Plant Leaf Disease Detection using Feature-Extraction Methods.

[1]Sudeep.P, [2] Gaddam Durgasantosh , [3]G.Tejith , [4]Prof.Geetha.s.

[1,2,3] *Dept. of Computer Science and Engineering, Vellore Institute of Technology, INDIA, Chennai.*

[4]Prof. CSE Dept , Dept. of Computer Science and Engineering, Vellore Institute of Technology, Chennai, Tamilnadu, India.

***Abstract*— Plant disease is a huge challenge for farmers, which threatens their economy and food security. The rapid revolution in smartphone culture and computer vision models had created a great opportunity for image classification in agriculture. Convolutive neural networks (CNN) are considered to be at the cutting edge of image recognition technology and provide the capability to provide rapid and accurate diagnosis.In this document, the performance of a pre-formed ResNet34 model in the detection of crop diseases is investigated The developed model is deployed as a web application and is capable of recognising 7 plant diseases from healthy foliar tissues. For training and verifying the model, a dataset of 8,685 leaf pictures recorded in a controlled setting was created. The proposed method may obtain an accuracy of 97.2 percent and an F1 score of better than 96.5 percent, according to validation data. This proves CNNs' technical capability in diagnosing plant illnesses and paves the way for AI solutions for small-scale farmers.**

Keywords—deep learning, transfer learning, classification, CNN, plant disease detection, ResNet architecture, precision agriculture

I.INTRODUCTION AND LITERATURE SURVEY

To meet expected demand by 2050, worldwide crop production must increase by at least 50% [1]. Currently, the majority of production takes place in Africa and Asia, where 83 percent of farmers are family-run and have little to no horticultural experience [2, 3]. As a result, yield losses of more than 50% are typical as a result of pests and illnesses [4].

The old approach of human analysis by visual inspection is no longer viable for categorising agricultural diseases. Computer vision models provide a quick, standardised, and accurate answer to this problem. A classifier can also be used as an application once it has been trained [5]. All you need is an internet connection and a smartphone with a camera to use it. 'iNaturalist' [6] and 'PlantSnap' [7] are two popular commercial apps that show how this can be done. Both apps have been successful in not just providing users with expertise but also in creating an interactive online social network.

Smartphones are becoming more accessible and affordable every year. By 2020, the world's smartphone users will number around 5 billion [8]. One billion of these people live in India, and another one billion live in Africa. These figures have climbed every year for the last decade, according to Statista [9]. With these facts in mind, AI apps are expected to play a significant part in defining the future of agriculture.

In recent years, the application of CNNs in plant disease categorization has yielded good results [10]. The multi-layered supervised network has gained favour among academics as a result of the continuous appearance of superior findings [11]. CNN topologies have altered substantially since the publication of LeNet (1988). Sophisticated

In current architecture, functions like ReLu nonlinearity and overlapping pooling [12] have become commonplace. These advancements have aided in the reduction of training time and error rate [12]. Above all, big and complicated 21st-century datasets have necessitated the evolution of architecture [13].

ResNet (2015), a more modern architecture, added even more ground-breaking features [14]. There are dynamic skip connections as well as a lot of batch normalisation in this. This provides for a significantly faster rate of learning during training [15]. ResNet was compared to VGGNet, GoogLeNet, and DenseNet by Wu et al. in 2019 and found that ResNet generated the best results in classifying grape leaf illnesses [16].

Architectures such as AlexNet, LeNet, and GoogleNet (2014) are routinely included into the backbone of bespoke builds in recent research [16, 17]. Based on LeNet's Soybean Disease Classification research, Wallelign recommended such a build. Three convolution layers, one max-pooling layer, and a fully linked MLP with Relu activation were used in the model, which had a 99 percent accuracy rate [18].

The performance of a model relies heavily on data pre-processing. Infections caused by viruses, bacteria, and fungi can be difficult to detect since their symptoms often overlap. Any detectable alteration in colour, shape, or function that occurs as a result of the plant's response to the pathogen is considered a symptom [19]. Because of this complication, RGB data is preferred [10, 20]. This results in clean, noise-free images that take longer to train than greyscale data but are better for plant disease identification models overall [21].

