



A Novel Framework for Prevention of Rice Plant Disease Using Deep Learning

Balaji Thennarangam¹

¹Senior Software Engineer, Sydney, New South Wales, Australia, balaji.t123@gmail.com

ABSTRACT

Agriculture is the backbone of our country. Due to climate change and pollution, yield of rice plant are decreased in the past decades. Farmers are not having sufficient awareness for their plant and cultivation. We proposed a novel disease predication system for rice plant with Normal, Bacterial Leaf, Brown Spot, Leaf Smut, Sheath Blight parameters. We have collected 1000 dataset from different rice plants and implemented with our proposed architecture. We are trying to inculcate deep neural networks and artificial intelligence technologies to investigate the rice plants for disease prediction. In this simulation we analyzed VGG-16, Xception, Inception, ResNet, Hill Climbing-ResNet, Modified Hill climbing ResNet, CS-ResNet and CS-MHC ResNet algorithms. Eventually we got the high accuracy CS-MHC ResNet algorithm.

1 Introduction

India is notable for agrarian country; wherein around 70% of the populace relies upon horticulture. Ranchers have wide scope of variety to choose reasonable yields for their homestead. Notwithstanding, the development of these harvests for ideal yield and quality produce is generally specialized. It very well may be improved by the guide of innovative help. The administration of perpetual yields requires close controlling particularly for the administration of illnesses that can influence creation altogether and afterword the post-reap life. The picture handling is best strategy utilized in horticultural applications for following purposes. Anticipate plant illness from picture of plants. The plant illness analysis is restricted by human visual capacities on the grounds that the majority of the principal indications are minuscule. This interaction is drawn-out, tedious. There is need for plan framework that consequently perceives, arranges and quantitatively recognizes plant infection manifestations. In the event of plant infection the sickness is known as any debilitation of ordinary physiological capacity of plants, delivering trademark indications. A side effect is a reality going with something and is seen as proof of its reality. Infection is brought about by microorganism which is any specialist causing sickness. Infection the executives is a difficult errand. For the most part illnesses are seen on the leaves on plants or stems of the plant.

India is notable for agrarian country; wherein about 70% of the populace relies upon horticulture. Ranchers have wide scope of assortment to choose reasonable harvests for their homestead. Be that as it may, the development of these harvests for ideal yield and quality produce is generally specialized. It tends to be improved by the guide of innovative help. The administration of enduring yields requires close controlling particularly for the administration



of infections that can influence creation fundamentally and afterword the post-collect life. There is need for plan framework that naturally perceives, characterizes and quantitatively identifies plant infection side effects.

If there should be an occurrence of plant illness the infection is known as any impedance of typical physiological capacity of plants, creating trademark indications. A side effect is a reality going with something and is seen as proof of its reality. Infection is brought about by microbe which is any specialist causing illness. Illness the executives is a difficult undertaking. It diminishes the close by leaves warmth in a brief timeframe. Utilizing video investigating we can undoubtedly recognize the impacted region in the leaves. In reference the ordinary leaves are taken for the examination reason with the goal that we can undoubtedly recognize the impacted leaves. Increment the data set the exactness will be high, pictures taken for the examination ought not be impacted with any of the illness.

2 Literature Survey

Revathi P et al. (2012) had discussed that The paper comprises , of two stages to recognize the impacted piece of the infection. At first Edge discovery based Image division is done, and at finally picture examination and grouping of illnesses is done utilizing our proposed Homogeneous Pixel Counting Technique for Cotton Diseases Detection (HPCCDD) Algorithm. The objective of this examination work is recognize the infection impacted piece of cotton leaf sport by utilizing the picture investigation strategy.

Al-Hiary et al. (2011) had resulted that in present paper to discovery of leaf illnesses. In this pre-owned technique is triple: 1) distinguishing the contaminated item dependent on k-implies bunching; 2) separating the elements set of the tainted articles utilizing shading co-event approach for surface examination; 3) recognizing and arranging the sort of sickness utilizing NNs, in addition, the introduced conspire orders the plant leaves into contaminated and not-contaminated classes.

Kumar SR et al. (2015) had established that the course of picture division was dissected and leaf district was portioned by utilizing Otsu strategy. In the HSI shading framework, H part was picked to portion infection spot to diminish the aggravation of brightening changes and the vein. Then, at that point, illness spot districts were portioned by utilizing Sobel administrator to inspect infection spot edges. At long last plant illnesses are reviewed by working out the remainder of sickness spot and leaf regions.

