Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EMPIRICAL STUDY ON FUNGAL DISEASES IN VARIOUS PLANTS USING DIFFERENT DEEP LEARNING APPROACHES

G.SRAVANTHI[1] , P.SAI KIRAN[2]
[1]Research scholar, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.
[2] Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India.
[2] Professor, Department of Computer Science and Engineering Prasad V Potluri Siddhartha Institute of technology ,AP, India.
E-mail: [1]sravanthi887@gmail.com , [2] psaikiran@pvpsiddhartha.ac.in

ABSTRACT

The productivity of the agriculture decreasing day by day due to various factors. The quality of the agriculture is impacted by the pests and diseases infected on the plants. Many researches proposed traditional image processing techniques to identify the diseases and design a recommendation system but all these are expensive and inaccurate systems, which are not affordable by farmers. When a new era known as "Machine Learning" as evolved, researchers extracted necessary features from the plant images and converted them into csv files to classify the diseases in plants using these approaches. Even these approaches are time consuming, so researchers are moved to deep learning approaches in which the intermediate steps takes places automatically in between input and output like pre-processing feature extraction. In this paper, the model studied about different deep learning approaches available on the disease detection system in various plants. Among the deep learning models, the researchers who have implemented transfer learning approaches have obtained high accuracy and few have achieved good kappa cohen values also. In traditional models the system needs to assume random weights for the neurons to produce the dot vectors of every layers. These assumed values some times may give more error rate which results in back propagation. Transfer learning helps the model to get the optimal weights without assumptions of each neuron from the pre-trained model it implements. The major advantage of any pre-trained model lies in faster training of network with millions of different categories images. One of the popular dataset used by most of the researchers for this study is "ImageNet". Using the concept of transfer using the ImageNet irrespective of any pre-trained model implemented the accuracy lies in between 92% to 96%.

Keywords: *Segmentation, Image Enhancement, Augmented Data, Annotation, Transfer Learning*

1. INTRODUCTION

The destruction of crops is majorly due to bacterial, fungal and viral diseases. The identification of these diseases at early and in different scenarios using deep learning approaches helps the farmers. Table 1 disease about the few fungal infections because most of the researchers experimented with it.

Table 1: Fungal Disease Classification

Disease Name	Leaf Image	Symptoms	Plant Affected
Early Blight		Older leaves appear as brown concentric circles	Vegetables, fruits, and shaded trees

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Late Blight		The leaves appear as water soaked, gray-green spots.	Pepper, potato, and tomato
Rusts		1. In the early stage white spots appear under leaves 2. During the growth, spots turn into reddish-orange spores	Roses, hollyhacks, beans, tomato
Powdery Mildew		The leaves turn into curls and blister	It is common in many plants
Downy Mildew		1. The upper surface of older leaves fade from yellow to white patches 2. Even though the plant is supplied with an ample amount of water the leaves fall off	This is generally observed in edible plants and also in grapevine, tobacco
Leaf Curl		In developing leaves reddish areas develop and these areas become thick	Peaches and nectarines
Club Root		1. The Plant grows poorly during day time 2. Plants regain their life during night time 3. Outer leaves turn into yellow or purple	Cauliflower, cabbage, and broccoli
Molds		The leaves, stems, and flowers appear as grayish colored soft and mushy spots	It is common in many plants

Smuts		1. They produce mushroom like tumors 2. The fungus appears on stalks, leaves, tassels, and ears	Generally found in backyard gardens and small farms

Using deep learning techniques, the entire process of feature extraction and classification is taken care by the network itself but those are weak in handling noise. This model focuses on various traditional noise handling mechanisms. Noise can occur during the image capture process from digital cameras, which is described as differing intensity levels than the genuine value. Impulsive noise, additive noise, and multiplicative noise are the three most frequent types of image noise[16]. The best way to remove the noise is usage of filters. There are two types of filters: Time domain filters and frequency domain filters.