The reliability of a model might be harmed by smaller datasets or unvarying data. This can be accomplished in a number of ways, including through the use of augmentation or transfer learning approaches. In addition to reducing overfitting, augmenting training images can improve a model's overall performance [22, 18].

This can be accomplished by incorporating functionalities such as zoom, rotation, colour changes, and contrast adjustments. The altered photos, on the other hand, should mirror the validation dataset's expectations [18]. When used incorrectly, a classifier's accuracy can deteriorate despite the additional data collected.

The method of transfer learning has also proved very successful when working with smaller datasets. This involves fine-tuning the weights of a pre-trained model. The ImageNet database is commonly used for this purpose and contains over 14 million images [23]. In 2016, Mohanty et al. exposed these benefits in a study focused on crop disease classification. Here, superior results were recorded using transfer learning

Because ImageNet contains photos that are irrelevant to a plant-specific task, it is unclear whether pre-training on a botanical database, rather than ImageNet, would improve performance. According to recent study, pre-training on ImageNet may improve generalisation, but pre-training on a plant-specific task may prevent overfitting. These assertions, on the other hand, are inconclusive. The topic is understudied because to a scarcity of substantial botanical databases [25]. Pre-trained models can also benefit from augmentation. However, when applied to untrained CNNs, the impacts are stronger because to the knowledge previously acquired by such a model [26].

The model's capabilities are heavily influenced by the quality and type of training data. A classifier's accuracy becomes dependent on this composition when trained on imagery with simple backdrop data [20]. As a result, when tested with in-field photography, it is likely to be unreliable. Many of the existing plant disease databases, such as the 'PlantVilllage' collection [10], lack in-field photography. Research [24, 20] emphasises the importance of such a dataset.

By isolating a leaf from its background, segmentation can be useful in this scenario [27]. This technique can also be employed in cases when the classifier needs to be aware of the surroundings. Understanding the breadth of pathogen damage around the infected tissue, rather than only the affected tissue, is one example [28, 29]. Segmentation is not a new concept; it has been used to classify diseases since the 1990s. Good results were recorded even at this early stage. Early research also helped to establish the limitations, demonstrating that the approach could not overcome poor image quality. As a result, the significance of proper data collection and pre-processing is emphasised [30]. Segmentation will continue to be important in 2020. Combining this with specialist imaging offers a lot of research potential [31].

What stage of disease identification is achievable depends on the type of training data used. Specific imagery is required for early illness detection [32]. Chlorophyll fluorescence imaging (CFI), infrared thermography (IRT), hyperspectral imaging (HSI), and multispectral imaging (MSI) are all capable of detecting symptoms that aren't obvious to the naked eye. These can be used separately or in combination [32].

IRT, for example, has a remarkable ability to detect temperature changes. Days before symptoms appeared, this method was helpful in diagnosing crop diseases such as downy mildew in roses [33] and FHB in wheat [32].

This topic of early detection is relatively unexplored due to the limited availability of such data. [22, 33] The technology needed to capture this specialised imagery is becoming more affordable, with a growing academic interest in the area. At this stage however, it is not an accessible tool for remote farmers. Therefore, it would be unrealistic to include it in a project intended for such users [34].

I. Materials and Methods

The steps for constructing and deploying the classifier are described in this section. CNN divides classification into three phases, each of which focuses on a different task. All of the work for this study was done on a single machine, which has the specs indicated in Table 1.

A. Data Acquisition

All Apple and other fruits imagery derive from ‘The PlantVilllage Dataset’ [35], an open-access repository which contains in total 54,323 images.

All images are captured in a controlled environment. Due to this, model bias is expected. To access this, a test dataset containing 50 images, sourced from Google is also established. These images contain additional plant anatomy, in-field background data and varying stages of disease.

Hardware & Software	**Characteristics**
Memory	8.0GB
Processor	Intel(R) Core™ i5-9300H CPU @ 2.40GHz
Graphics	NVIDIA GeForce RTX 2060 6GB GDDR6
Operating system	Windows 10 Home 64

B. Data Pre-Processing

The dataset is split into two parts: 80 percent for training and 20% for validation. The training data is first subjected to augmentation settings. These are generated 'on the fly,' with each operation having a weighted chance of showing up in each epoch [37].

