Journal of Positive School Psychology http://journalppw.com
2022, Vol. 6, No. 10, 2553-2562

Banana Leaf Disease Detection Using Glcm Based Feature Extraction And Classification Using Deep Convoluted Neural Networks (Dcnn)

T. Mahendran[1] and K. Seetharaman[2]

[1]*Department of Computer Applications, Arignar Anna Government Arts College, Villupuram – 605 602. Tamilnadu. India. Email: maheinfex@gmail.com*
[2]*Department of Computer and Information Science, Annamalai University, Annamalainagar – 608 002. Tamilnadu. India. Email: kseethadde@yahoo.com*

Abstract:
In India about 70% of population rely on yield from agriculture. The plants, leaves have been affected by the disease caused by insects that transfers the infection to other plants in agriculture. During the infection of these diseases the production has been decreased in the farm. Therefore it is necessary to identify these infections at the earliest. The disease detection in banana has turned out be more perplexing in the farm. The banana plant disease detection through image processing becomes more efficient also it is highly essential for farmers in evaluating the plant growth without any manual support economically. This paper proposed leaf disease detection by feature extraction using GLCM and Deep convoluted neural network (DCNN) based classification. The dataset has been collected based on pre-historic dataset of cultivation field and this data has been processed. The features have been extracted using GLCM and the image has been classified using DCNN. Then finally the disease affected area has been identified by extracting features and this feature has been classified for enhancing the accuracy of detecting the disease so we use GLCM-DCNN. Then the simulation results shows the accuracy, recall, precision and f-1 score as the parameters of proposed method. This technique will detect the disease early and helps the farmer to induce pesticides to avoid spreading of disease.

Keywords: banana plant disease, leaf disease, GLCM, DCNN, feature extraction and classification.

Introduction:

The production of agriculture is where the country is relies on economy. For this reason the identification of disease becomes highly essential in agriculture since the infection is normal for plants. Disease detection without any manual support and the classification has become unavoidable study field which requires the computer vision with automation else the system with machine vision by using image processing techniques [1]. The most common disease that occur in banana leaves are panama disease, moko disease, sigatoka disease, black spot, banana bunchy top, infectious chlorosis, banana streak virus and banana bract mosaic virus disease. Various types of disease that is dangerous for Banana namely banana sigatoka and banana speckle. The black sigatoka is caused by the fungus Mycosphaerella fijiensis. Their beginning symptoms are minuscule; a chlorotic spot as well as they grows to thin brown streaks that are bounded by leaf veins. Leaf speckle is a fungal disease. Its indications at earlier stage would be light brown little spots, when time passes there will be maximizing of size that turns to black. When this disease is not treated, this can kill the plant. Otherwise, when it is identified at the earliest, this could be treated can save the plant [2].

The identification of plant disease by their appearance and the outlier symptoms has been identified using Artificial intelligence (AI) which is integrated with deep learning prototypes where the activities of human has been taken under significance. The application on mobile phones which are incorporated with AI makes use for farmers in giving disease alert that is useful in diagnosing and preventing the crop. Though farmers are not able afford for these applications, they need manual help in detecting the disease of the crop. The Global System for Mobile Association (GMSA) predicted that global smartphone subscriptions would reach 5 billion by 2020, of which nearly one billion in Africa. The technologies such as AI, IoT (Internet of Things), robotics, satellites, cloud computing, and machine learning has been used in developing agriculture as well as facilitating farmers [5].

The innovative technique of image processing is deep learning which has been used for object detection that has extended accuracy of classification in many diseases of crop. One of the technique of deep learning which use frequently is transfer learning. In this technique design for pre-model has been acquired as novel application. Deep transfer learning has been created for new architecture of image processing as well as the analysis of prediction that obtains higher accuracy also it has great possibility for detecting the disease of crop. Through numerous datasets of training image DTL has been turned to be highly efficient technique in identifying the disease of farm which has been given by mobile apps. And this has turn to be highly discrete real time usage for farm.

The existing study has been evaluated on basis of AI in detecting the disease of crops such as wheat. Also for datasets of plants which are not infected and disease infected plants. The detection of crop disease has been carried out on basis of computer vision design by extracting their feature gives effective outputs; however the feature extracting is very difficult for computation also this incorporates the specialists understanding for healthy representation. Some prohibited and trained dataset image of disease crop are available. Above 50,000 images collected from various crops and diseases of Plant Village platform.

