International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 08 | Aug 2022 www.irjet.net p-ISSN: 2395-0072

Green leaf disease detection and identification using Raspberry Pi

[1]Supriya S, [2]Dr. Aravinda H L

[1] *Students (UG), Assistant Professor*
[1]*Department of telecommunication engineering*
[1]*Dr.Ambedkar Institute of Technology, Bengaluru, India*

---***---

Abstract - *Agriculture is a back bone of Indian economy. A majority of the entire Indian economy is still sustained by agriculture which is the mainstay of villages. With the involvement of technology on the fields a good upsurge in yield and production can be observed. It can also give a positive impact on quality and productivity. Disease is the major problem faced by the farmers. It gives a down surge in the quality and quantity of agricultural products. A study of plant disease is basically the study of visually observable patron on the various parts of the plant. In the earlier days the disease detection process was carried out manually by an expert person on the field. Though most of the times the results were accurate it requires a lot amount of work and processing time. This proposed system uses raspberry pi to detect the healthy and unhealthy banana plants by training with convolution neural network algorithm and mathematical computations using tensorflow.*

Key Words: Convolutional Neural Network, Raspberry pi camera, Raspberry pi module 4, OpenCV, Tenserflow,

1.INTRODUCTION

This document is template. We ask that authors follow some simple guidelines. In essence, we ask you to make your paper look exactly like this document. Banana is the most vital fruit consumed in the parts of Asia and Pacific regions. Banana plants are affected by various disease whose symptoms appear on the leaves. The disease is 'Banana Bunchy top virus', 'Banana Streak virus', 'Black Sigatoka', 'Yellow Sigatoka' and 'Panama Wilt'.

The discrimination between normal and affected plant leaf is measured based on color variation. At first the Raspberry pi camera is enabled and it begins capturing the plant leaf. These images are forwarded for the further purpose of Image pre-processing, Feature extraction, Segmentation and finally classification. Once the identification process is completed the disease is displayed with the confidence level. With that the farmer can opt for suitable cure for the plant.

Banana Bunchy Top Virus

The name Bunchy top comes from one of the most characteristic symptom of the plant, where the leaves are dwarf, upright and bunched at the plant top. Other symptoms include new leaves being narrower, yellow and bunchy experience. Morse code streaking appearance is a very prominent symptom, which give a dark color dash like appearance on the leaf surface. The edge of the leaves are also rolled upwards. This disease can be controlled by spraying meta-systox. It can also be controlled by the uprooting the infected plants.

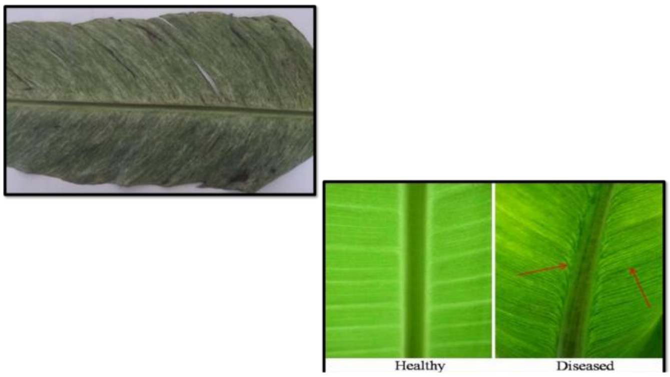


Fig 1.1-Image Depicting Banana Bunchy Top Virus and also difference between healthy and diseased leaf

Banana Streak Virus

The prominent symptoms of this disease include chlorotic streaks on the midrib of leaves. Splitting of pseudo-stem is also another symptom. This disease can be controlled by cleaned planting material and detention.

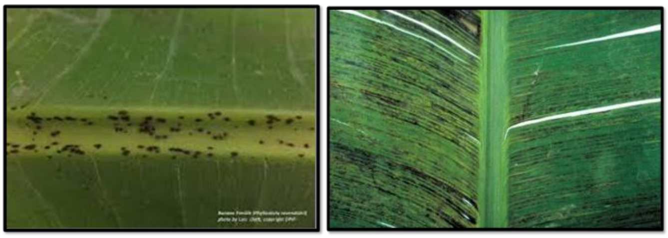


Fig 1.2- Banana Streak Virus disease

Black Sigatoka

The dominant banana disease all over the world. It's basically a leaf spot disease of banana plant. Early leaf symptoms involve tiny reddish-rusty brown flecks which are evident on underside of leaf. These flecks gradually lengthen, widen and darken to form reddish brown leaf streaks. The very prominent symptom is appearance of red or brown spots with yellow border on leaf's edge. This disease can be controlled by spraying fungicides like copper of Oxychloride on foliage and pseudo-stem.