Dhingra G et al. (2018) had discussed that the portrays utilization of farming utilizing PC vision innovation to perceive and arrange sickness of plant leaf. The paper manages connection between sickness indications and effect on item yield. It additionally manages increment the quantity of preparing information and testing to achieve better precision. This strategy is erratic and conflicting. Additionally, it includes a striking measure of mastery in the field of plant disease diagnostics (phytopathology) notwithstanding the lopsided handling times. Hence, picture handling has been applied for the acknowledgment of plant infections.



Bani-Ahmad S et al. (2011) had proposed discovery of plant sicknesses utilizing mechanization and group its infections. Here pixels are assembled on set of component into all out k classes. At the point when leaf has more than one illness then there is more bunches that cause sickness. ANN is utilized to recognition and characterization of illness. Further exploration need to build the exactness of recognition.

Mokhtar U et al. (2018) had introduced Gabor wavelet change strategies to remove tomato leaf highlight. They utilized SVM to identify leaf infections. For tests considering genuine example pictures of tomato leaf and creator noticing two kinds of infection in tomato leaves including early scourge and fine mould. In pre-processing stage pictures are resized to 512*512 goals to find the computational time. Applied foundation deduction technique to eliminate foundation of picture. In the characterization, utilizing of piece work the SVM was prepared and tried.

3 Implementation

3.1 VGG-16

VGG16 is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition”.

Fig. 1. VGG-16 model architecture – 13 convolutionallayers and 2 Fully connected layers and 1 SoftMax classifier VGG-16 - Karen Simonyan and Andrew Zisserman introduced VGG-16 architecture in 2014 in their paper Very Deep Convolutional Network for Large Scale Image Recognition. Karen and Andrew created a 16-layer network comprised of convolutional and fully connected layers. Using only 3×3 convolutional layers stacked on top of each other for simplicity.

- The first and second convolutional layers are comprised of 64 feature kernel filters and size of the filter is 3×3. As input image (RGB image with depth 3) passed into first and second convolutional layer, dimensions changes to 224x224x64. Then the resulting output is passed to max pooling layer with a stride of 2.
- The third and fourth convolutional layers are of 128 feature kernel filters and size of filter is 3×3. These two layers are followed by a max pooling layer with stride 2 and the resulting output will be reduced to 56x56x128.
- The fifth, sixth and seventh layers are convolutional layers with kernel size 3×3. All three use 256 feature maps. These layers are followed by a max pooling layer with stride 2.
- Eighth to thirteen are two sets of convolutional layers with kernel size 3×3. All these sets of convolutional layers have 512 kernel filters. These layers are followed by max pooling layer with stride of 1.
- Fourteen and fifteen layers are fully connected hidden layers of 4096 units followed by a softmax output layer (Sixteenth layer) of 1000 units [2].