Though many images has been considered to be simple background with removed leaves as well as images has been trained with CNN are not attained while using the real farm images. The strong and highly implemental identification system has been simulated by enormous diseased and healthy images has been obtained through various area of plants that are infected along with budding with various circumstances of surroundings are required. By specialists of plant pathology, all the images have been requiring labelling and pre-training. Till now the techniques of existing identification of disease in crops designs has been concentrated on symptoms of leaf. Inappropriately, many indications are appeared in other plant parts also where the optimal example is banana pest and disease linked symptoms [6].

The rest of the paper is organized as follows: in Section 2, we present the related work. Section 3 explains technical details of the proposed approach and the architecture. Furthermore, experimental evaluation and results are reported in Section 4. Finally, Section 5 concludes the paper and provides an outlook to future work.

Related works:

In a plant the detection of hazardous virus and bacteria becomes highly important for assuring harmless and ecological for agriculture [7]. The existing designs has been developed with higher consideration recently and this can attain fast as well as feasible pathogen detection, target extraction by the essential sample which is incredibly enhanced in detection. The highly significant Serological and molecular techniques has been used recently while enormous number of samples required to be tested. For most of the plant pathogens, the antibiotics like monoclonal and recombinant are used certainly also it has contribution in detecting certain serology. Detection through molecule has been enhanced by purifying the nucleic acid automatically from pathogens by columns or robotics [8]. PCR which is novel modification namely simple otherwise multiplex integrated in single tube which is closed using PCR, co-operative- PCR also observing for real-time by amplicons or numerical PCR, access increased sensitivity for detecting the single or numerous pathogens in a distinct evaluation. Recent evolution in nucleic acid has been done using technology of microarray evaluation, though this needs extracting of genes from DNA/RNA also their techniques for pre-amplification in order to enhance the sensitivity for detection. The molecular techniques has their own disadvantages where they require manual support and highly time consuming also extended process is needed particularly for preparing the samples which obtains feasible output. To assuring the plant diseases reliable tool used are molecular techniques, since this cannot be used for initial testing in processing numerous plant samples because of time required for this process [9].

Lee et al. (2015) [10] determined the design of CNN for detection of plant disease without manual support on basis of their leaf. Grinblat et al. (2016) [11] presented comparatively simple but effective neural network in efficient detection of three various legume kinds on basis of patterns in leaves which are identified morphologically through their veins. Mohanty et al. (2016) [12] contrasted two frequently used and implemented system design for CNNs for detecting 26 variants of plant disease, by extended leaf database with images that has 14 variants in plants. The outputs are highly efficient by evaluating their automatic detection rate of 99.35%. Though their major limitation is with whole substantial of image that comprises of single images for simulation arrangements but not for real time implementation of agricultural farm. Sladojevic et al. (2016) [13] proposed the same technique in detecting the plant disease by their leaf images through comparable quantity of data accessible in web services that comprises of minimum number of diseases and variants of plants. Their output efficiency is obtained among 91% and 98%, which relies on data which is used for testing. At present Pawara et al. (2017) [14] related few conventional pattern detection techniques by CNN designs bas on their performance for recognising the plant by 3 various dataset images which can be plants or fruits or plant leaves, this finalise CNN is highly conventional technique. Finally, Seetharaman et al. (2021) [15] designed prototype of CRNN in identifying 9 various disease and pest of banana fruit where the output gives higher satisfaction.

The maximum simulation effort is necessitate by image processing technique on basis of few initials that might minimize the experimental cost. Some researchers fulfilled the technique for linking the features of texture, colour and shape which identify the existence of disease. Though it can concentrate on those leaves which possess on disease at a time where their initial indications are not concentrated. In (2022) [16] Region-Based Convolution Neural Network (RCNN) is used where it achieves above 99% of accuracy during the testing the image from similar database. Though the model has been tested in opposing the image gathered by sources of trusted websites, here their accuracy has been decreased by 31.4%. The dataset has been considered with certain circumstances also the extreme stage of disease has been detected by the dataset concludes their application for digital real time farming. Moreover the datasets which are already present are not considered as more than one disease are present in the same plant; hence the prototypes which are trained and tested has been sued for detecting the disease with higher visibility and these are not required to be prominently essential for crop.

