International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Ensemble of Densely Connected Convolutional Networks for Brinjal Leaf Disease Detection

[1]K. Chelladurai, [2]N. Sujatha

Submitted: 04/12/2023 **Revised**: 13/01/2024 **Accepted**: 24/01/2024

Abstract: One of the growing concerns in global agriculture is the rise of plant diseases caused by pathogens like viruses, bacteria, and fungi. Detecting these diseases early and implementing effective preventive measures is crucial to limit their spread. Manual disease detection in plants is a time-consuming process. In recent years, deep learning, involving image processing and computer vision, has shown promise. For instance, India's brinjal crop has suffered yield losses due to delayed disease identification. Utilizing automatic disease detection through image processing can assist farmers. While various techniques exist for comparing infected and healthy leaves, the scarcity of diverse datasets containing different leaf diseases has hindered progress in plant disease detection. This paper presents a new dataset and an improved deep learning model based on an ensemble of Densely Connected Convolutional Networks (DenseNet) for brinjal leaf disease detection. Our dataset comprises 8,080 annotated brinjal leaves categorized into seven classes, including six types of diseased leaves and one representing a normal leaf. The enhanced deep learning model is an ensemble of multiple DenseNet architectures designed to enhance overall model performance. Ensemble methods, which combine predictions from multiple models, have been employed to make predictions more accurate and robust compared to individual models. In this paper, we present DenseNet Ensembles, incorporating DenseNet121, DenseNet169, DenseNet201, and DenseNet264. Experimental results demonstrate that the Ensemble DenseNet achieves the highest prediction accuracy at 94.4% when compared to contemporary methods. This advancement represents a significant contribution to the field of agriculture, offering a promising solution to combat plant diseases and improve crop yield sustainability.

Keywords: *Plant leaf disease diagnosis, Brinjal disease, Deep learning, CNN, Transfer learning-based models.*

1. Introduction:

Agriculture is the vital part of the nation as it is the source of production of food for humans. India is initially an agricultural country since two-thirds of the population depends only on agriculture. Brinjal is one of the significant vegetable yields of India. The area under which brinjal is cultivated is estimated to be 0.55 million hectares. Its total production in India is around 8.2 million tones. Although it's cultivated in large areas, brinjal is easily prone to diseases which cause 60 to 70 %. Brinjal is a hardy crop which can be easily grown in dry area with low irrigation facilities. It can be grown throughout the year and India is the second biggest maker of brinjal. The concern to farmers is when the brinjal plant becomes infected with various pathogens including bacteria, fungi, viruses, etc. So Hence it is important to find a way to detect and identify of plant diseases. Deep learning technology from recent years offers an improved system for early crop disease detection and evaluation. It is revealed that this methodology is an intelligent strategy for diagnosing leaf disease. The quality of the crop is secured only on the early identification of diseases that affect it [1]. Other difficulties the farmers face during identification of diseases is in crop plantation than in vegetable plantation, because in crop plantations the plants are spaced unevenly. Hence an efficient and low cost computational technique is needed for the detection of disease in plants. Deep learning algorithm was discovered to be a low cost, quick efficient way for recognizing agricultural disease. This algorithm was developed for the identification of plant leaf disease. [2] the technology used in deep learning (DL) is block chain technology [3-5] ins addition to big data technology [6-8]. The DL provides excellent computing system [9] which has led to the new data creation intensive overflow in agricultural activities

Two methods namely, convolutional neural networks (CNN) and recurrent neural networks (CNN), in particular, are deep learning approaches used in agriculture. CNN is one of these algorithms and is composed of recurrence of many convolutional layers, pooling layers, and totally connected layers. [10]. CNN features are mainly applicable for hand written character recognition and image processing technique. CNN is most beneficial for voice recognition, text and

1Research scholar P.G & Research Department of Computer Science, Sri Meenakshi Govt. Arts College for Women,Madurai Kamaraj University, Madurai, Tamil Nadu,India
kchelladurai05@gmail.com
2Associate Professor P.G & Research Department of Computer Science, Sri Meenakshi Govt. Arts College for Women, Madurai Kamaraj University, Madurai,Tamil Nadu, India
sujamurugan@gmail.com

video processing, object detection, picture categorization, medical image analysis, and other tasks. Convolutional layers pooling and fully linked layers make up CNN. [11].