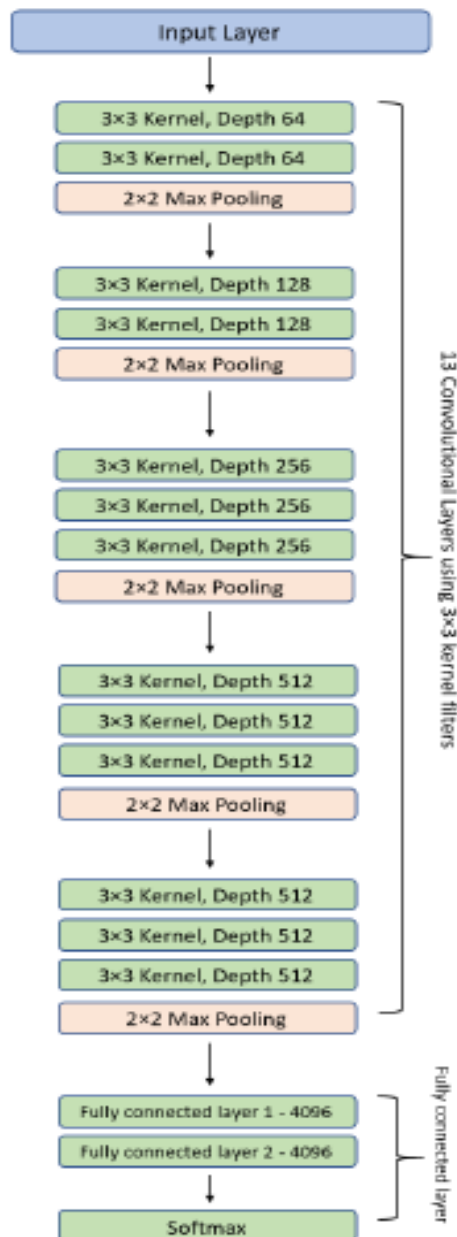


Figure. 1: The precise structure of the VGG-16 network

The data first goes through the entry flow, then through the middle flow which is repeated eight times, and finally through the exit flow. Note that all Convolution and Separable Convolution layers are followed by batch normalization (not included in the diagram). All Separable Convolution layers use a depth multiplier of 1 (no depth expansion).

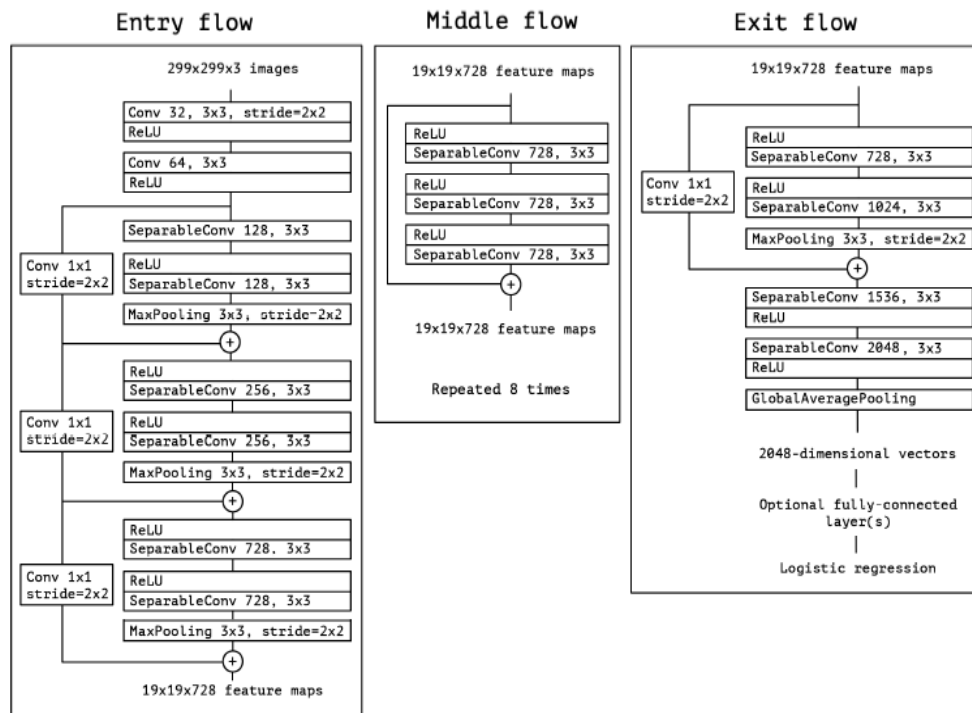


Figure 2: *The Xception architecture*

3.2 ResNet

In 2015, He, et al. introduced ResNet and the residual block (Fig. 4), consisting of two convolutional layers and a non-parameterized shortcut connection which passes the previous block's output to the next block.

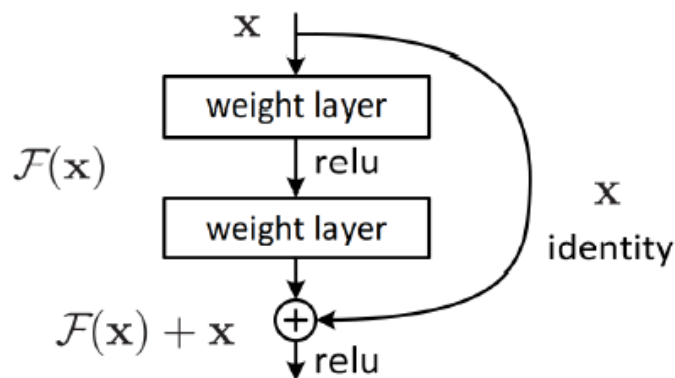


Figure 3: *ResNet-v1 shortcut connections*

Challenge using a 152-layer ResNet, and established the property that having more layers tends to produce higher recognition accuracy. Continued improvements can be demonstrated with even 1, 000 layers—a previously unattainable feat. Following this result, they modify the residual block so that ReLU activation is not applied to the shortcut connection, providing further improvement with ResNet-v2 in 2016. This simple structural feature has made its way