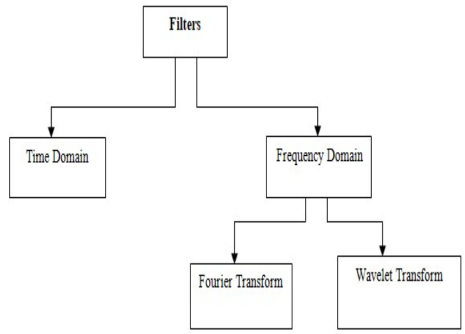

Figure 1: Classification of filters

Segmentation:

"Segmentation" is the technique of separating an image into separate parts based on interest. It divides the image into linear and curved structures. Object recognition and compression are two major applications of segmentation. Region based segmentation, Edge Detection segmentation, Clustering based segmentation, and Segmentation based on Weakly Supervised Learning are four prevalent approaches [18].

Table 2: Comparison Of Various Segmentation Techniques

S.No	Type of Segmentation	Name of Sub classification	Mechanism	Advantages	Disadvantages
1	Region-based Segmentation	Threshold based segmentation	The images are segmented into different regions based on the gray values of the threshold target	1. The mechanism is simple and the operation speed is faster 2. The image with high contrast can be segmented easily	1. If the images are overlapped or if the gray portion of the image does not have any significance then this mechanism cannot give accurate results. 2. it is sensitive to noise and grayscale unevenness

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2		Regional growth segmentation	The basic idea of this algorithm is to merge the similar pixels	1. It provides good boundary information. 2. It requires very few seed points to complete the task. 3. The growth criteria can be specified freely	1. Computational cost is high 2. It creates a shadow effect
3	Edge based Segmentation	Sobel Operator	Using the first derivative concept, it calculates the gradient luminance function of an image	1. It can easily detect the edges and their orientations	1. It is sensitive to noise
4		Laplacian Operator	In this mechanism, it first performs the low pass and filtering and then detects the edges by combining laplacian operator with a smoothening operator	1. It correctly identifies the edges 2. Wide area of the pixels can be tested	1. It cannot find the orientation of the edge.
5	Clustering based Segmentation	-	It divides the image based on the feature points. The feature space is clustered in general with k-means clustering algorithm [11]	1. Simple and fast. 2. It has linear time complexity. 3. It can be applied to large scale datasets.	1. It is difficult to estimate. 2. The time complexity is very expensive.
6	Segmentation based on weakly supervised learning	-	It segments the image by finding the unmarked pixels with the help of expected maximization algorithm	1.Automatic training of images can be done 2. The bounding box training can give better results	1. It is poor in performance

2. LITERATURE SURVEY:

In this paper, the model has considered the different types of neural networks because of the failures of the machine learning approaches. While choosing the existing works, the proposed model focused on the papers that are emphasis on the load balancing with the increase of dataset size. It also focused on the dimensionality reduction because feature extraction plays a vital role in the finding the infection and type of disease that a plant is suffering from. The paper also chosen the works with GAN's to know about the limitations that occur during the creation of augmented images. It also studied about the networks that deal with multi classification problem so that the proposed model can focus more number of viral diseases. It also studied about the IoT sensors to capture the live images of leaves to study about the pre-processing and feature extraction techniques with semi mix of manual and neural network.

In [1] Chen et al, designed light weight networks to identify the disease among the rice crops. The identification of diseases in the rice crop is very necessary because, they spread the disease very fastly. This model focuses on the lesion features by identifying them through the process of MobileNet-V2.The attention model of CNN divides the images into two partitions namely channel and spatial. Based on the target variable, stages are identified and a feature map is generated by enhancing the quality of the channel vectors of low stage. The spatial features are extended by applying the average pooling for high dimensional features and maximum pooling layers for low dimension features. The model has one pre-trained model which takes ImageNet as input and one base model whose input is obtained from plant disease dataset. This base model updates its weights, by getting trained from the pre-trained model. In the base model, the bottom layer weights are freezed after it obtains the minimal error rate weights.