The places where Brinjal is grown in abundance in Bangladesh, China, India and Philippines. The most agriculturist addressed that the common diseases in Brinjal are tobacco mosaic, pseudomonas solanacearun, bacterial with and cercospora leaf spot.

This paper focuses on the detection of the Brinjal leaf diseases using the combined process of deep learning and image processing techniques. This includes

i) Grouping the healthy and diseased leaf image
ii) Segmentation process
iii) The diseased leaf is removed based on its color, texture, and shape
iv) Classified according to the sort of disease it possess

The next portions of this work are divided into the following categories: section 3, gathering of the Brinjal data set; section 4, methodology; and section 5, results and conclusions.

2. Review of Literature

Deep learning methods are a powerful tool in agriculture in leaf disease detection. The related works in Brinjal leave diseases using deep learning process is given below. Anand et al. [12], diagnosed the brinjal plant leaf disease using artificial neural networks and image processing. K-means clustering algorithm is used for segmentation and neural network for classification are the methodologies followed. They revealed that artificial neural networks are highly good at identifying leaf diseases. Abisha et al.[13], employed artificial neural network to categorize diseases affecting brinjal leaves according to their color, texture, and structural characteristics. For efficient feature extraction, segmentation and image fusion methods are employed. They exposed that features like color, texture, or intensity are insufficient to boost the system's performance over 65%. Aravind Krishnaswamy Rangarajan et al. [14] employed pre-trained visual geometry group 16 (VGG16) architecture to classify diseases in egg plants. For evaluation, they employed VGG16 to convert images to the Hue Saturation Value (HSV), YCbCr, and grayscale color spaces. The dataset made up of RGB and YCbCr photos taken in the field yielded an accuracy of 99.4% for them. According to Mahadevakumar et al. [15], Diaporthe vexan, a dangerous fungal pathogen, causes the leaf blight and fruit rot diseases of brinjal.

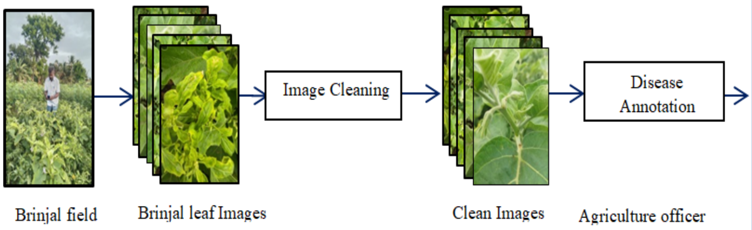
From the above literature it is very clear that more works are based on the classification of leaf diseases in brinjal leaves based on different method. In many work, deep learning algorithm is used to train the dataset and obtain very high accuracy. Thus for the identification of leaf diseases in brinjal leaves and to obtain an improved accuracy, DenseNet model is used in this paper. This model is designed mainly for classification of images using dense connections between layers. A feed forward mechanism is used to connect each layer to the one below it. For the best outcome in brinjal leaf diseases, this methodology was refined. Additionally, the detection of brinjal leaf diseases using this deep learning model can be greatly enhanced, and its classification accuracy may be raised. The brinjal plant leaf images were gathered using a smart phone camera in different brinjal farming lands to validate the proposed DenseNet model. Hence this methodology can solve the problem of classification and automatic detection of plant leave disease in brinjal.