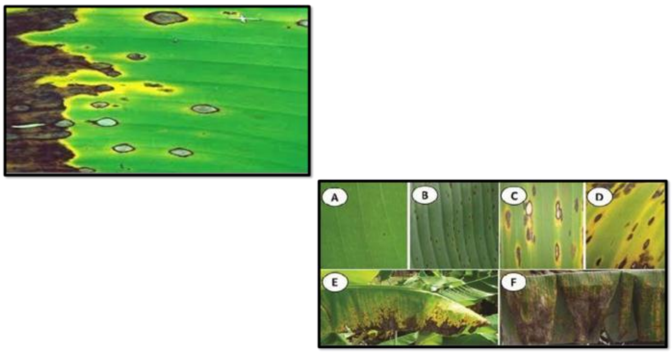


Fig 1.3- Black Sigatoka

Yellow Sigatoka

Another leaf spot disease of banana plant. Symptoms include appearance of small yellow streak on upper side of leaves. The other symptoms are small yellow patches having gray center and yellow border. This can be controlled by application of Thiophante Methyl.

Fig 1.4- Yellow Sigatoka

Panama Wilt

Symptoms of the disease are yellowing of leaves starting from the edge and extending upto mid rib of the leaves. The symptom splitting of pseudo-stem causes the collapse of the entire plant. Cure of this is uprooting the severely affected plants.

Fig 1.5- Panama Wilt

2. Literature Survey

[1] discusses the use of the Raspberry Pi for the capturing and the processing of the images. Raspberry Pi 4 is being incorporated in the current proposed system.

[2] uses the ANN 'Feed Forward neural network' which involves all the nodes in the processing and is time consuming. But the proposed system uses CNN which is a better in terms of speed and processing.

[4] uses the Matlab as coding language, the proposed system uses Python.

[5] uses the Back Propagation Algorithm which has drawbacks like getting stuck easily in local minima and slow speed of convergence whereas the proposed system uses the CNN which overcomes all the drawback of Back Propagation Algorithm.

[6] uses MATLAB for the coding platform, the proposed system uses Python.

[7] uses the Nearest Neighbor Classification [KNN] which gives an accuracy of 58.16% whereas the proposed system uses the Convolution Neural Network [CNN] which gives an accuracy of 79.04%.

[10] uses the mobile camera with a resolution of 2MP for the capture of the image, the proposed system uses raspberry pi camera with the resolution of 5MP.

[11] uses the Lenet-5 CNN type whereas the proposed model uses the AlexNet CNN model which has more depth, having eight layers with trainable parameters.

[12] uses the 5 layer Convolution Neural Network and has gained the efficiency of 75% whereas the proposed model uses the VGG16 which uses 16 layers of CNN, training the model repeatedly, hence giving an enhanced functionality in training accuracy in turn the model accuracy.

[13] uses less number of epoch, thus giving the validation accuracy of 0.0389 whereas the proposed system runs an epoch for 50 times achieving a validation accuracy of 0.9578.

[14] uses the SVM for the training purpose which is not accurate since it is found to achieve very less accuracy even for a good dataset, this proposed system uses the CNN algorithm for the model training which is improved model in terms of accuracy and speed.

[15] version of tensorflow incorporated is 2.7 which doesn't have the availability of package named 'keras' whereas the proposed project uses tensorflow 3.9 which has all the packages of keras available.

[21] scope is limited to two diseases of grape plant whereas proposed system gives a wider platform to expand the disease detection to other plant with a variety of diseases

[23] uses genetic algorithm for color image segmentation whereas the proposed system uses OpenCV

[30] uses major axis and minor axis of the leaf for the classification purpose whereas the proposed system uses the canny edge detection method which is a Gaussian based operator computing second order derivative of the digital image.