In [2] Punam Bedi et al, proposed hybrid model of auto encoder for disease identification. The model is trained to reduce the dimensionality of the features; it preserves the important features by reconstructing the image. The reconstruction of the image is based on the upper limit so it has minimum error rate. The image size of 256*256 is drastically reduced to 32*32 and the model computes the normalized error rate instead of MSE, whose computation is shown in equation (1)

$$NRMSE\left(X^{O},X^{R}\right)=\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(X^{O}-X^{R}\right)^{2}}}{P_{maximum}-P_{minimum}} \quad \text{(Eq-1)}$$

Where,

$P_{maximum}$ Represents maximum pixel intensity

$P_{minimum}$ Denotes minimum pixel intensity

The model utilizes the decoder model to classify the images but the trainable parameters are customized based on the training dataset, which is shown in equation (2)

$\text{Trainable Parameters} = \sum_{i=0}^{n}(\text{filter}(\text{length}_i * \text{height}_i * \text{channel}_i) + \text{num\_filters}$ - (2)

In [3] Thippa Reddy et al proposed hyper tuned CNN model for classification of diseases in tomato plants and whale optimization integrated with PCA for feature extraction. The one hot encoding process transforms the important features into data points by projecting them on to the n-dimensional vector space. The data points generated are higher in dimensions so it initially applies PCA to reduce the dimensions but the model focuses on the highly relevant features. These are extracted by applying the whale optimization algorithm, which updates the agents location based on the best search fitness function. Finally, using grid search approach it identifies the necessary estimators for the CNN model. During this process it has identified those only hidden layers with 4 neurons each are sufficient for classification of disease.

In [4] Amreen Abbas et al implemented CGAN using transfer learning approach to work with the voluminous labelled agricultural data. The model has collected the images from plant village dataset, which limited images for research. The model has increased its dataset size by creating the synthetic images using conditional GAN approach because it can avoid the overfitting problem. The layers of the generator and discriminator components are discussed in table 3.

Table 3: Layer Analysis In GAN Components

S.NO	Generator	Filter Size	Discriminator	Filter Size
1	Input	128*128*3	Input	4*4*3
2	Embedding	25	Dense	Same
3	Dense	Same	Embedding	25
4	Reshape	64*64*3	Reshape	4*4*256
5	Concatenate	64*64*6	Concatenate	4*4*259
6	Conv2d	32*32*6	Conv2d	32*32*259
7	Flatten	2048		
8	Dropout	2048		

The synthetic images are passed through the DenseNET, a pre-trained model is customized at the bottom part by performing the fine tuning on the ReLu and Softmax layers for implementing the multi classification.

In [5] Ümit et al implement EfficientNet, which has variations from scratch B0 to B7 model. All the layers of this network use “Swish” as activation function, which solved the problems caused by both gradient descent and dying ReLu. The major component is MC Bottleneck, which has the power to connect the expansion and compression layers to connect directly. Along with height and depth, this model takes care of resolution by applying compound scaling co-efficient. The model takes the input of size 132*132, applies optimization through Adam with a learning rate of 0.001. Instead of passing the entire dataset as input, this model divides them into mini batches and updates the weights through back propagation. The model has achieved high accuracy on augmented dataset rather than on original images using B4 & B5 variants on multiple classes of the diseases. The deployment on the mobile application is also cost effective using this approach, which is economical for farmers also.

In [6] Hassan et al, extended CNN to depth separable CNN by reducing the number of parameters associated with the model. This research has focused on the multiple diseases in different plants rather than focusing on the single type of plant. Out of the existing pre-trained models, this research has identified EfficientNet B0 requires only 1 layer for multi classification of

Journal of Theoretical and Applied Information Technology
15th November 2022. Vol.100. No 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

disease but it suffers from dimensionality problem. This model integrates modified Inspection and EfficientNet models to solve the complicated issues by reducing the spatial features dynamically. Inspection model takes care of color, segmented parts of the leaf. EfficientNet converts the images to gray scale, noise reduction, and edge detection. The model requires only one drop out layer, which is unfrozen at necessary intervals. The depth of the layers is reduced by applying the batch normalization layer with a pile of activation functions to improve the accuracy of the model.