into many other deep CNNs, providing broad success (e.g. DenseNet, Inception-ResNet-v2). ResNet-v2 152 labels 78.9% of samples correctly using a single model and 320x320 single-crop on the ILSVRC2012 challenge's 50k validation samples, remaining a high-performer today [6].

3.3 Modified Hill climbing (MHC) ResNet

A heuristic search that executes the task (1). As a search strategy, we utilized a genetic algorithm called the Modified hill-climbing search. Fig. 5 depicts the scheme of the search

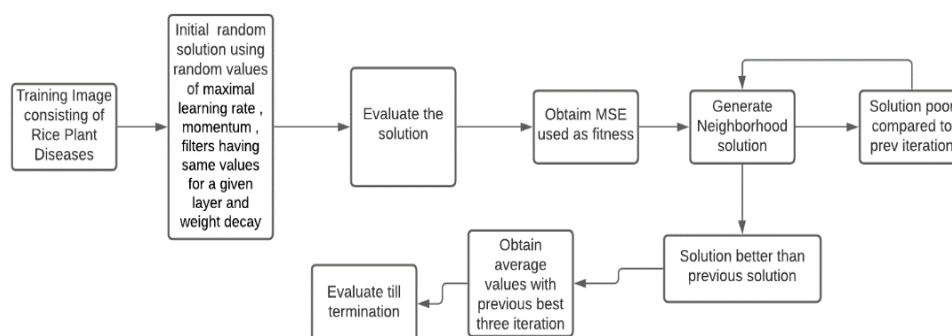


Figure 4: The scheme of a genetic algorithm based on the Modified hill-climbing and enhanced with network morphism.

The algorithm begins with a training data input. Then, a pre-trained original neural network serves as a baseline architecture for climbing a so-called hill. In response to the application of functional-saving modifications, the original network produces a certain number of descendants. These modifications ensure that each descendant performs the same as its parent network. Moreover, due to the genetic algorithm, the descendants suit better for training than their parents. Each descendant is trained on a small number of epochs and then evaluated by a precision measure – the best descendant moves to the next step, where they form new descendants. The search procedure ends after a certain number of epochs. The algorithm presents the so-called best averaging technique, which then serves for final long-term training. Fig. 6 demonstrates a heuristic architecture search based on Modified hill-climbing algorithm. The algorithm does not have to choose a new model at each iteration, and can also hold the one from the previous step if others do not improve. Consequently, the current best model at iteration may also be considered a averaged network.

3.4 Cuckoo Search (CS) -ResNet

Cuckoo Search (CS) is a new heuristic algorithm inspired from the obligate brood parasitic behavior of some cuckoo species as they lay their eggs in the nests of host birds. Some cuckoos have a specialty of imitating colors and patterns of eggs of a few chosen host species. This reduces the probability of eggs being abandoned. If host bird discovers foreign eggs, they either abandon the eggs or throw them away. Parasitic cuckoos choose a nest where the host bird just



lays its eggs. Eggs of cuckoo hatch earlier than their host eggs and when it hatches, it propels the host eggs out of the nests. Hence cuckoo chicks get a good share of food and sometimes they even imitate the voice of host chicks to get more food [9].

Mostly cuckoos search food by a simple random walk, where the random walk is a Markov chain whose next position is based on current position and transition probability of next position. Using Lévy flights instead of simple random walks improve the search capabilities. Lévy flight is a random walk in step-lengths following a heavy-tailed probability distribution. Each cuckoo acts as a potential solution to the problem under consideration. The main aim is to generate a new and potentially better solution (cuckoo) to be replaced with a not so good solution. Each nest has one egg but as the problem complexity increases, multiple eggs can be used to represent a set of solutions. There are three basic idealized rules of CS. First rule says that each cuckoo lays one egg and dumps it in a random nest. The second rule is that the nest with the highest fitness will carry over to next generations whereas the final rule defines that the number of available host nests is kept fixed and the egg laid by cuckoo is discovered by host bird with a probability $P \in [0, 1]$. And depending on p , the host bird either throws the egg away or abandons the nest. It is assumed, that only a fraction p of nests is replaced by new nests.