3. METHODOLOGY

3.1 NEURAL NETWORKS

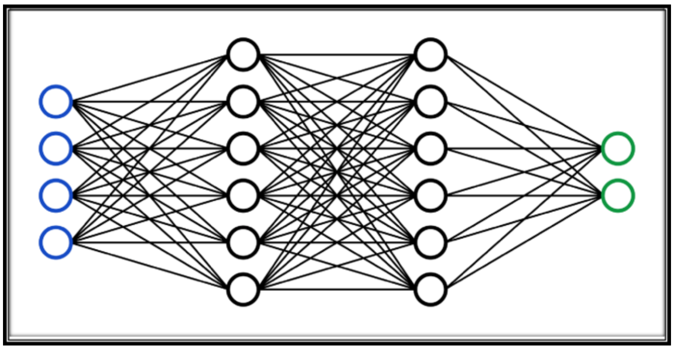


Fig 3.1- Image Showing the Neural Network

Neural network is one of the method in artificial intelligence which trains the computer for data process in a method mimicking the human brain. A type of machine learning process deep learning makes use of interconnected neurons which form a layered structure resembling the human brain. Thus neural network attempt to solve the complicated problems (image processing or recognizing objects) on an increase accuracy

An artificial neural network is a system combined with hardware and software components post the operation of neurons in human brain. A numerous processes operate in parallel to form tires in ANN. Tire 1 of the model receives the row input first (similar to optic nerves in human system). The success of tires input is the output of previous tire rather than raw input. The final tire gives the output of the entire system.

ANN have a significant feature of being adaptive where the modify themselves from initial training and subsequent runs trains them with information about the world. Its initially fed with the huge amount of training data which consist of providing input and informing the network what the output should be.

Biased data sets are the current challenge in training the systems which find the answers on their own by recognizing data pattern. Machine propagates bias when data which feeds algorithm is not neural.

Neural network sometimes gets identified for their so called hidden layers which makes them almost synonymous to deep learning. Some of the types of neural network include

1. Feed forward neural network- the information is passed unidirectional through various input notes until it makes it way to the output mode. Their function is more predictable since they may or may not have hidden layers. They trained to process good amount of noise. They find their applications in facial recognition and computer vision.

2.Recurrent neural network – the output of processing model is saved and fed back to the model which is how the model is set to learn the prediction of the output of a layer. Every node of RNN is a memory cell. The beginning of neural network of both FNN and RNN are same but the further process involves storing of processed information to reuse it in feature. When the system predicts wrongly it performs back propagation in which it self-learn and works towards correct prediction. Finds its application in text to speech conversation.

3.Convolution neural network – it's a computational model which uses a variation of multilayer perceptron. It consists of one or more convolutional layers, create feature maps which record an image region which is ultimately broken into rectangle, which can either be entirely connected or pooled. CNN is very popular under image recognition. They find their application with AI based facial recognition in mobile phones, texted digitization and natural language processing with artificial assistance like Alexa, SIRI, etc…

4.Deconvolutional neural network – utilizes a reversed CNN model process which aims to find the features or signals originally considered unimportant by CNN. Its finds a application in image analyses

5.Modular neural network – contains a hub of neural networks working differently from each other. The networks don't interfere with each other's activities during the computation. They find their application in a solving a big complex computational process efficiently and accurately.

3.2 CONVOLUTION NEURAL NETWORK

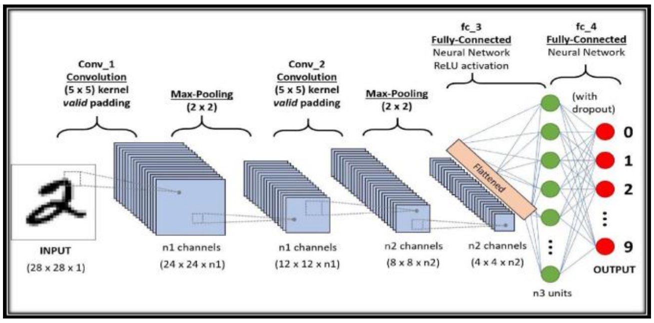


Fig 3.2- Convolution Neural Network

Is a deep neural network which is designed for structured array processing. They find their application widely spread in computer vision and have become state of art for many visual application like image classification. They have also found success in natural language processing for text classification. They are known for recognizing the patterns in input images which makes them apt for computer vision. They operate directly on raw image and do not need any pre-processing. It's a feed forward neural network with up to 20 or 30 layers. Convolution neural networks usually contain many convolution layers which are stacked upto on one another where each of them have the capability to recognized sophisticated shapes. Usage of convolution layer mirrors the structure of human visual cortex. The hidden layers are usually the convolution layer followed by activation layer some of them are pooling layers.