In [7] Nidhi Kundu et al developed a framework based on interpretations of the machine learning models to identify diseases in millet. In this research, author aims to develop an intelligent system for both collection and classification instead of utilizing standalone machine learning approaches. The model has gathered real time images from the farming lands by attaching necessary sensors to the agriculture land instead of working on the existing dataset. The classification of rust and blast is achieved by the CustomNet, in which each convolution layer is followed by the max-pooling layer. Finally a flatten layer followed by dense layer is attached at last and training of the model is performed using ImageNet. The model uses Grad-CAM to visualize the features extracted from the image. A sample of the visualization is shown in figure 2.

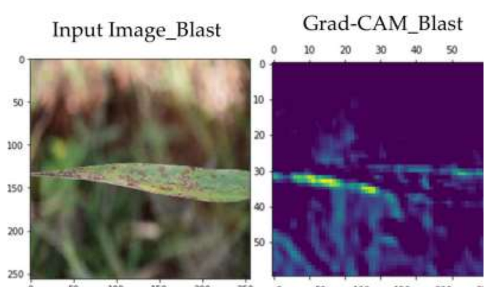

Figure 2: Grad-Cam Visualization

In [8] Esgario et al developed an IoT deep learning app for assisting farmers, which has two stages of identification. It estimates the severity of the plant disease by semantic segmentation process and symptoms are analyzed by lesions. UNet and PSPNet are integrated to generate semantic images, in which UNet takes care of geometric operations and PSPNet performs intensity transformations. The pre-processing of the images like resizing, back ground subtraction, color conversions are taken care automatically by neural network. Unnecessary features are eliminated by gradient method, whose weights are less than threshold value. This entire process is re-trained to get a fine tune model and then lesions are designed using the boundary boxes. These regions are partitioned into different segments and are masked. Each region is compared against the annotated labels and classification is performed.

In [9] Mostafa et al, designed an integrated framework of image processing with Customized fine tune CNN to enhance the production of crops. Initially, the images are equalled by performing bicubic interpolation operation and using histograms the quality of the image is enhanced. Affine transformations are applied to dataset to produce augmented images. Intelligent object detection is performed by customizing the CNN layers with fine tune of different pre-trained models. The detailed layer architecture is described in table 4.

Table 4: Description Of Layers Customization In Pre-Trained Models

Pre-trained model	Input Size	Convolution Layers	Normalization Layers	Pooling Layers	Dense Layers	Activation Function
Alex Net	227*227*3	5 Grouped conv 2d layers	2 Cross Normalization layers	2 Max-pooling layers	3	ReLu+ Softmax
GoogLeNet	28*28*64	9 Inspection layers	-	-	1	Softmax
SqueezeNet	56*56*16	7 Fire Squeeze layers	1 last normalization layer	4 Global pooling layers	-	ReLu+ Softmax
ResNet-50	56*56*256	4 Residual layers	-	-	1	Softmax

In [10] Sama Bari et al, designed enhanced RCNN framework in which data augmentation is performed using Gaussian noise by interpolating the gray scale. The images are annotated by passing VOC labels through XML. The model constructs feature map for every image and its candidate information is gained using RPN score. The pixels locations are continuously regressed frame by frame to classify the images. A slide window is passed over the infected area and the boundary box to extract the co-ordinates of the location. The network gets trained by using the Caffe DL model. It has balancing parameter which normalizes the RPN score to find the distinct value for each feature and the number of classes depends on the number of vectors in ROI region.

In [11] Rakesh et al, analyzed viral diseases in plants. The images obtained are processed with a color constancy algorithm to improve the illumination. For identifying the disease the process is divided into three stages. In the first stage, the candidate regions are extracted which are known as "Hot-Spots". In the second stage, using local descriptors the extracted images are analyzed. In the third stage, all the gathered information is processed with a meta classifier. All the Hot-Spots are properly identified and the meta classifier calculates module weights of all individuals to make a global assessment. The mate classifier is a combination of various classifiers. Primarily, the image is segmented over color channels using the Naïve Bayesian classifier, which accepts the blob threshold and identifies the diseased part as a candidate. The main advantage of this algorithm is it removes useless information from the image at an early stage. In the secondary phase, every disease and descriptor is trained with Random Forest classifier by tagging the labels. The confidence score for the particular disease is evaluated by all the possibilities of the candidate region. The descriptors are attached for each region and the shape, color and features are extracted by using one of the decision making classifier algorithms.