Fig 1 Sample disease images from Brinjal leaf dataset

3. Brinjal Dataset

Figure 1 shows the procedure for gathering data and annotating it for the Brinjal Doctor dataset. From actual brinjal fields in a village close to the Tenkasi region of Tamil Nadu, India, we collected RGB photos of brinjal leaves. Data was gathered between February and May 2022. In order to take high-resolution RGB photos, we used a smartphone. Approximately 12,000 JPEG-format photos with a 1,080 by 1,400 pixel resolution made up our initial dataset. We next carefully examined each sample and purged duplicate and substandard photos. After picture cleaning, 8,082 photos made up our dataset.

Together with an agricultural official, we next went about manually labeling each photograph with a disease class based on the presence of infections. The final dataset after annotation had 7 classes representing 6 illnesses and healthy leaves. Bacterial Wilt, Cercospora Leaf Spot, Alternaria Leaf Spot, Damping Off, Tobacco Mosaic Virus, Collar Rot, and Healthy Leaves are among the disease noted for Brinjal (Figure 1). Figure 2 showcases sample images of leaves affected by the 6 distinct diseases.



S.No	Disease Name	Count
1	Bacterial Wilt	1080
2	Fruit Rot	1180
3	Altermaria leaf Sopt	1040
4	Little leaf of Brinjal	1220
5	Mosaic virus	1360
6	Collar rot	1120
7	Healthy Leaf	1080
	Total	8080

Fig 2 Data collection and annotation process

4. Methodology

In recent years, deep learning-based methods gained huge attention in detection diseases in many plants. In this paper, we propose in improved Densely Connected Convolutional Networks (DenseNet) and evaluate its performance on our dataset. Deep neural network architectures known as DenseNet were created for image classification and other computer vision problems. DenseNet is characterized by its dense connections between layers, which are different from traditional convolutional neural networks (CNNs).

Each layer is connected to every other layer in a feedforward manner in a DenseNet [16]. Each layer receives direct information from all below layers thanks to its tight interconnectedness. As a result, it encourages feature reuse, lessens the vanishing gradient issue, and permits very deep networks without encountering the degradation issue (wherein adding more layers results in decreasing performance). Convolutional layers, batch normalization, and ReLU (Rectified Linear Unit) activation functions are all included in each of the densely connected blocks that make up DenseNet. The network's information flow is improved by skip connections, which concatenate the feature maps from all earlier layers.

The advantages of DenseNet include improved gradient flow, efficient parameter usage, and better feature propagation. DenseNets are commonly employed in deep learning applications where great performance and efficiency are required, and they have attained cutting-edge results in a variety of computer vision tasks.

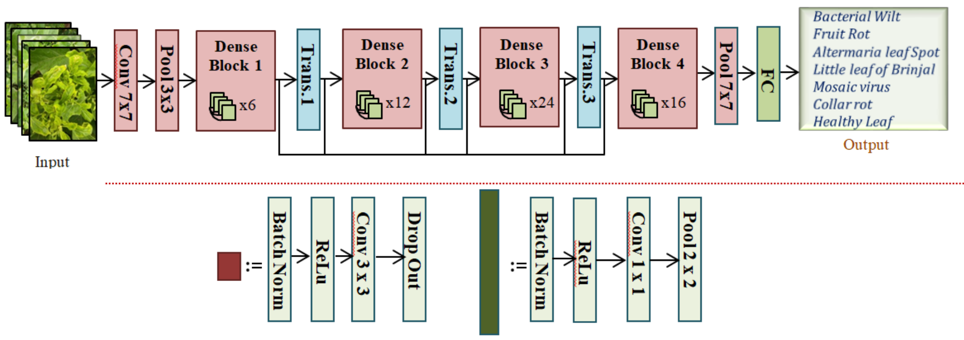


Fig 3 DenseNet architecture [10]