Flipping (random), padding mode (reflection), and zoom with crop (scale = (1.0,1.5)) are among the options used. 'Zoom with crop' was later removed after it was discovered that it had cropped diseased leaf regions incorrectly. All photos are then resized and normalised. A compress function is used to resize the image to 150 by 150 pixels. The RBG ImageNet statistics are used to normalise a pre-trained model. Figure 1 shows an example of the finished pre-processed photographs.

C. Classification by CNN

1) Phase One – Trialling of Image size

Phase one will look into the impact of image size on model performance. A total of five image sizes ranging from 150 x 150 to 255 x 255 are evaluated.

To begin, download the Resnet34 pre-trained weights. All levels are frozen by default in transfer learning, with the exception of the final two layers. These include new weights and are tailored to the classification of plant diseases. Without backpropagating the gradients, freezing allows these layers to be being trained individually. The 1cycle policy is used to train the remaining layers in the same way.

The remaining layers are released once this is completed. A plot of learning rate vs loss is generated and analysed to facilitate the fine-tuning process. A suitable learning is chosen as a result, and the model is run. The model is re-created to the additional four image sizes after the results have been recorded (Table III.). In each trial, all processes, including the learning rate, are repeated.

TABLE III. IMAGE SIZE TRIAL INFORMATION

Trial	Image Size	No. Epochs	Learner Rate
1	150 x 150	4	1e-05 and 1e-04
2	195 x 195	4	1e-05 and 1e-04
3	224 x 224	4	1e-05 and 1e-04
4	244 x 244	4	1e-05 and 1e-04
5	255 x 255	4	1e-05 and 1e-04

TABLE II. DATASET USED FOR CLASSIFICATION

Leaf Category	Images
Apple	3171
Cherry	1906
Grape	4062
Rice	2657
Pepper	2475
Potato	2152
Strawberry	1565
Tomato	18170
Total	36148

2) Phase Two – Model Optimisation

The ResNet34 model is optimised by using the most appropriate image size. Additional augmentation options have been added to the model to boost its performance even more (Fig. 2). Brightness changes (0.4,0.7) and warping are examples of operations (0.5).

The final two layers are segregated and trained at the default learning rate after that. After then, fine tuning is done by running several trials to test a variety of learning rates and epoch counts.