In [12] Abayomi-Alli et al, presented disease detection system using convolutional neural networks by dividing the entire process into 3 stages. The images are taken from PlantVillage dataset. The images in the dataset are resized-score mechanism is applied for normalizing the images; the main aim of normalization is to get all the pixel values in the same range. LeNet, which is similar to ImageNet, simple convolutional neural network architecture, is used for classification purposes. Three fully connected with softmax activation function is used for classification and max pooling layers are used for feature extraction, with 5X5 layer. ReLu activation function can help in finding the non-linearity in the images

In [13] Quan Huu Cap et al developed a Generative Adversarial Network known as "LeafGAN", which acts as a data augmentation tool by creating new diseased images from the healthy images. This system preserves the background of the image as well as generates images of high quality. The core component of this model is LFLSeg, which is a label-free and weakly supervised segmentation module. In this model, it uses feature maps to extract the segmentation information[6], and this in return helps the model to learn about dense and interior regions of the leaf images implicitly. The output of the segmented image is projected as a heat map so that it calculates the probability of each pixel in the final decision. Finally, this model has boosted the diagnosis system and solved the problems that arise due to the overfitting of the data.

In [14] Haseeb Nazki et al proposed Pipelined Generative Adversarial Networks for plant disease detection to address the problem of imbalanced data shifting. The working of this model consists of two major components. The first component is AR-GAN, which is used for generating the data augmentation synthetically by translating an image from one domain into another domain. A parameter known as a discriminator decides whether an image belongs to a particular domain or not. Based on the dataflows and loss functions, the image is reconstructed so that its performance is improved over cycle GAN. AR-GAN has a network that has an activation reconstruction for feature extraction. The second component is RESNET-50 CNN for disease detection with the same configuration as the baseline with RELU as activation functions. The network is fine-tuned by using ImageNet pre-trained weights.

In [15] Daniel Ho et al suggested a population-based augmentation algorithm, which uses a dynamic strategy. The main goal of this algorithm is to optimize the hyperparameter by using schedule learning policies. The PBA first runs a gradient descent algorithm on each epoch and then it evaluates the validation data. Truncation selection is applied to the bottom 25% of the data based on the weights and the top25% of the data based on the hyperparameters. Sungbin Lim [16] proposed the Fast AutoAugment Algorithm based on density matching [17-20]. The model constructs a search space for the images and defines two efficient operations known as calling probability and the magnitude. The search strategy uses the probability distribution on a pair of training datasets, the values

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

are parameterized and evaluated the accuracy and loss values. The performance is measured by comparing the amount of the data that is similar in both datasets and it uses K-fold stratified shuffling. At last, the policy is explored by using Bayesian Optimization by employing a kernel density estimator.

Table 5: Comparative Study On Existing Approaches

S.No	Author Name	Algorithms	Merits	Demerits
1	Chen	Light Weight Network	Transfer learning mechanism are applied for extended layers	Not discussed placing of the sensor and balancing of the load. Bottle neck compresses the image representation and increases number of layers.
2	Punam Bedi	Hybrid Auto Encoder	Trainable parameters are reduced	Not discussed placing of the sensor and balancing of the load. Error rate is high due to the selection of low dimension features
3	Thippa Reddy	Hyper Tuned Grid Search CNN model	The turning process has reduced the complexity of architecture	Not discussed placing of the sensor and balancing of the load. The conservation process of image to csv file after extracting features made the process proactive
4	Amreen Abbas	C-GAN with transfer learning	Synthetic images are	Not discussed placing of the sensor and balancing of the load. The process of fine tune misclassifies the data due to high learning rate
5	Ümit	EfficientNet	The flops attached to the bottlenet applies uniform operations on all the layers and reduces the operations by k*k, where k represents the kernel size	Not discussed placing of the sensor and balancing of the load. Number of epochs implemented for training is limited because of which model may suffer from under fitting problem
6	Hassan	Depth Separable CNN	Only 5 million parameters are sufficient to train the model	Not discussed placing of the sensor and balancing of the load. The architecture is complicated because of the 38 diseases classification involvement
7	Nidhi Kundu	CustomNet	Since every alternate layer is designed using max-pooling, it enhances the quality of the essential features and detected edges	Not discussed placing of the sensor and balancing of the load. It is very costly to equip each plant with IoT sensors. So the model can be extended by using the satellite images of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