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Coevolution	112 x 112	7 x 7 conv, stride 2			
Pooling	56 x 56	3 x 3 max pool, stride 2			
Dense Block(1)	56 x 56	[1 x 1conv 3 x 3conv] x 6	[1 x 1conv 3 x 3conv] x 6	[1 x 1conv 3 x 3conv] x 6	[1 x 1conv 3 x 3conv] x 6
Transition Layer(1)	56 x 56	1 x 1 conv			
	28 x 28	2 x 2 average pool, stride 2			
Den Dense Block(2)	28 x 28	[1 x 1conv 3 x 3conv] x 12	[1 x 1conv 3 x 3conv] x12	[1 x 1conv 3 x 3conv] x 12	[1 x 1conv 3 x 3conv] x12
Transition Layer(2)	28 x 28	1 x 1 conv			
	14 x 14	2 x 2 average pool, stride 2			
Dense Block(3)	56 x 56	[1 x 1conv 3 x 3conv] x 24	[1 x 1conv 3 x 3conv] x 32	[1 x 1conv 3 x 3conv] x 48	[1 x 1conv 3 x 3conv] x 64
Transition Layer(3)	14 x 14	1 x 1 conv			
	7 x 7	2 x 2 average pool, stride 2			
Dense Block(4)	7 x 7	[1 x 1conv 3 x 3conv] x 16	[1 x 1conv 3 x 3conv] x 32	[1 x 1conv 3 x 3conv] x32	[1 x 1conv 3 x 3conv] x 68
Classification Layer	1 x 1	7 x 7 global average pool			
		1000D fully- connected , softmax			

Fig 4 Layers of DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet-264

Each layer of the DenseNet is connected to every other layer in a feedforward manner, exhibiting a dense connectivity pattern. This connectedness promotes the network's feature reuse and gradient flow, which improves gradient propagation and lessens the vanishing gradient problem.

The following are the layers in a DenseNet architecture:

1. **Input Layer**: The input to a DenseNet is typically an image or a tensor representing the input data. The dimensions of this input tensor depend on the specific task and dataset.

2. **Initial Convolution Layer**: The input tensor is passed through an initial convolutional layer that performs a set of convolutions to extract low-level features. Small filters (such as 3x3) are frequently used in this layer, which is followed by batch normalization and a non-linear activation function (such as ReLU).

3. **Dense Blocks:** The network's building blocks, dense blocks make up the majority of DenseNet. A series of densely coupled convolutional layers make up each dense block. Feature maps from earlier layers are concatenated along the depth dimension within each dense block. This indicates that each layer's input comes from the feature maps of all layers that came before it in the same block. Small filters (like 3x3) are often used in each convolutional layer within a dense block, which is then followed by batch normalization and a non-linear activation function.

4. **Transition Layers:** To manage the rise in computing complexity, transition layers between dense blocks shrink the spatial dimensions of the feature maps. A 1x1 convolutional layer with average pooling make up a typical transition layer. By reducing the amount of feature maps, the 1x1 convolution effectively compresses the data before it is sent to the following dense block.

5. **Global Average Pooling Layer**: Following the application of all dense blocks, a global average pooling layer is used to shrink the feature maps' spatial dimensions to 1x1. This operation generates a vector of features by calculating the average value of each feature map.

6. **Fully Connected Layer (Dense Layer)**: For classification tasks, the output of the global average pooling layer is often fed into a dense fully connected layer with a softmax activation function.

7. **Output Layer**: The final output layer provides the predicted class probabilities (for classification) or the regression output (for regression) based on the task.

DenseNet's dense connectivity and transition layers contribute to its efficiency and effectiveness in deep learning tasks. To accommodate various applications and computing resources, this architecture contains variants including DenseNet-121, DenseNet-169, and DenseNet-201, which vary in terms of the number of layers and characteristics. Figure 2 depicts the DenseNet model's architecture. Figure 3 depicts the layers of four DenseNet variants: DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet-264.

4.1 Ensembles of DenseNet: A powerful approach in machine learning and computer vision that makes use of the advantages of several DenseNet designs to boost overall model performance is known as a DenseNet ensemble. Compared to individual models, ensemble approaches produce predictions that are more reliable and accurate [17]. The four variations of DenseNet—DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet—are combined to form DenseNet Ensembles, which are described in this study. The predictions of individual DenseNets are combined using Voting Ensembles, which aggregate predictions through majority voting or weighted voting. Each DenseNet in the ensemble casts one vote, and the class with the most votes is predicted.