Convolution layer

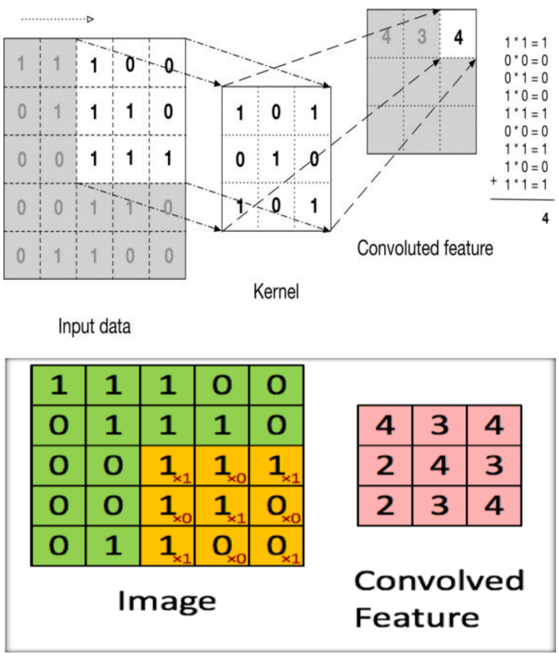


Fig 3.3- Convolution Layer

Matrix of pixels of input image is convolved with a kernel matrix. The convolved feature is smaller in size than that of the input of the matrix. This level happens on a continues basis until the important features are extracted. The convolution feature creates a large amount of data which makes it hard to train the model. In order to compress the data pooling is required. Padding, which expands the input matrix by adding fake pixels to the border, this is done because convolution reduces the size of the matrix. On the convolved features two types of operation are performed

1. Valid padding – reduce dimensionally
2. Same padding – retain the same size or increase the dimension.

Pooling layer

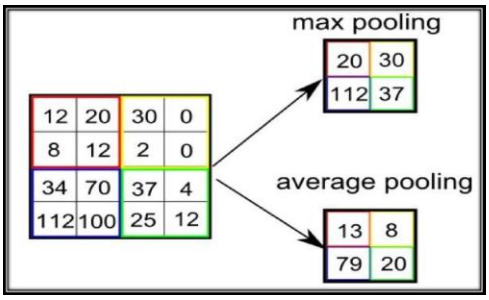


Fig 3.4- Pooling Layer

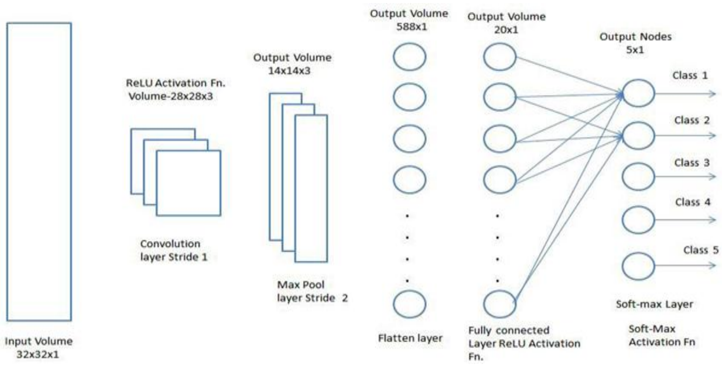
Objective of this layer is to reduce the spatial size of convolved feature which in turn reduces the computational power requirement. It helps in extraction of dominant features. It has two types

1. Max-pooling – returns maximum value of pixel from the area covered by kernel.

2.Average pooling – returns average of values in the kernel covered area of image.

The proposed project model uses max pooling.

Fully connected layer



International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 08 | Aug 2022 www.irjet.net p-ISSN: 2395-0072

The convolved feature has to be flattened and then has to be fed to regular neural network for classification. The input image is converted to a suitable form of multi level perceptron thus flattening the image into column vector. Flattened output is fed to feed forward neural network and back propagation is applied at every iteration training. After a series of epochs, one cycle through the entire training data set, the model gains the ability to distinguish between dominating and low level features in the images and classify them using Softmax classification technique.