				the crop area.
8	Esgario	IoTDL	Semantic segmentation helps the model to identify the similar regions and eliminates the irrelevant things	Not discussed placing of the sensor and balancing of the load. The processing of the image in the limited space of the mobile increases the waiting time of the user
9	Mostafa	Customized fine tune CNN	The model tries to improve the kappa cohen index, which is a good statistical measure. It exhibits its confidence based on the range of values obtained by the model	Not discussed placing of the sensor and balancing of the load. The model uses traditional image pre-processing techniques before passing the input to the CNN, which is time consuming and expensive process
10	Sama Bari	Enhanced RCNN	Noise reduction is reduced very effectively using Gaussian	Not discussed placing of the sensor and balancing of the load. Model can build a CNN model that can adapt to the size of the object in the image
11	Rakesh	VirLeafNet	1. Preprocessing using Global Color Constancy 2. Leaf Segmentation with Statistical inference methods 3. Images are classified by meta classifiers	Not discussed placing of the sensor and balancing of the load. Identifying the diseases at early stages can improve the quality and productivity of crops
12	Abayomi-Alli	LeNet CNN	1. Image resized and normalized with Z-score 2. LeNet CNN for classification	Not discussed placing of the sensor and balancing of the load. Different learning rates and optimizers can be used for the improvement of accuracy

Research Gaps:

1. The light weight mechanism implemented two layered bottle neck approach, which has compressed the image representation because of which the research cannot focus on the viral infections like mildew, patches and others [18].
2. The Hybrid auto encoder and hyper tuned models are failed because the grid search mechanisms extracts the features by checking with every possible combination this increases the computational time for selecting the features alone.
3. GAN's creates synthetic images but fine-tuned estimators in networks [20-23] because of the over training has produced predictions with more misclassification.
4. Traditional segmentation and pre-processing techniques doesn't give accurate values because of their inefficient mechanism of clustering the similar pixels [24-25] or due to mis annotation process during the labelling.

Proposed Methodology:

The proposed model uses the high resolution cameras to capture the live plant images from the agriculture lands. The model then increases the size of the dataset using the style GAN's and also implements basic image manipulation techniques so that the system takes care of minute variations also. During this process, it studies the impact of resources on the model using the GPU's provided by the software known as "Co laboratory". It also implements the bottle neck layers in between the dense layers of networks to back propagate to initial state if the system crashes due to heavy load. This bottle neck layers also helps the model to extract the essential features without implementing the complete auto encoder model. Before classifying the infected areas, the model utilizes the pre-trained model ALEXNET to save the best training epoch in the cloud as .h5 model. The main advantage of this .h5 file is even though new infection diseases are need to be identified then there is no need to train the model from scratch later the last layers of this pre-trained model is customized by attaching the ensemble classifiers to perform multi classification. Using the enhanced N-grams in NLP and neural network approaches the model designs a recommendation system for curing the diseases.

Conclusion:

Many of the researchers worked on disease detection using publicly available dataset known as “plant village”, whose images are collected under controlled conditions. Controlled conditions produce the images in the stable environment of high resolution images. In real time scenario, while collecting the plant images from either sensor or cameras these may produce noisy or blur images due to the movement of plants because of the surrounding atmosphere. When the system which is trained on the controlled environment is evaluated with the real time images gathered from the uncontrolled conditions then there is a possibility for more number of misclassification rates. The traditional deep learning approaches have given good accuracies with transfer learning but all of them are not practically possible. The research need a model that can generate the augmented images that can replicate the real world scenario and reduce the miss classifiers With the variations in deep learning techniques, there is a huge amount of chances to create different augmented images and trace their signals through IoT sensors. So, the proposed model planned to combine traditional approaches with pre-trained model to handle different signal variations. Based on the observations in the literature review, we have considered the following objectives for further research:

a. The image acquisition process can be extended to the outdoor collection of plants from different geographical environments. All the existing researchers collected the plant leaves from the plant village dataset, which is collected by a scientific research centre with a high resolution camera. So, the research should develop an IoT based continuous monitoring system that can capture the images of the plants during different climatic and seasonal conditions. The system should also utilize the sensors that can record the essential components required by plants for their growth because due to the atmospheric nature also the plants position varies.