The predictions generated by individual DenseNets are amalgamated through Voting Ensembles [18], employing methods such as majority voting or weighted voting. Each DenseNet within the ensemble casts one vote, and the predicted class is determined by the class receiving the most votes. This process can be represented mathematically as:

$$\text{Ensemble Prediction } = \arg\max_{c} \sum_{i=1}^{N} \text{Vote}(c, i)$$

- Where, $EnsemblePrediction$ represents the final prediction made by the ensemble.
- $argmax$ signifies selecting the class (c) that maximizes the sum of votes.
- $\sum$ represents the summation over all individual models (i) in the ensemble.
- $Vote(c,i)$denotes the vote cast by the i-thDenseNet for class c. This can be a binary vote (0 or 1) in majority voting or a weighted vote based on confidence scores in weighted voting.

Table 1: Comparison of precision, recall, f1-score, and accuracy of Ensemble DenseNet with five existing deep learning models.

Model	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**Accuracy (%)**
Deep CNN	88.2	90.5	89.3	87.8
DenseNet-121	92.1	91.8	91.9	91.5
DenseNet-169	91.5	93.2	92.3	91.7
DenseNet-201	93.7	92.9	93.3	93.0
DenseNet-264	92.8	94.1	93.4	92.5
Ensemble DenseNet	**94.5**	**94.8**	**94.6**	**94.4**

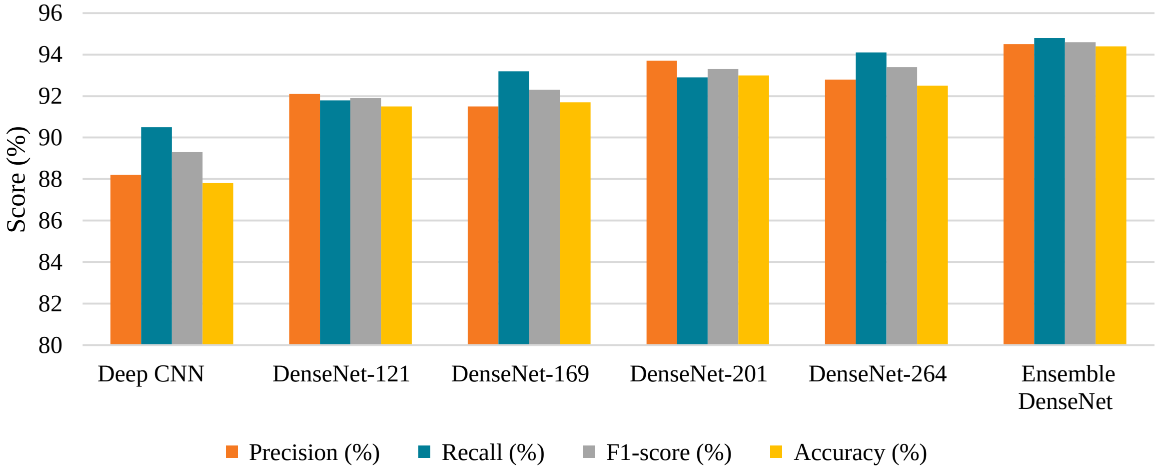


Fig 5: Comparison of precision, recall, f1-score, and accuracy of Ensemble DenseNet with five existing deep learning models.