3.3 BLOCK DIAGRAM

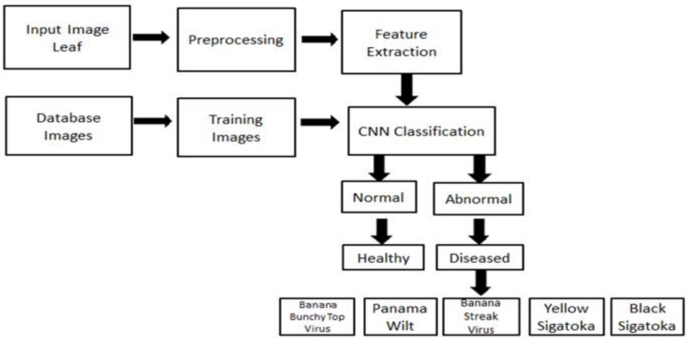


Fig 3.5- Block Diagram

3.4 ALGORITHM

1. The banana leaf image is captured using the raspberry pi camera.

2. The image captured is preprocessed.

3. The features required for the diseases mentioned are extracted and then given to the CNN classification.

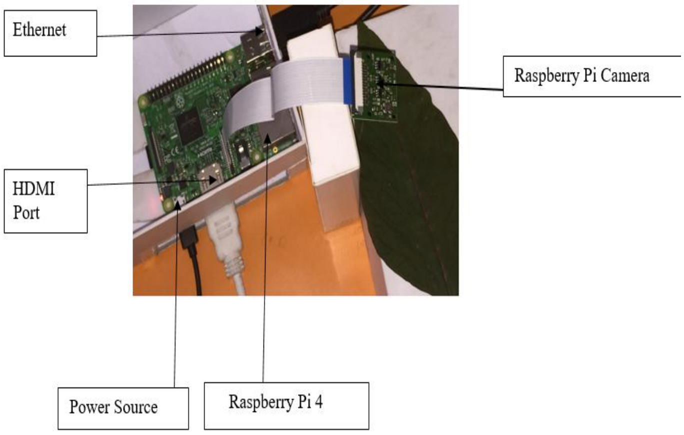
4. Along with the input image we are providing it the trained images for CNN classification.

5. There the already trained images and test images are compared.

6. Then if the leaf is healthy, it displays as a healthy leaf.

7. If leaf is diseased, it displays as a diseased leaf along with the specific name of the disease mentioned above.

3.5 CIRCUIT DIAGRAM



The Raspberry pi 4 features include CPU, GPU, memory, USB ports, video outputs and Network. The CPU quad-core is 64-bit ARM cortex A53.The GPU has 400MHZ videocore IV multimedia. The memory is 8GB LPDDR2-900 SDRAM (900 MHZ). There are 4 USB ports. The video outputs are HDMI, composite video (PAL and NTSC) via 3.5mm jack. The network range is about 10/100 Mbps Ethernet and 802.11n Wireless LAN. Peripherals have 17 GPIO plus specific functions and HAT ID bus. The bluetooth range is about 4.1. The power source is about 5V via micro-USB or GPIO header. The raspberry pi camera board is fully compatible with the both model A and model B Raspberry pi. It has 5Mp omnivision 5647 camera module. The still picture resolution for the pi cam is 2592 into 1944. The video supports 1080p @30fps,720p @60fps and 640 into 480pl90 recording. It has 15-pin MIPI camera serial interface- plugs directly into the the Raspberry pi board. The Raspberry pi camera is able to deliver a crystal clear 5MP resolution image, or 1080p HD video recording at 30fps. The module attaches to Raspberry pi, by a way of a15 pin MIPI camera serial interface (CSI) which was designed especially for interfacing to cameras. The cable slots into the connector situated between the ethernet and the HDMI ports, with the silver connectors facing the HDMI port.