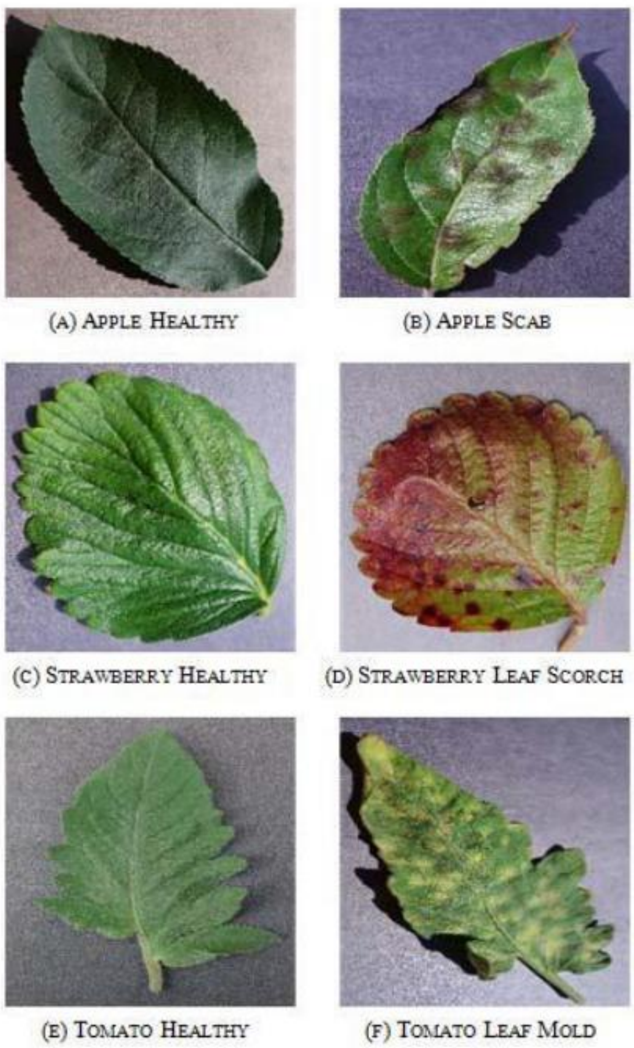


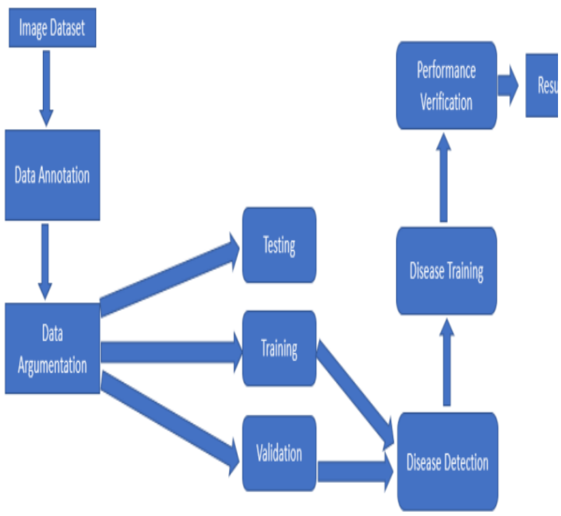
Fig. 1. *IMAGES FROM THE DATASET*

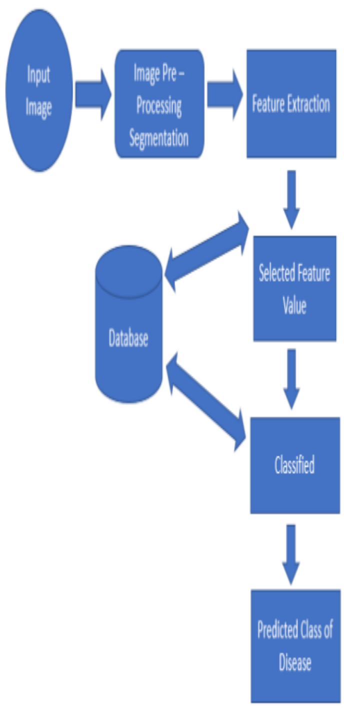
3) *Phase Three – Feature Extraction*

All of the data we collect in real life is in vast quantities. We'll need a method to decipher this data. It is not possible to process them manually. This is where the idea of feature extraction comes into play.

Feature extraction is a step in the dimensionality reduction process, which divides and reduces a large set of raw data into smaller groupings. As a result, processing will be simpler. The fact that these enormous data sets have a large number of variables is the most crucial feature. To process these variables, a large amount of computational power is required. As a result, feature extraction aids in the extraction of the best feature from large data sets by selecting and combining variables into features, effectively lowering the amount of data. These features are simple to use while still accurately and uniquely describing the real data set.

IV. System overview





II. Results

1) *Phase One – Trialling of Image Size*

Phase One results show that for image sizes ranging from 155 x 155 to 255 x 255, it is possible to attain an accuracy and F1 score of better than 90%. As expected, increasing the image size enhances feature extraction while simultaneously increasing the processing time (Table IV.). This preliminary investigation yielded outstanding results. The model would be allowed if it achieved an accuracy of at least 80%, as previously specified. Even at this early stage, the outcomes considerably exceed the standards for admission.

Each model was given a range of learning rates from 1e-05 to 1e-04 and run for four epochs to get this outcome.

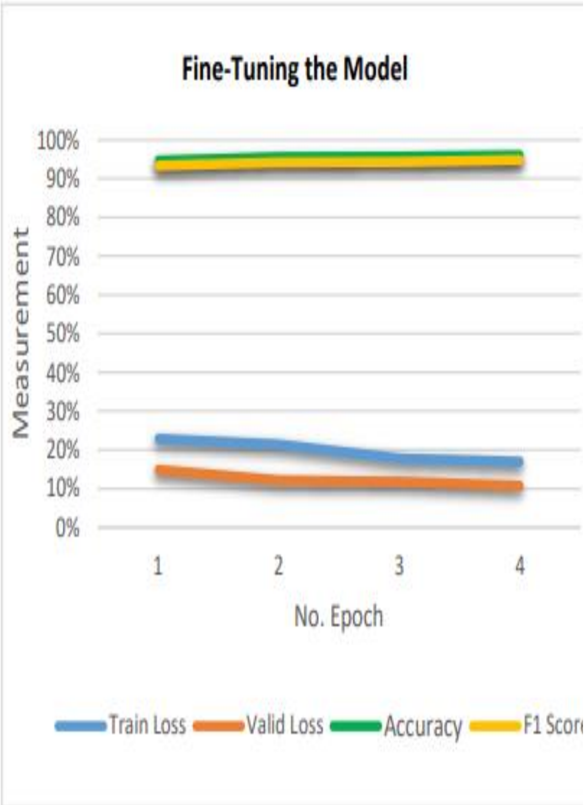
Image size 244 offered the best overall results, including the highest accuracy and F1score. Despite the fact that literature says that an image size of 224 x 224 is appropriate for plant disease classification tasks (10a), this model appears to gain only little from a larger image size. Because of these considerations, image size 244 was chosen for the remainder of this study.