b. Utilization of sensors for every plant in the crop area will increase the cost of the system. This is again economical burden on the farmer, so the proposed system should increase the size of the dataset and produce the artificial distorted image by performing a data augmentation process with the help of scaling, rotation and translation operations along with GAN’s. The enhancement of the dataset for training and testing purposes can improve the accuracy of the system because deep learning systems need more variety of data to get accurate training during every epoch.

c. Existing works found a solution using variants of the CNN and binary classification layers to identify whether a plant is healthy or not using the plant village dataset got an accuracy of 98% on training dataset but got only 72% on testing dataset. Few researchers collected images from agriculture land and implemented CNN’s but the performance of the model on both training and testing is 75% and 60% respectively. So the proposed model needs to identify and classify the plant diseases in both controlled and uncontrolled conditions.

d. Many works presented the classification of the diseases but no system provided the impact of heavy data on the neural networks like their execution time, resources and memory required and they didn’t focus on the remedies that the farmer has to undergo to cure the infected plants. The proposed system should develop a system that utilizes the less resources and doesn’t impact the working of networks because of heavy load dataset. It should also recommend the pesticides that can cure the infections.

REFERENCES:

[1] Chen, J., Zhang, D., Zeb, A., & Nanehkaran, Y. A. (2021). Identification of rice plant diseases using lightweight attention networks. Expert Systems with Applications, 169, 114514.

[2] Bedi, P., & Gole, P. (2021). Plant disease detection using hybrid model based on convolutional autoencoder and convolutional neural network. Artificial Intelligence in Agriculture, 5, 90.

[3] Gadekallu, T. R., Rajput, D. S., Reddy, M. P. K., Lakshmanna, K., Bhattacharya, S., Singh, S., … Alazab, M. (2020). A novel PCA–whale optimization-based deep neural network model for classification of tomato plant diseases using GPU. Journal of Real-Time Image Processing.

[4] Abbas, A., Jain, S., Gour, M., & Vankudothu, S. (2021). Tomato plant disease detection using transfer learning with C-GAN synthetic images. Computers and Electronics in Agriculture, 187, 106279.

[5] Atila, Ü., Uçar, M., Akyol, K., & Uçar, E. (2020). Plant leaf disease classification using EfficientNet deep learning model. Ecological Informatics, 101182.

[6] Hassan SM, Maji AK, Jasiński M, Leonowicz Z, Jasińska E. Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach. *Electronics*. 2021; 10(12):1388.

[7] Kundu N, Rani G, Dhaka VS, Gupta K, Nayak SC, Verma S, Ijaz MF, Woźniak M. IoT and Interpretable Machine Learning Based Framework for Disease Prediction in Pearl Millet. *Sensors*. 2021; 21(16):5386. https://doi.org/10.3390/s21165386

[8] Esgario, J. G. M., de Castro, P. B. C., Tassis, L. M., & Krohling, R. A. (2021). An app to assist farmers in the identification of diseases and pests of coffee leaves using deep learning. Information Processing in Agriculture.

[9] Mostafa AM, Kumar SA, Meraj T, Rauf HT, Alnuaim AA, Alkhayyal MA. Guava Disease Detection Using Deep Convolutional Neural Networks: A Case Study of Guava Plants. *Applied Sciences*. 2022; 12(1):239.