4. COMPONENTS REQUIRED

4.1 HARDWARE COMPONENTS

4.1.1 RASPBERRY PI 4

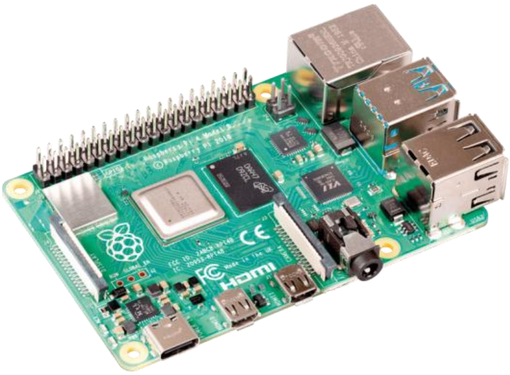


Fig 4.1- Raspberry Pi module 4

Broadcom BCM2711, Quad core Cortex-A72 64-bit SoC @ 1.5GHz

2GB, 4GB or 8GB LPDDR4-3200 SDRAM

Bluetooth 5.0

Gigabit Ethernet

2 USB 3.0 ports; 2 USB 2.0 ports.

Raspberry Pi standard 40 pin GPIO header

2 × micro-HDMI ports

4.1.2 RASPBERRY PI CAMERA 1.3v

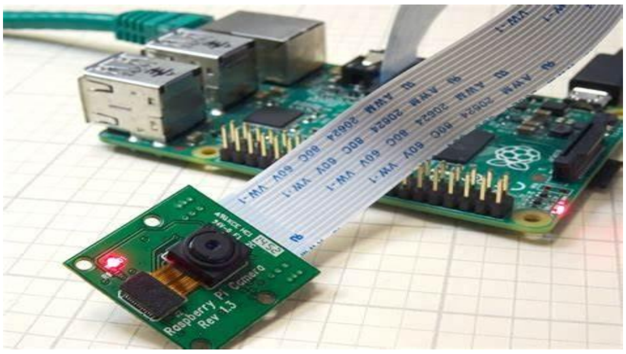


Fig 4.2- Raspberry Pi Camera

5MP omnivision

Still Picture Resolution: 2592 x 1944

Video: Supports 1080p @ 30fps (frames per second)

15-pin MIPI Camera Serial Interface - Plugs Directly into the Raspberry Pi Board

4.2 SOFTWARE REQUIREMENTS

Python 3.10

TensorFlow2.8 library

OpenCV4.5.5

5. RESULTS

Core goal of the proposed project is detect the various diseases that affect the banana plant by capturing the image using raspberry pi camera and predicting the disease and thus displaying it on the monitor screen along with confident level

```
Found 837 files belonging to 5 classes.
```

Fig 5.1- Image files Considered for Training

```
['.ipynb_checkpoints',
 'Banana streak virus',
 'Panama wilt',
 'healthy',
 'sigatoka']
```

Fig 5.2- Names of Classes Considered

Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 16)	448
max_pooling2d (MaxPooling2D)	(32, 127, 127, 16)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	9280
max_pooling2d_1 (MaxPooling 2D)	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 128)	73856
max_pooling2d_2 (MaxPooling 2D)	(32, 30, 30, 128)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	73792
max_pooling2d_3 (MaxPooling 2D)	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 128)	73856
max_pooling2d_4 (MaxPooling 2D)	(32, 6, 6, 128)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	73792
max_pooling2d_5 (MaxPooling	(32, 2, 2, 64)	0

```
conv2d_1 (Conv2D)           (32, 125, 125, 64)     9280

max_pooling2d_1 (MaxPooling  (32, 62, 62, 64)      0
2D)

conv2d_2 (Conv2D)           (32, 60, 60, 128)      73856

max_pooling2d_2 (MaxPooling  (32, 30, 30, 128)     0
2D)

conv2d_3 (Conv2D)           (32, 28, 28, 64)       73792

max_pooling2d_3 (MaxPooling  (32, 14, 14, 64)      0
2D)

conv2d_4 (Conv2D)           (32, 12, 12, 128)      73856

max_pooling2d_4 (MaxPooling  (32, 6, 6, 128)       0
2D)

conv2d_5 (Conv2D)           (32, 4, 4, 64)         73792

max_pooling2d_5 (MaxPooling  (32, 2, 2, 64)        0
2D)

flatten (Flatten)           (32, 256)              0

dense (Dense)               (32, 128)              32896

dense_1 (Dense)             (32, 64)               8256

=================================================================
Total params: 346,176
Trainable params: 346,176
Non-trainable params: 0
_________________________________________________________________
```