Proposed Methodology:

The aim for this proposed technique is to extract and classify the disease of banana at their initial level and this can inhibit the disease spreading to nearby plants. The dataset of banana leaf has been gathered from pre-historic data of farm. The leaf images has been stored in the database in which 10 samples has been taken in account for disease detection that has been needed in additional processing. Architectural diagram for proposed system is given in figure 1.

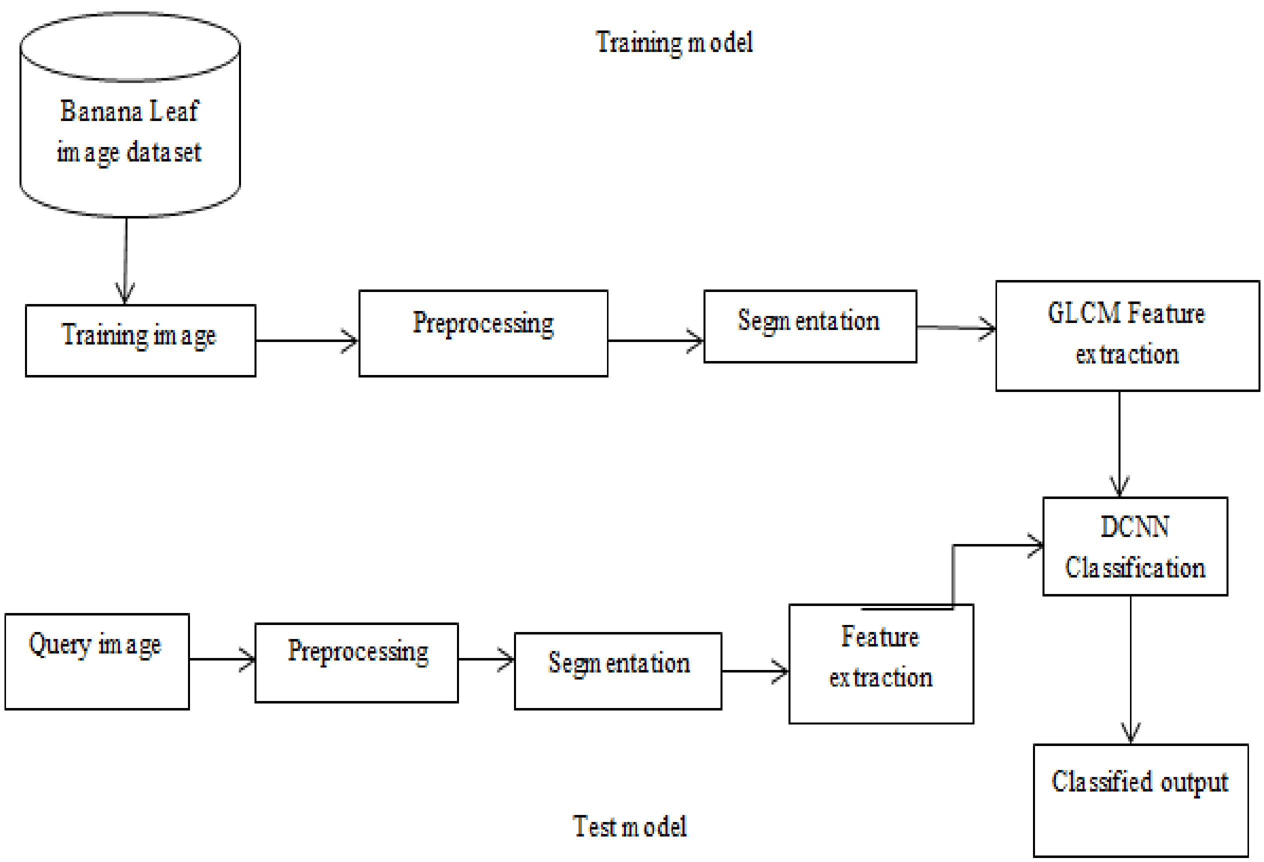

Figure-1 Proposed Architecture

The above figure 1 proposed architecture. Initially the image has been pre-processed for image resizing, noise removal and data cleaning. Then the image has been segmented and their feature has been extracted using GLCM and this extracted features has been classified using DCNN. The classified output will be disease detected part of banana leaf.