5. Results and Discussion

We used the Keras and TensorFlow libraries to create five deep learning models in the Python framework, and we ran all of our tests in the Google Colab environment with GPU support. A training set and a testing set were created from the dataset. Out of a total of 8,080 photos, the training set had 6,464 images (80%), and the test set contained 1,616 images (20%). Additionally, we extracted a validation set from the training set, comprising 1,293 images (20%). Consequently, the final training set consisted of 5,171 images. We added image data augmentation during model training using a variety of transformation strategies, including rotation (±5 degrees), shear intensity (±0.2), zoom (±0.2), width and height shift (±5%), and horizontal flip. Additionally, every image was normalized after being scaled to 256 by 256 pixels in resolution. All models used a batch size of 32, a learning rate of 0.001, and a training period of 100 epochs.

The proposed Ensemble DenseNet is compared to five deep learning models in Table 1 and Figure 4 based on four assessment metrics: accuracy, precision, recall, and F1-score. Each model's performance across four metrics is closely scrutinized in the evaluation of several deep learning models for classifying brinjal illness using RGB photos. With a Precision of 88.2%, a Recall of 90.5%, an F1-score of 89.3%, and an overall Accuracy of 87.8%, the Deep CNN model displays excellent results, demonstrating a well-rounded capacity to reliably classify diseases from RGB photos. With remarkable Precision of 92.1%, Recall of 91.8%, F1-score of 91.9%, and Accuracy of 91.5%, DenseNet-121 follows closely, demonstrating its accuracy and efficacy in disease categorization.

Similarly, DenseNet-169 and DenseNet-201 deliver strong results, with Precision values of 91.5% and 93.7%, and Recall values of 93.2% and 92.9%, respectively. Their F1-scores of 92.3% and 93.3%, along with Accuracies of 91.7% and 93.0%, emphasize their balanced performance and precision in positive predictions. The substantial capabilities of DenseNet-264 in disease identification are demonstrated by its high Precision of 92.8%, Recall of 94.1%, F1-score of 93.4%, and Accuracy of 92.5%. The Ensemble DenseNet, on the other hand, stands out as the top performer, attaining the highest Precision (94.5%), Recall (94.8%), and an outstanding F1-score (94.6%). With an overall Accuracy of 94.4%, this ensemble approach capitalizes on the strengths of individual models, showcasing the effectiveness of ensemble techniques in significantly enhancing the accuracy and robustness of disease classification in RGB images.

The Ensemble DenseNet model achieved the highest score with 94.4% accuracy, 94.5% precision, 94.8% recall, and F1 score of 94.6%. Precision, Recall, F1-score, and Accuracy are four important measures that are used to assess each model's performance. Notably, the group of DenseNet models, referred to as "Ensemble DenseNet," performs better than the individual models, attaining the maximum Precision and Recall scores of 94.5% and 94.8%, respectively. This ensemble approach harnesses the strengths of multiple models to enhance disease classification accuracy, as evident in its impressive F1-score of 94.6% and overall Accuracy of 94.4%.

These results underscore the significance of ensemble techniques in improving the robustness and effectiveness of deep learning models for image-based disease classification. These outcomes show that our Brinjal Doctor Dataset is suitable for automated tasks involving the classification of Brinjal diseases. In the future, we also intend to assess more pre-trained models using various transfer learning techniques.

6. Conclusion

Farmers must manually identify Brinjal illnesses, which is a difficult task. As a result, there is a growing need to provide automated systems that are scalable to handle different illnesses and plants. A significant barrier to comparing current deep learning-based models and widespread adoption of these solutions has been the absence of publicly accessible datasets with annotated disease names. The Brinjal Dataset for automated Brinjal illness identification is presented in this study. There are 8 080 annotated photos of Brinjal leaves in 7 categories (6 illnesses and normal leaves). In addition, we provide an enhanced deep learning model built on a collection of closely coupled deep neural networks. The ensembling method is based on a voting mechanism that combines predictions from individual DenseNet models. The results demonstrate that the Ensemble DenseNet achieved superior accuracy at 94.4%, followed by 92.5% with the DenseNet-264 model. These results underscore the significance of ensemble techniques in enhancing the robustness and effectiveness of deep learning models for image-based disease classification. These outcomes further demonstrate the value of our Brinjal Doctor Dataset for jobs requiring automated Brinjal disease classification. In the future, we also intend to assess more pre-trained models using various transfer learning techniques.