3.8 CS-MHC ResNet

Cuckoo Search Algorithm (CSA) is inspired from the “brood parasitic” cuckoo species in combination with certain birds and fruit flies. Levy flight has been applied for global exploration and proved its efficiency through achieving good results. This resulted in CSA being balanced between exploration and exploitation. However, sometimes it exploits solutions poorly with slow convergence. For that reason, the proposed algorithm balances between the global exploration of the CSA and the deep exploitation of the MHC.

CSMHC starts the search by applying the standard cuckoo search for the number of iterations. The best-obtained solution is then passed to the HC to accelerate the search and overcome the slow convergence of the standard cuckoo search algorithm [10].

As shown in Figure 7, the MHC is an iterative algorithm that starts with an arbitrary solution to a problem and subsequently attempts to determine a better solution by incrementally changing a single element of the solution. When the change produces a better solution, incremental change is performed on the new solution, which is repeated until no further improvements can be found. It then returns the solution to the CSA to check it through the fraction probability $P\alpha$

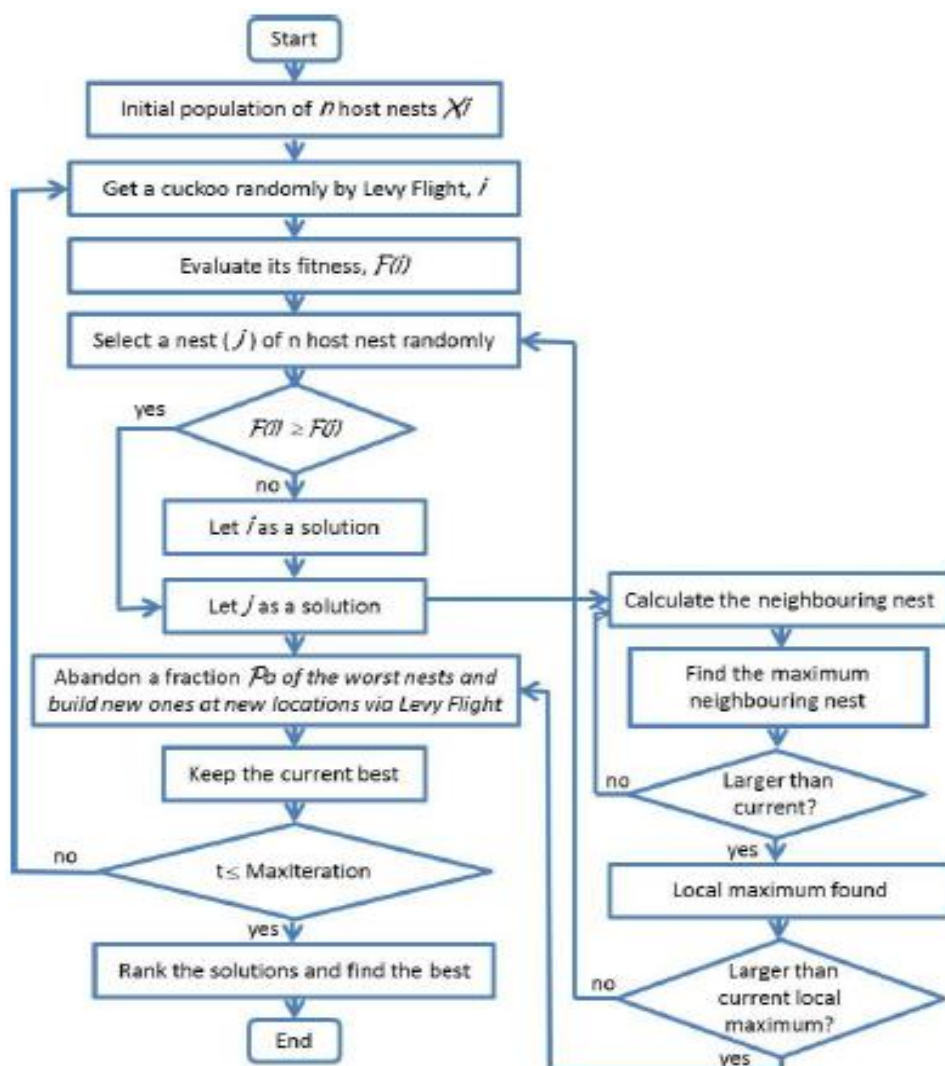


Figure 5: Flowchart of the CSAHC Algorithm

4 Result & Discussion



Fig 4.1 Leaf smut



Figure 4.2 Brown spot



Figure 4.3 Bacterial leaf

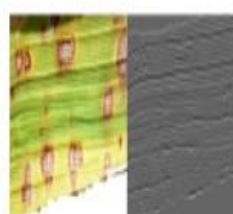


Fig 4.4 Sheath Blight



Table 1: Average Sensitivity of CS-MHC

	VGG-16	Xception	Inception	ResNet	Hill Climbing-ResNet	Modified Hill climbing ResNet	CS-ResNet	CS-MHC ResNet
Sensitivity - Bacterial Leaf Blight	0.8711	0.8778	0.8933	0.9089	0.9111	0.9156	0.9178	0.92
Sensitivity - Brown Spot	0.8655	0.88	0.8909	0.9273	0.9291	0.9291	0.9309	0.9327
Sensitivity - Leaf Smut	0.8655	0.8745	0.8909	0.9036	0.9073	0.9091	0.9127	0.9182
Sensitivity - Sheath Blight	0.8125	0.825	0.835	0.8625	0.8675	0.8725	0.875	0.8825
Sensitivity - Normal	0.92	0.9233	0.9267	0.9378	0.9411	0.9433	0.9444	0.9522
Sensitivity - Average	0.86692	0.87612	0.88736	0.90802	0.91122	0.91392	0.91616	0.92112

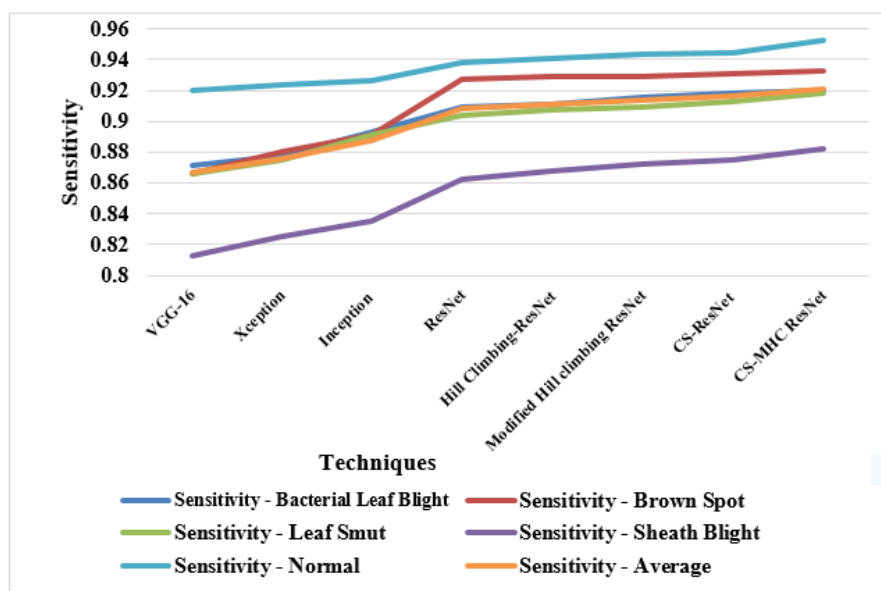


Figure 6: Average Sensitivity of CS-MHC

From the figure it can be observed that the CS-MHC ResNet has higher Average Sensitivity by 6.06% of VGG-16, by 5.007% of Xception, by 3.73% of Inception, by 1.43% of ResNet, by 1.08% of Hill Climbing-ResNet, by 0.7847% of Modified Hill climbing ResNet, and 0.53% of CS-ResNet respectively.