Feature Extraction using Gray level co-occurrence matrix (GLCM):

One of the frequently used textures analysing technique is GLCM which is employed in evaluating the characteristics of image which has been correlated with the statistics of order 2. Matrix design has been done for assessing the relationship among the pixels in spatial domain. So this technique is on basis of the texture data which has been taken from the output of another correlation. Every input of GLCM is (i,j), according to the pair of occurrences numbers for gray levels as i and j, and this is divided through the d distance of input image. The calculation of comparison among the various GLCM has been done by the 22 features and various number of feature has been used in existing works this proposed simulation technique differentiates the 22 features of the input image for comparison. Here the simulation of spatial comparison between the image pixels along with the comparison of pixels which is available in the input image by their direction and distance represented by Θ and d respectively. Every image has been extracted and quantized as 16 grey levels as well as 4 GLCMs (M) for Θ = 0, 45, 90, along with 135 degrees where d = 1 has been acquired. Every GLCM will be extracted with five features. Hence for every image 20 features has been extracted. The feature normalization has been ranges among 0 to 1 which get through the classifiers as well as every classifier acquires similar pair of features.

The features that are utilized as a part of this investigation are Texture features utilizing Co-occurrence matrix representation. GLCM is the second-arrange factual technique for extracting texture features. To start with, the picture is converted into l-grey-level and GLCM is produced by the number of intensity pairs present between the neighbour and current pixels for every scaling as well as orientational feature. Feature vector is developed by utilizing the average of matrices for every scaling and orientational feature. Standardized GLCM is computed by:

$$G(i,j) = \frac{N(i,j)}{\sum_{m=0}^{l-1}\sum_{n=0}^{l-1} N(m,n)} \quad (8)$$

Here i and j represent the grey values in l-grey image. $N(i,j)$ denotes co-occurrence relative recurrence frequency matrix by:

$$N(i,j) = num\left(\{[(x_1,y_1),(x_2,y_2)]\} \middle| x_2 - x_1 = d\cos\theta, y_2 - y_1 = d\sin\theta, I(x_1,y_1) = i, I(x_2,y_2) = j\right) \quad (9)$$

here pixel positions are represented by (x_1, y_1) and (x_2, y_2), and I(·) denotes the pixel's grey level. num· means the quantity of pixel matches satisfying the conditions of comparison.

Classification using Deep convolution neural network (DCNN):

Once the feature vector is obtained from input image, then the image is represented as a fixed length vector, and requires a classifier for classifying feature vectors. Generally, a common CNN contains few layers like input, convolution, activation, pool, fully connected, and output layer. The layers of CNN establish the relationship among various nodes and the input information is forwarded through various layers sequentially, and the pool structure of CNN continuously performs decoding, deducing, convergence and mapping the signal features of input information to the feature space of the hidden layer. Fully connected layer performs classification and the outputs are obtained with respect to the extracted features. The architecture of DCNN is shown in figure 2.