Reference

[1] WaW,Yang T.L., LiR., ChenC., LiuT.,Zhou K., et al., 2020 . Detection and enumeration of what grains based on a deep learning method under various scenarios and scales., J.Integr.Agric., Volume 19 issue 8

[2] Chen C.J., Huang Y.Y.,Li Y.S ., chen Y.C., Chang c.y Huang Y.M., 2021 identification of fruit tree pests with deep learning on embedded drone to achieve accurate pesticide spraying .IEEE Access volume9, issue 1,pp.21986-21997

[3] Bisuwas M, kaisee MS DRIAS: Digital record keeping in land administration system relying on Blockchain. In proceedings of sixth international congress on information and communication technology. Springer Singapore 2022:965-973

[4] Janat MU AhamedR.Manum A, FeadausJ,Osta R Biswaf M, August,Drganic food supply chin Traceeability using block chain technology. In 2021 international conference on science and contemporary technologies9ICSCT0 IEEE 2021:1-6

[5] Biswas M, Al FaysalJ,Ahmed KA. Landchain A Blockchin Based secured land registration system. In 2021, international conference on science & contemporary technologies (ICSCT). IEEE 2021: 1-6

[6] BiswasM.WhaiduzzamanMD,.Efficient mobile cloud computing through computation offloading., Int. J.Adv.Tecchnol. 2018;IO920:32

[7] MahiM.NayeenJ,HosscunKMBiswas M WhaiguzzamanM.Sentrac: A novel real time sentiment analysis approach through twitter cloud environment in advances in Electrical and computer Technologies, Springer, Singapore 2020:21-32

[8] Ray B,SahaKK,BiswasM,Rahman MM December User perspective on usage and privacy of ehealth systems in Bangladesh A Dhaka based survey. In 2020 IEEE Asia-Pacific conference on computer science and Data Engineering (CSDE) IEEE 2020:1-5

[9] Sterling T.BrodowiczM.Anderson M. High performance computing: modern systems and practice. MoraganKaifmann: 2027

[10] Zhu.n., Liu,Z.,Hu, k., wang,Y., Tan, J., Guo,y., Deep learning for smart agriculture concepts tools applications. And opportunities. Int.JAgric Biol.Eng.2018,11,32-44.

[11] Ajit,A., Acharya,K.,Samanta,A. Arevies of convolutional neural networks in proceedings of the 2020 international conference of emerging trends in information technology and engineering (ic-ETITE)

[12] Anand R., Veni S. and Aravinth J., An application of image processing techniques for detection of diseases on Brinjal leaves using K-Means Clustering method, Fifth International Conference on Recent Trends in Information technology, IEEE, 2016.

[13] Abisha S., and Jayasree T., Application of Image processing Techniques and Artificial Neural

Network for detection of diseases on brinjal leaf, IETE journal of Research, 1696716 (2019).

[14] AravindKrishnaswamyRangarajan and Raja Purushothaman, Disease classification in Eggplant using Pre-trainedVGG16 and MSVM, Scientific reports, nature research (2010) 10, 2322.

[15] Mahadevakumar S., and Janardhana GR., Leaf blight and fruit rot disease of brinjal caused by DiaportheVexans in six agro ecological regions of South West India, Plant pathology and Quarantine 6(1), 5-12 (2016).

[16] Huang, Gao, et al., Densely connected convolutional networks, Proceedings of the IEEE conference on computer vision and pattern recognition, 2017.

[17] Dong, Xibin, et al., A survey on ensemble learning, Frontiers of Computer Science 14 (2020): 241-258.

[18] Leon, Florin, Sabina-Adriana Floria, and CostinBădică, Evaluating the effect of voting methods on ensemble-based classification, 2017 IEEE international conference on Innovations in intelligent Systems and applications (INISTA), IEEE, 2017.