[10] Bari BS, Islam MN, Rashid M, Hasan MJ, Razman MAM, Musa RM, Ab Nasir AF, P.P. Abdul Majeed A. 2021. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. PeerJ sComputer Science 7:e432

[11] Joshi, R. C., Kaushik, M., Dutta, M. K., Srivastava, A., & Choudhary, N. (2020). VirLeafNet: Automatic analysis and viral disease diagnosis using deep-learning in Vigna mungo plant. Ecological Informatics, 101197. doi:10.1016/j.ecoinf.2020.101197

[12] Abayomi-Alli, O. O., Damaševičius, R., Misra, S., & Maskeliūnas, R. (2021). Cassava disease recognition from low-quality images using enhanced data augmentation model and deep learning. Expert Systems. doi:10.1111/exsy.12746

[13] Saikawa, Takumi & Cap, Quan & Kagiwada, Satoshi & Uga, Hiroyuki & Iyatomi, Hitoshi. (2019). AOP: An Anti-overfitting Pretreatment for Practical Image-based Plant Diagnosis. 5177-5182.

[14] Nazki, Haseeb. (2018). Synthetic Data Augmentation for Plant Disease Image Generation using GAN.

[15] Ho, Daniel & Liang, Eric & Stoica, Ion & Abbeel, Pieter & Chen, Xi. (2019). Population Based Augmentation: Efficient Learning of Augmentation Policy Schedules.

[16] Lim, Sungbin & Kim, Ildoo & Kim, Taesup & Kim, Chiheon & Kim, Sungwoong. (2019). Fast AutoAugment.

[17] Shin, J., Chang, Y. K., Heung, B., Nguyen-Quang, T., Price, G. W., & Al-Mallahi, A. (2021). A deep learning approach for RGB image-based powdery mildew disease detection on strawberry leaves. Computers and Electronics in Agriculture, 183, 106042.

[18] Padmanabhuni, Ms. S. S. (2020). an extensive study on classification based plant disease detection system. journal of mechanics of continua and mathematical sciences, 15(5).

[19]. IlaiahKavati, A. Mallikarjuna Reddy, E. Suresh Babu, K. Sudheer Reddy, RamalingaSwamyCheruku,Design of a fingerprint template protection scheme using elliptical structures,ICTExpress,Volume 7, Issue 4,2021,Pages 497-500,ISSN 2405-9595,https://doi.org/10.1016/j.icte.2021.04.001.

[20] Swarajyalakshmi v papineni, A.Mallikarjuna Reddy, Sudeeptiyarlagadda , SnigdhaYarlagadda, HarithaAkkineni "An Extensive Analytical Approach on Human Resources using Random Forest Algorithm" International Journal of Engineering Trends and Technology 69.5(2021):119-127.

[21] Swarajya Lakshmi V Papineni, SnigdhaYarlagadda, HaritaAkkineni, A. Mallikarjuna Reddy. Big Data Analytics Applying the Fusion Approach of Multicriteria Decision Making with Deep Learning Algorithms, International Journal of Engineering Trends and Technology, 69(1), 24-28, doi: 10.14445/22315381/IJETT-V69I1P204.

[22] C. R. T, G. Sirisha and A. M. Reddy, "Smart Healthcare Analysis and Therapy for Voice Disorder using Cloud and Edge Computing," 2018 4th International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Mangalore, India, 2018, pp. 103-106, doi: 10.1109/iCATccT44854.2018.9001280

[23] Sudeepthi Govathoti, A Mallikarjuna Reddy, Deepthi Kamidi, G BalaKrishna, Sri Silpa Padmanabhuni and Pradeepini Gera, “Data Augmentation Techniques on Chilly Plants to

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Classify Healthy and Bacterial Blight Disease Leaves" International Journal of Advanced Computer Science and Applications(IJACSA), 13(6), 2022. http://dx.doi.org/10.14569/IJACSA.2022.0130618.

[24] Mallikarjuna A. Reddy, Sudheer K. Reddy, Santhosh C.N. Kumar, Srinivasa K. Reddy, "Leveraging bio-maximum inverse rank method for iris and palm recognition", International Journal of Biometrics, 2022 Vol.14 No.3/4, pp.421 - 438, DOI: 10.1504/IJBM. 2022. 10048978.

[25] Chouhan, S. S., Singh, U. P., Sharma, U., & Jain, S. (2021). Leaf disease segmentation and classification of Jatropha Curcas L. and Pongamia Pinnata L. biofuel plants using computer vision based approaches. Measurement,171, 108796.