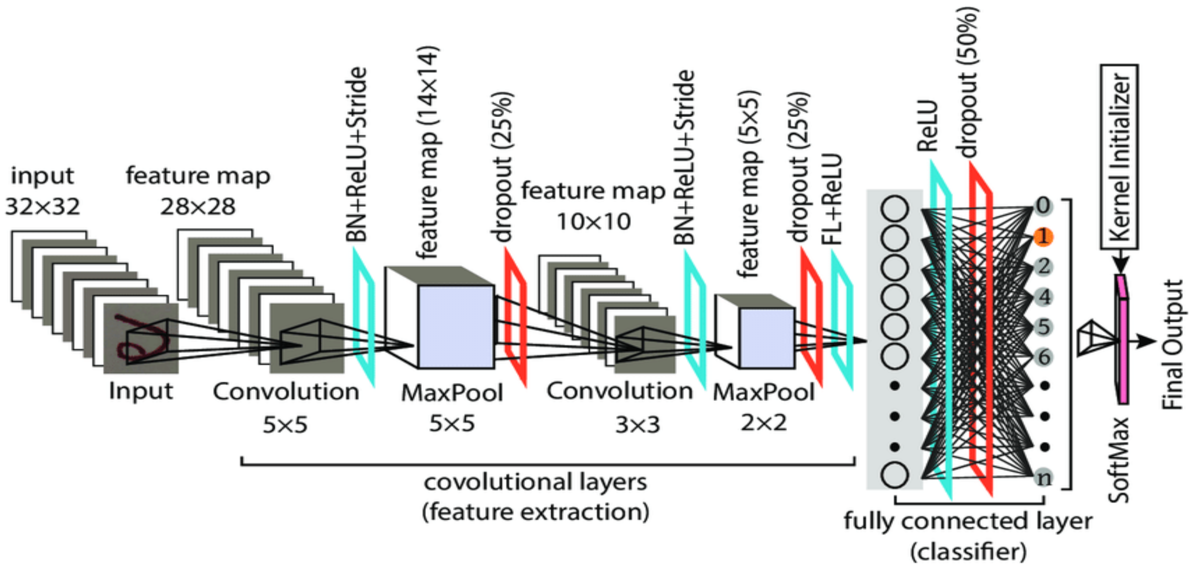

Figure 2- DCNN architecture

Deep Convolution is a significant analytical mathematical operation. A third function id generated by this operator using two functions namely f and g, where the third function represents the overlapping area between the functions f and g which is either translated or flipped and the calculation is given by:

$$z(t)^{def} = f(t) * g(t) = \sum_{\tau=-\infty}^{+\infty} f(\tau)g(t-\tau) \qquad (10)$$

The integral form for the above equation is given by,

$$z(t) = f(t) * g(t) = \int_{-\infty}^{+\infty} f(\tau)g(t-\tau)d\tau = \int_{-\infty}^{+\infty} f(t-\tau)g(\tau)d\tau \qquad (11)$$

In classifying image, a digital image is considered as a discrete function f (x, y) of a 2D space. By considering g (x, y), a 2D convolutional function, the output image z (x, y) is given by

$$z(x,y) = f(x,y) * g(x,y) \qquad (12)$$

Here, the convolutional operation is employed for extracting the features of image. Likewise, with applications involving deep learning approaches, when a color image is given as input, it is a high-dimensional array with dimension of 3 × image width × image length; thus, the convolutional kernel in CNN is described as accounting in deep learning algorithm. Computing parameter also is a high-dimensional array. Then, for the given 2D image, the respective convolutional operation is given by:

$$z(x,y) = f(x,y) * g(x,y) = \sum_t \sum_h f(t,h)g(x-t,y-h) \qquad (13)$$

The integral form is the following:

$$z(x,y) = f(x,y) * g(x,y) = \iint f(t,h)g(x-t,y-h)dtdh \qquad (14)$$

For the given convolution kernel of m × n,

$$z(x,y) = f(x,y) * g(x,y) = \sum_{t=0}^{t=m}\sum_{h=0}^{h=n} f(t,h)g(x-t,y-h)$$
(15)

here f indicates the input G with the convolution kernel size of m and n. Convolution is generally realized in the computer as a product of a matrix. Consider that the image size is M × M and convolution kernel size is n × n. While computing, convolution kernel multiplies the image of size n × n with every image region, which is like obtaining the region of image with n × n which represents the length of the column vector. While performing the operation of zero-zero padding with step 1, totally (M − n + 1) ∗ (M − n + 1) results are possible; when representing the small regions of the image as n x n column vector, the actual image can be given as the matrix [n∗ n∗ (M − n + 1)]. Consider K as the number of convolution kernels, the result of the input image after convolution is k∗ (M − n + 1) ∗ (M − n + 1); i.e., number of convolution kernels × image width × image length. Every trained parameter in the proposed model is initialized with the random value ranging from −0.05 to 0.05. Training phase comprises of two stages namely forward and back propagation. The aim of the forward propagation is to estimate the results of classifying input data with the parameters used currently. The back propagation updates the parameters in order to reduce the inconsistency between the actual and desired classification output.