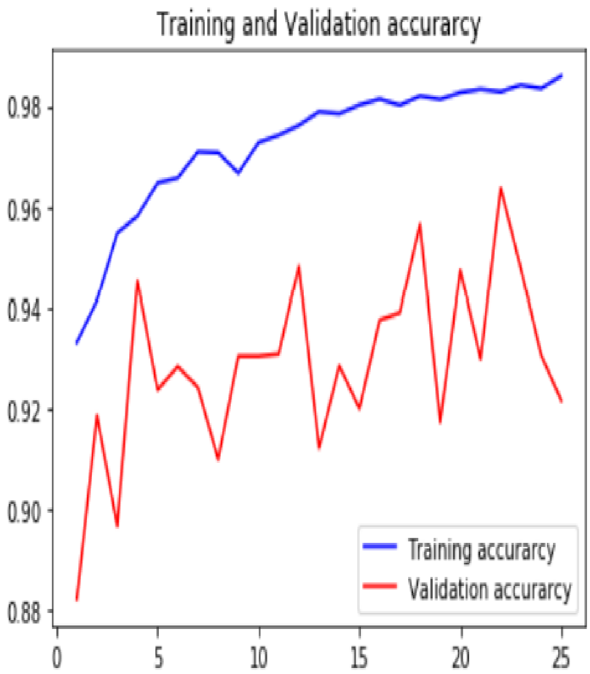
2) *Phase Two – Model Optimisation*

The model had an accuracy of 0.9465 and an F1 score of 0.9359 before fine-tuning.A plot of learning rate (logarithmic scale) v loss was examined to facilitate fine-tuning . This shows that the loss between learning rates 1e-06 and 1e-04 is rather small. However, as the learning rate exceeds 1e-04, there is a significant rise in loss. With these considerations in mind, various trials assessing learning rate were conducted.

The best results were obtained with a learning rate of 1e-05 to 1e-04. A minor boost in accuracy (1.5 percent) and F1-Score (1.3 percent) was achieved by fine-tuning this hyperparameter. However, the closing training and validation values on the last epoch imply that the model may be slightly underfitting (Fig. 5). To address this, the number of epochs was gradually raised. There was a noticeable improvement in the mode's fit around the tenth epoch. A final reading revealed a 2.8 percent increase in accuracy and a 3.1 percent increase in F1-score .

The validation dataset, as previously noted, has a very particular composition: one leaf and a plain background. Use of the classifier should match this image layout for an accurate reading, similar to those indicated in this section.