Table 2: Average Precision of CS-MHC

	VGG-16	Xception	Inception	ResNet	Hill Climbing-ResNet	Modified Hill climbing ResNet	CS-ResNet	CS-MHC ResNet
Precision - Bacterial Leaf Blight	0.8467	0.8531	0.8683	0.8872	0.8913	0.8957	0.8959	0.9079
Precision - Brown Spot	0.8546	0.8705	0.8845	0.9043	0.9076	0.9109	0.9159	0.9277
Precision - Leaf Smut	0.853	0.8605	0.8734	0.9136	0.9156	0.9191	0.9194	0.9199
Precision - Sheath Blight	0.8486	0.8639	0.8675	0.8846	0.892	0.8949	0.8997	0.9028
Precision - Normal	0.9314	0.9337	0.9402	0.9473	0.9485	0.9486	0.9497	0.9512
Precision - Average	0.86686	0.87634	0.88678	0.9074	0.911	0.91384	0.91612	0.9219

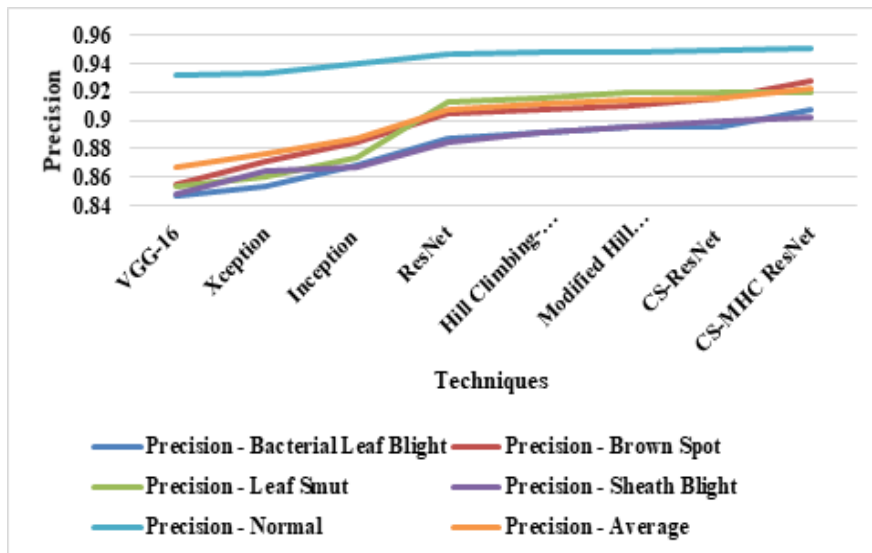


Figure 7: Average Precision of CS-MHC

From the figure it can be observed that the CS-MHC ResNet has higher Average Precision by 6.15% of VGG-16, by 5.06% of Xception, by 3.88% of Inception, by 1.58% of ResNet, by 1.18% of Hill Climbing-ResNet, by 0.87% of Modified Hill climbing ResNet, and 0.62% of CS-ResNet respectively.



Table 3: Average F-Measure of CS-MHC

	VGG-16	Xception	Inception	ResNet	Hill Climbing-ResNet	Modified Hill climbing ResNet	CS-ResNet	CS-MHC ResNet
F-Measure - Bacterial Leaf Blight	0.8587	0.8653	0.8806	0.8979	0.9011	0.9055	0.9067	0.9139
F-Measure - Brown Spot	0.86	0.8752	0.8877	0.9157	0.9182	0.9199	0.9233	0.9302
F-Measure - Leaf Smut	0.8592	0.8674	0.8821	0.9086	0.9114	0.9141	0.916	0.919
F-Measure - Sheath Blight	0.8302	0.844	0.8509	0.8734	0.8796	0.8836	0.8872	0.8925
F-Measure - Normal	0.9257	0.9285	0.9334	0.9425	0.9448	0.9459	0.947	0.9517
F-Measure - Average	0.86676	0.87608	0.88694	0.90762	0.91102	0.9138	0.91604	0.92146