Fig 5.3- Convolution Layer Coded Output

```
Epoch 22/50
21/21 [==============================] - 173s 6s/step - loss: 0.4220 - accuracy: 0.8233 - val_loss: 0.2979 - val_accuracy: 0.8438
Epoch 23/50
21/21 [==============================] - 175s 6s/step - loss: 0.3883 - accuracy: 0.8289 - val_loss: 0.4490 - val_accuracy: 0.7656
Epoch 24/50
21/21 [==============================] - 173s 6s/step - loss: 0.3838 - accuracy: 0.8496 - val_loss: 0.3480 - val_accuracy: 0.8438
Epoch 25/50
21/21 [==============================] - 173s 6s/step - loss: 0.3577 - accuracy: 0.8620 - val_loss: 0.3398 - val_accuracy: 0.8438
Epoch 26/50
21/21 [==============================] - 173s 6s/step - loss: 0.3389 - accuracy: 0.8698 - val_loss: 0.2845 - val_accuracy: 0.9375
Epoch 27/50
21/21 [==============================] - 173s 6s/step - loss: 0.3945 - accuracy: 0.8527 - val_loss: 0.4005 - val_accuracy: 0.8438
Epoch 28/50
21/21 [==============================] - 175s 6s/step - loss: 0.4067 - accuracy: 0.8403 - val_loss: 0.1849 - val_accuracy: 0.9688
Epoch 29/50
21/21 [==============================] - 175s 6s/step - loss: 0.3077 - accuracy: 0.8690 - val_loss: 0.5377 - val_accuracy: 0.8108
Epoch 30/50
21/21 [==============================] - 173s 6s/step - loss: 0.3644 - accuracy: 0.8434 - val_loss: 0.3213 - val_accuracy: 0.7969
Epoch 31/50
21/21 [==============================] - 175s 6s/step - loss: 0.2734 - accuracy: 0.8780 - val_loss: 0.6681 - val_accuracy: 0.7500
Epoch 32/50
21/21 [==============================] - 175s 6s/step - loss: 0.3373 - accuracy: 0.8620 - val_loss: 0.4384 - val_accuracy: 0.7969
Epoch 33/50
21/21 [==============================] - 173s 6s/step - loss: 0.3085 - accuracy: 0.8698 - val_loss: 0.2355 - val_accuracy: 0.8906
Epoch 34/50
21/21 [==============================] - 175s 6s/step - loss: 0.2663 - accuracy: 0.8958 - val_loss: 0.3244 - val_accuracy: 0.9062
Epoch 35/50
21/21 [==============================] - 173s 6s/step - loss: 0.2708 - accuracy: 0.8853 - val_loss: 0.3373 - val_accuracy: 0.8594
Epoch 36/50
21/21 [==============================] - 175s 6s/step - loss: 0.2582 - accuracy: 0.9023 - val_loss: 0.3000 - val_accuracy: 0.8906
Epoch 37/50
21/21 [==============================] - 173s 6s/step - loss: 0.2165 - accuracy: 0.9116 - val_loss: 0.1376 - val_accuracy: 0.9844
Epoch 38/50
21/21 [==============================] - 173s 6s/step - loss: 0.1692 - accuracy: 0.9411 - val_loss: 0.8106 - val_accuracy: 0.7656
Epoch 39/50
21/21 [==============================] - 174s 6s/step - loss: 0.4083 - accuracy: 0.8496 - val_loss: 0.3604 - val_accuracy: 0.7838
```