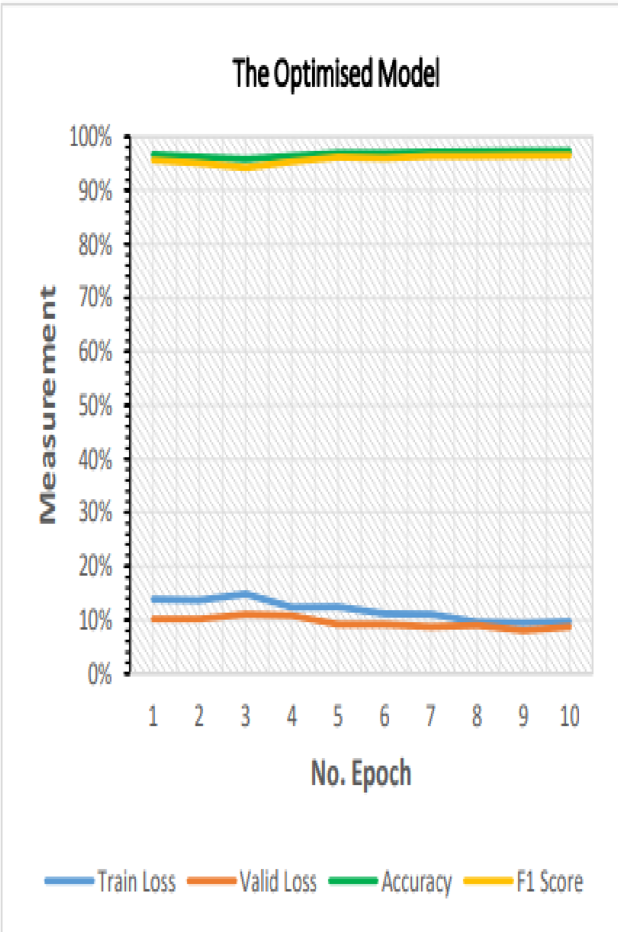


TABLE IV. RESULTS - PHASE ONE

Test	Image size	Train Loss	Valid Loss	Accuracy	F1 Score	Time (hours)
1	155	0.1660	0.1222	0.9557	0.9439	2:83
2	195	0.1588	0.1150	0.9585	0.9460	3.62
3	224	0.1778	0.1256	0.9522	0.9359	4.29
4	244	0.1310	0.1153	0.9603	0.9450	5.20
5	255	0.1607	0.1249	0.9562	0.944	5.42

3) Phase Three– Visualisasations

The CNN's inner workings are revealed through the use of heat maps. In order to extract plant disease traits, colour, shape, and texture appear to be key elements (Fig.7, Fig.8). Color appears to be especially important in helping to distinguish comparable disorders by offering a new level of differentiation. As previously mentioned [10, 20], this explains the usefulness of RGB data in disease classification tasks. The CNN is effective in recognising traits in all three species. This is especially true for rice disease classes, which have a limited number of symptoms that are more difficult to detect.

The validation dataset results are listed in the confusion matrix in Figure 10. There were no errors in any of the Potato or Tomato classes. Rice performed poorly as a species, indicating that there may be a problem with the data. Rice Brown Spot had the highest rate of misclassification. Healthy was wrongly identified in 13.9 percent of the photos, and RiceLeafBlast was incorrectly classified in 9.9 percent of the photographs. Brown spot is characterised by uneven dark dots. While this may be misconstrued for leaf blast-like lesions, there should be some overlap with healthy samples. Each Rice class had an average of 12.65 percent of students that were misdiagnosed.

The misclassified photos were plotted and grouped according to loss to further study this topic (Fig. 11). A closer look reveals that the quality of several of the photographs is suspect. An reliable diagnosis based on these photographs would be difficult even for the most expert eye. This data could be incorrectly tagged or represents a weak class representation. As a result, material that isn't useful to the classifier should be excluded from the training dataset.

When in-field imagery is used, the model's accuracy drops dramatically, as expected. Only 44 percent of the 50 photos were correctly diagnosed.

This is due to a mix of factors, including new plant morphology and alternative background data, that augmentation could not overcome. Adapting to such circumstances is exceedingly difficult because the model was not trained on such data.

Diversifying the training data to incorporate photos recorded in an uncontrolled setting has the potential to greatly strengthen the model.

As previously stated, there is currently a scarcity of 'in-field' plant disease photography. The significance of providing such resources is demonstrated by these findings.