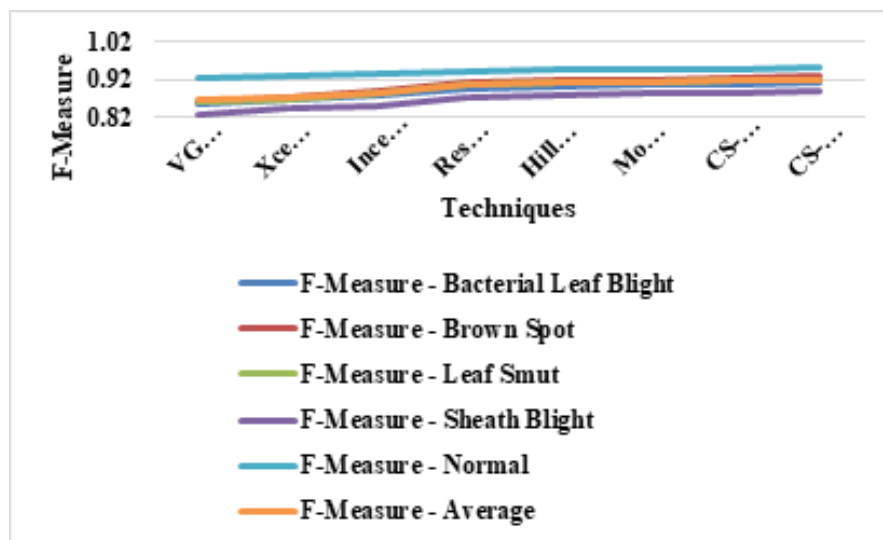


Figure 8: Average F-Measure of CS-MHC

From the figure it can be observed that the CS-MHC ResNet has higher Average F-Measure by 6.11% of VGG-16, by 5.04% of Xception, by 3.81% of Inception, by 1.51% of ResNet, by 1.13% of Hill Climbing-ResNet, by 0.84% of Modified Hill climbing ResNet, and 0.58% of CS-ResNet respectively.



Table 4: Average Misclassification Rate of CS-MHC

	VGG-16	Xception	Inception	ResNet	Hill Climbing ResNet	Modified Hill climbing ResNet	CS-ResNet	CS-MHC ResNet
Misclassification Rate	0.1239	0.1154	0.1053	0.086	0.0828	0.0804	0.0782	0.073

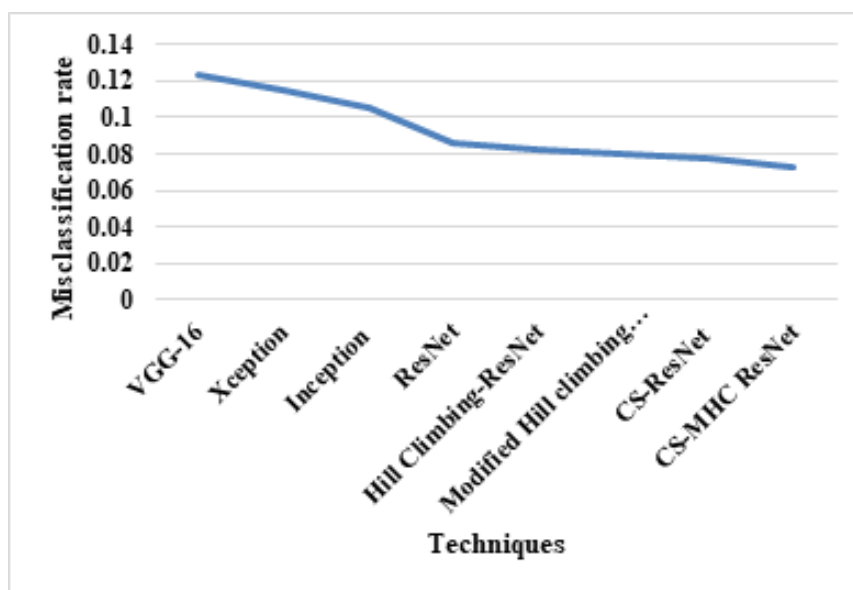


Figure 9: Average Misclassification Rate of CS-MHC

From the figure it can be observed that the CS-MHC ResNet has lower Average Misclassification Rate by 51.70% of VGG-16, by 45.01% of Xception, by 36.23% of Inception, by 16.35% of ResNet, by 12.58% of Hill Climbing-ResNet, by 9.64% of Modified Hill climbing ResNet, and 6.87% of CS-ResNet respectively.

5 Conclusion

In contemporary agriculture world, plant identification and classification of its disease is the crucial task for the researchers as well as farmers. But we are having the responsibility to serve the farmers to improve their plant-yield. Because they are facing lot of problems when plant cultivation in entire duration. Rice is the most important food for south Indians and its cultivation period is 4 months to 6 months. So we have analyzed rice plant and its classification. We have implemented average sensitivity, F-measure and precision with above discussed algorithm and CS-MHC ResNet algorithm is giving high accuracy and low miscalculation of this research.