Forward Propagation:

DCCN model proposed here with $(L+1)$ layers where $L=4$ contains $n1$ input units in Input layer, $n5$ output units in Output layer, and numerous hidden units in C2, M3, and F4 layers. Let xi be the input for i^{th} layer as well as the output of $(l-1)^{th}$ layer, then $xi+1$ is computed as

$$x_{i+1} = f_i(u_i)$$
(16)

where

$$u_i = W_i^T x_i + b_i$$
(17)

and WTi represents the weight matrix on the input and bi indicates an additive bias vector and (·) denotes the activation function of the i^{th} layer. Here, tanh(u), the hyperbolic tangent function, is chosen as the activation function for C1 and F3 layers. max(u), the maximizing function is involved in M2 layer. As the DCNN classifier involved here is a multiclass type, output of F3 layer is given to the $n5$ softmax function where distribution over $n5$ class labels occurs. Softmax regression is described as

$$y = \frac{1}{\sum_{k=1}^{n} e^{w_{L,K}^T x_L + b_{L,k}}} \begin{bmatrix} e^{w_{L,K}^T x_L + b_{L,1}} \\ e^{w_{L,K}^T x_L + b_{L,2}} \\ e^{w_{L,K}^T x_L + b_{L,n}} \end{bmatrix}$$
(18)

The output vector y = $xL+1$ of the Output layer is the final probability of every class in the current iteration.

Back Propagation:

In this stage, parameters that undergo training are updated using gradient descent approach with minimal cost function and its partial derivative estimated relating to every parameter involved in training. The loss function is given as

$$J(\theta) =- 1/m \sum_{i=1}^{m}\sum_{j=1}^{n_5} 1\{j = Y^{(i)}\}\log(y_j^{(i)})$$
(19)

where m, Y and y(i) j indicates the number of training samples, estimated output, j^{th} value of original output for i^{th} sample of training and the size of the vector is $n5$. For the estimated output (i) for sample i, the probability is 1 for label class, and probability for other classes is 0. When j equals the estimated label of training sample i, j = Y(i) means 1; otherwise, it is 0. A minus sign is assigned before θ for convenient computation. Loss function relating to ui is derived as

$$\delta_i = \frac{\partial J}{\partial u_i}\{\begin{matrix} -(Y-y).f`(u_i), i = L \\ (W_i^T \delta_{i+1}).f`(u_i), i < L \end{matrix}$$
(20)

Thus, for every iteration, updating is done by

$$\theta = \theta - \alpha.\nabla_\theta J(\theta)$$
(21)

to adjust these parameters, where α represents learning factor (α taking 0.01), and

$$\nabla_\theta J(\theta) = \{\frac{\partial J}{\partial \theta_1}, \frac{\partial J}{\partial \theta_2} \ldots\ldots, \frac{\partial J}{\partial \theta_L}\}$$
(22)

When training iteration increases, the cost function is less indicating the original output is near to the estimated output. The iteration comes to an end if difference of them is smaller.

Performance analysis:

This section discusses the simulation results for banana leaf disease detection from the input dataset. Various outputs have been discussed below: initially the dataset folder has been generated where the different images for banana leaves are available for testing process. The indication of leaf disease has been identified with higher accuracy also trained properly and collected in the dataset. The parametric analysis is given below.

The below figure 4,5,6,7,8 presents the comparison of accuracy, precision, recall, F1-score and true positive and false positive rate for proposed technique and existing technique.