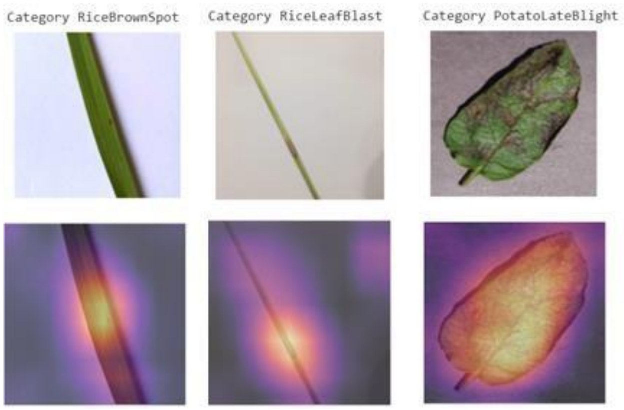


Fig. 7. Heat map example 1

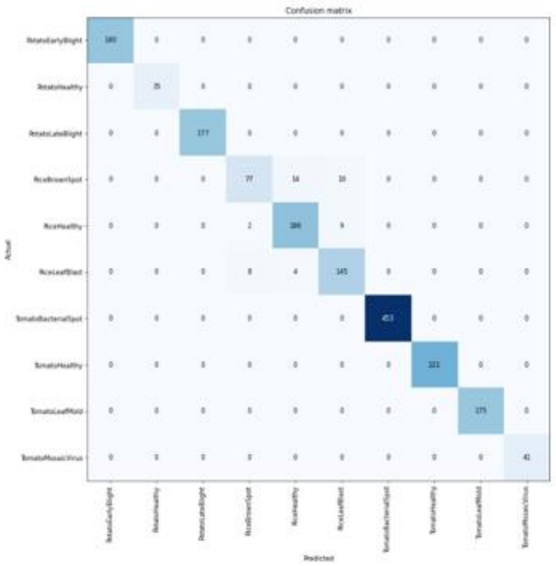


Fig. 10. Confusion matrix – validation dataset

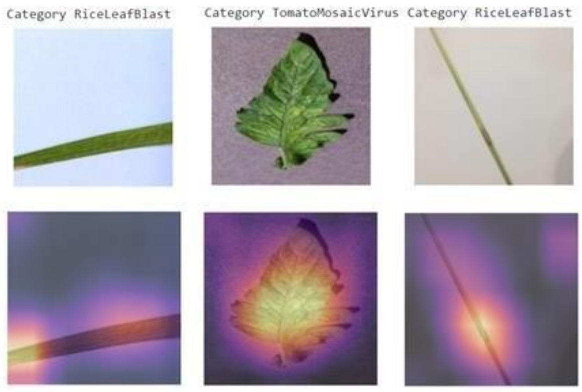


Fig. 8. Heat map example 2

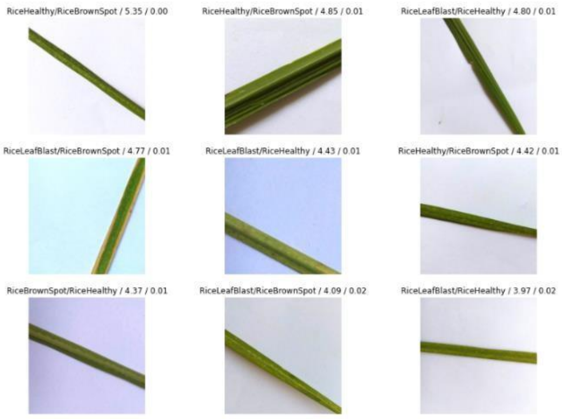


Fig. 11. Top losses plotted – validation dataset

Actual \ Predicted	PotatoEarlyBlight	PotatoHealthy	PotatoLateBlight	RiceBrownSpot	RoceHealthy	RiceLeafBlast	TomatoBacterialSpot	TomatoHealthy	TomatoLeafMold	TomatoMosaicVirus
PotatoEarlyBlight	4		1							
PotatoHealthy	1	1	1					2		
PotatoLateBlight	1		4							
RiceBrownSpot	1					4	1			
RiceHealthy					3	1		1		
RiceLeafBlast						4	1			
TomatoBacterialSpot			1				3		1	
TomatoHealthy							3	1	1	
TomatoLeafMold							2	1	2	
TomatoMosaicVirus							2		3	

Fig. 12. Confusion matrix – test dataset

III. Conclusion

Crop protection in organic farming is a difficult undertaking. This requires a thorough understanding of the crop being farmed as well as potential pests, diseases, and weeds. A new deep learning model based on a special architectural convolution network has been constructed in our system to detect plant illnesses using photos of healthy or diseased plant leaves. The aforementioned system can be expanded to a real-time video entry system, allowing for unattended plant care. An intelligent system that treats diagnosed diseases is another feature that can be introduced to various systems. Plant disease management has been shown in studies to enhance yields by up to 50%.

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