besides transfer learning is used to retrain all the models to be more suitable for the problem in hand. Observations are made with and without ROI. As ROI computation exploits guided backpropagation, it has its influence on the accuracy of models. When ROI is not used, the least accurate model is VGG19 with 80.76% accuracy while highest accuracy is achieved by DenseNet169 with 91.93%. With ROI, the least accurate model is Squeezenet v1 with 99.20% accuracy while highest accuracy is achieved by Inception V3 with 99.76%. The experimental results revealed that the usage of guided backpropagation for ROI computation has potential to leverage model accuracy.

## 5. Conclusion and Future Work

In this paper, we proposed a novel deep learning framework that exploits pre-trained deep learning models along with transfer learning towards faster convergence and higher level of accuracy. Besides our framework is enhanced with Region of Interest (ROI) computation to leverage detection accuracy and reduction of computational complexity. We proposed an algorithm known as Learning based Plant Disease Detection using Guided Backpropagation for ROI Computation (LbPDD-GBROIC). The proposed framework exploits pre-trained deep models such as AlexNet, DenseNet169, Inception V3, ResNet50, Squeezenet v1 and VGG19 along with transfer learning and ROI computation. Our empirical study using PlantVillege dataset revealed that ROI computation has significant impact on all models. Inception V3 model outperformed other models with 99.76% accuracy with ROI. In future, we intend to improve our methodology considering hyperparameter tuning so as to improve performance of deep learning models further.

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