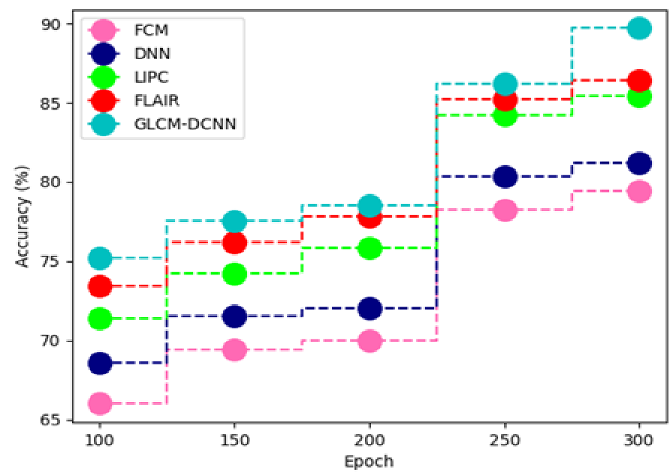

Figure-4 Comparison of accuracy

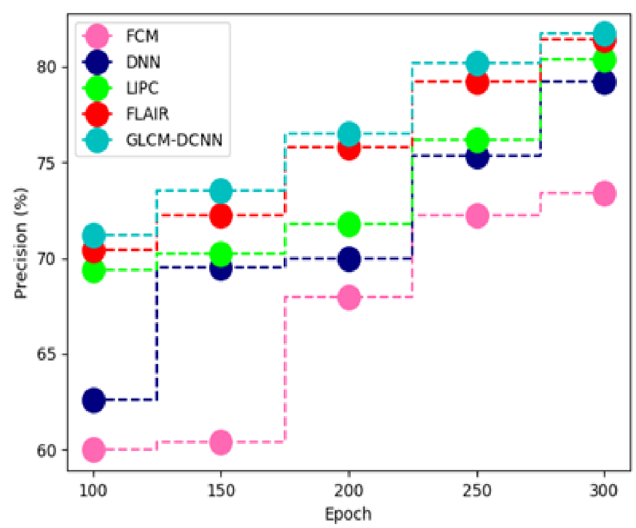

Figure-5 Comparison of Precision

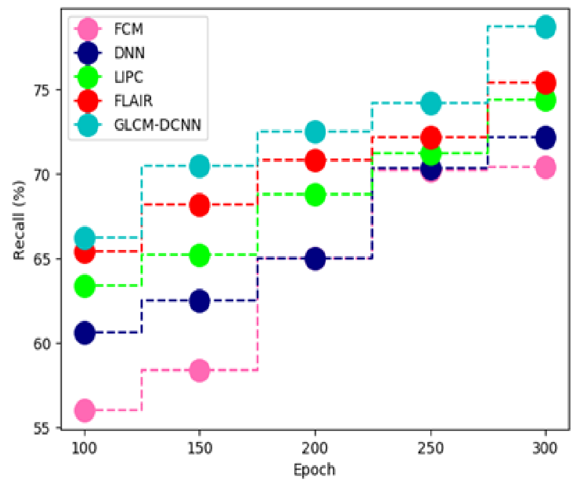

Figure-6 Comparison of Recall

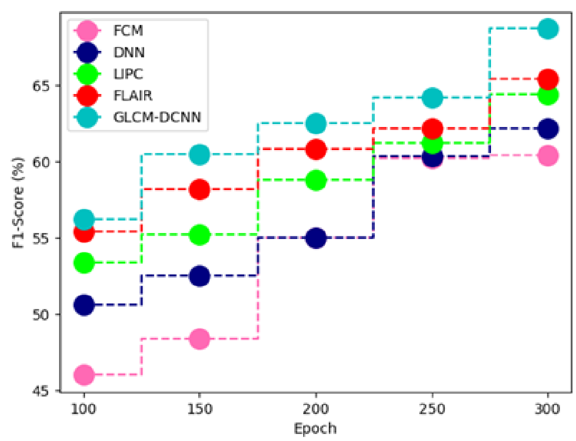

Figure-7 Comparison of F-1 Score

The below figure 8 shows the comparison of parametric metrics obtained for proposed technique.

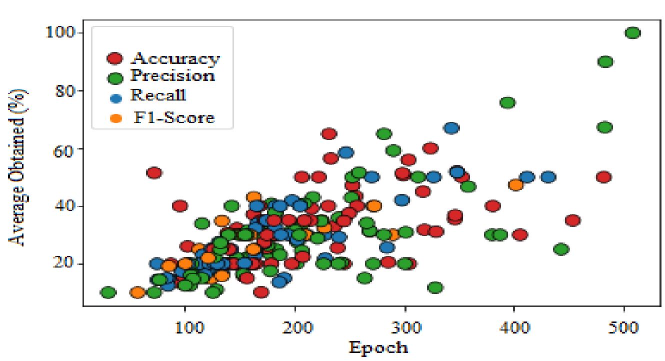

Figure-8 Overall Comparison of Proposed technique

Conclusion:

The detection of disease with enhanced accuracy by image processing techniques in identifying as well as classifies the images of banana plant. Here the simulation of classification and extracting the feature has been done using Python application. Manual system has been interchanged in detecting and classifying the disease of banana plant where the symptoms for consumption of time and the accuracy is low in comparison with proposed technique. This proposed technique has been used for farmers in determining the disease with higher accuracy and detected earlier before spreading with nearby plants. Then the proposed system gives optimal classification using DCNN along with feature extraction using GLCM which could generate greater quantity of yield. Hence two banana leaves has been detected and the future work can be carried out for fruit and stem of banana plant with various disease detection.

Reference:

1. Basavaraj Tigadi, Bhavana Sharma, “Banana Plant Diseases Detection and Grading Using Image Processing”, International Journal of Engineering Science and Computing, volume 2, issues 4, june 2016.
2. Gurleen Kaur Sandhu, “Plant Diseases Detection Techniques: A Review”, Interenational Conference on Automation, Computational and Technology Management(ICACTA), 2019.
3. Karthik.G, Praburam.N, “Detection And Prevention Of Banana Leaf Diseases From Banana Plant Using Embedded Linux Board”, Online International

Conference on Green Engineering and Technologies(IC-GET), 2016.

4. Sagar Patil, “A Survey on Methods of Plant Diseases Detection”, International Journal of Science and Research (IJSR), 2013.
5. Sandip P. Bhamare, Samadhan C. Kulkarni, “ Detection of Black Sigtoka on Banana Tree Using Image Processing Techniques”, International Journal of Electronics and Communication Engineering(IJECE).
6. Surya Prabha, J. Satheesh Kumar, “Study on Banana Leaf Diseases Identification Using Image Processing Methods”, International Journal of Research in Computer science and Information Technology(IJRCSIT) , Volume 2, issue 2(A), March 2014.
7. Konstantinos P. Ferentinos, Deep learning models for plant disease detection and diagnosis Computers and Electronics in Agriculture 145 (2018) 311–318.
8. Amara, Jihen, Bassem Bouaziz, and Alsayed Algergawy. "A deep learning-based approach for banana leaf diseases classification." Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband (2017).
9. Singh, Vijai, and Ak K. Misra. "Detection of plant leaf diseases using image segmentation and soft computing techniques." Information processing in Agriculture 4.1 (2017): 41-49.
10. Lee, S.H., Chan, C.S., Wilkin, P., Remagnino, P. 2015. Deep-plant: Plant identification with convolutional neural networks. 2015 IEEE Intl Conf. on Image Processing, pp. 452–456.
11. Grinblat, G.L., Uzal, L.C., Larese, M.G., Granitto, P.M., 2016. Deep learning for plant identification using vein morphological patterns. Comput. Electron. Agric. 127, 418–424.
12. Mohanty, S.P., Hughes, D.P., Salathé, M., 2016. Using deep learning for image-based plant disease detection. Front. Plant Sci. 7http://dx.doi.org/10.3389/fpls.2016. 01419. Article: 1419.
13. Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D., 2016. Deep neural networks based recognition of plant diseases by leaf image classification. Computat. Intelligence Neurosci. http://dx.doi.org/10.1155/2016/3289801. Article ID: 3289801.
14. Pawara, P., Okafor, E., Surinta, O., Schomaker, L., Wiering, M. 2017. Comparing local descriptors and bags of visual words to deep convolutional neural networks for plant recognition. 6th Intl Conf. on Pattern Recognition Applications and Methods (ICPRAM 2017).
15. K.Seetharaman, and T. Mahendran, Detection of Disease in Banana Fruit using Gabor Based Binary Patterns with Convolution Recurrent Neural Network, Turkish Online Journal of Qualitative Inquiry, PP. 6958 – 6966, Vol. 12(9), 2021.
16. Seetharaman, K., Mahendran, T. Leaf Disease Detection in Banana Plant using Gabor Extraction and Region-Based Convolution Neural Network (RCNN). J. Inst. Eng. India Ser. A (2022). https://doi.org/10.1007/s40030-022-00628-2.