Fig 5.4- Model Training

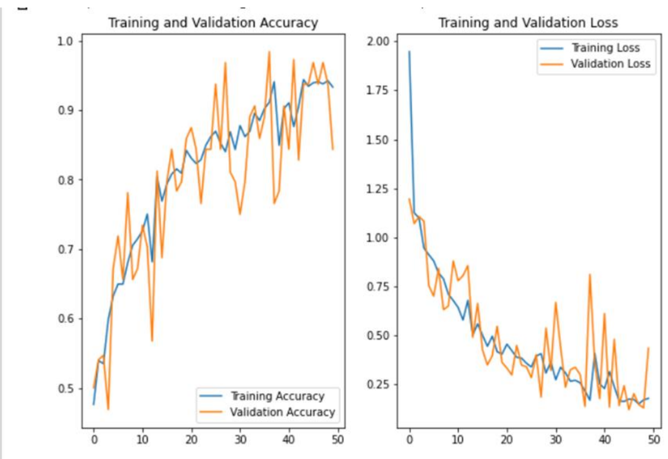


Fig 5.5-Training and Validation accuracy and loss

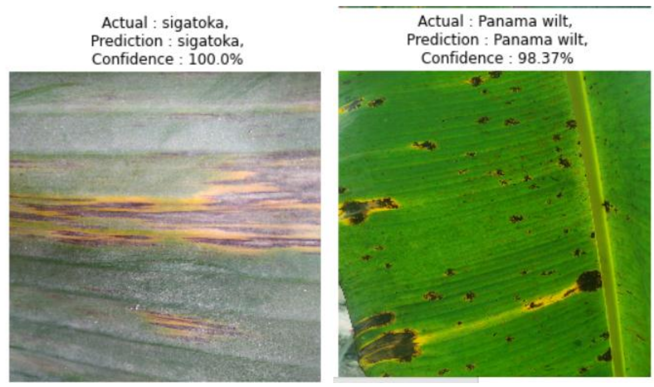


Fig 5.5- Results

5. CONCLUSION

Identification which is done manually in agricultural fields, most of the times, happens at the final stage which could result in economical losses. The main objective of the project is to automatically detect and identify the banana plant disease, which plays a vital role in causing loss at agricultural fields. The plant disease is identified by Image processing using the concept of CNN which is used to zoom the image and identify the affected part with more accuracy. Later the severity of the disease is identified by comparing value with the trained dataset and displaying it. The proposed system will reduce the manual work and used to increase the yield by identifying the disease in earlier stage. Hence the loss will be saved and helps in agricultural field efficiently

6. REFERENCES

[1] GREEN LEAF DISEASE DETECTION AND INFECTION IDENTIFICATION USING RASPBERRY PI Madhushree K V1, Poornima G2, Seema N3, Subash K B4, Srinath G M. International Research Journal of Engineering and Technology (IRJET)Volume: 07 Issue: 06 | June 2020

[2] Leaf Disease Detection Using Raspberry Pi LAYA YESUDAS 1, SANTHIYA.S 2 , PARIMALA.R 3 , MOHAMMAD HARRIS S4.APR 2019 | IRE Journals | CCCA – 2019 | Volume 2 Issue 10 | ISSN: 2456-8880

[3] Reddy, G. Rama Mohan, Nettam Sai Sumanth, and N. Sai Preetham Kumar. "PLANT LEAF DISEASE DETECTION USING CNN AND RASPBERRY Pi." INTERNATIONAL JOURNAL 5.2 (2020). Reddy, G. Rama Mohan, Nettam Sai Sumanth, and N. Sai Preetham Kumar. "PLANT LEAF DISEASE DETECTION USING CNN AND RASPBERRY Pi." INTERNATIONAL JOURNAL 5.2 (2020).

[4] Kanungo, Tapas, et al. "An efficient k-means clustering algorithm: Analysis and implementation." IEEE transactions on pattern analysis and machine intelligence 24.7 (2002): 881-892.

[5] Singh, Malti K., Subrat Chetia, and Malti Singh. "Detection and classification of plant leaf diseases in image processing using MATLAB." International journal of life sciences Research 5.4 (2017): 120-124.

[6] Devaraj, Abirami, et al. "Identification of plant disease using image processing technique." 2019 International Conference on Communication and Signal Processing (ICCSP). IEEE, 2019.

[7] Beyene, Hailay, Dr Narayan A. Joshi, and Dr Ketan Kotecha. "Plant Diseases Prediction Using Image Processing and Machine Learning Techniques: Survey." Int J Comput Appl 1.8 (2018): 226-37. 5, May 2018

[8] Bhamare, Sandip P., and Samadhan C. Kulkarni. "Detection of black sigatoka on banana tree using image processing techniques." IOSR Journal of Electronics and Communication Engineering (2013): 60-65. VIII SEM, DEPT. OF TCE, Dr. AIT Page | 52 Greenleaf Disease Detection and Identification using Raspberry Pi 2021-22

[9] Shrivastava, Sourabh, Satish Kumar Singh, and Dhara Singh Hooda. "Color sensing and image processing-based automatic soybean plant foliar disease severity detection and estimation." Multimedia Tools and Applications 74.24 (2015): 11467-11484.

[10] Dandawate, Yogesh, and Radha Kokare. "An automated approach for classification of plant diseases towards development of futuristic Decision Support System in Indian perspective." 2015 International conference on advances in computing, communications and informatics (ICACCI). IEEE, 2015.

[11] Gharge, Saylee, and Priyanka Singh. "Image processing for soybean disease classification and severity estimation." Emerging research in computing, information, communication and applications. Springer, New Delhi, 2016. 493-500.

[12] Kamble, Jagadish Kashinath. "Plant disease detector." 2018 International Conference On Advances in Communication and Computing Technology (ICACCT). IEEE, 2018.

[13] Sharma, Pushkara, Pankaj Hans, and Subhash Chand Gupta. "Classification of plant leaf diseases using machine learning and image preprocessing techniques." 2020 10th international conference on cloud computing, data science & engineering (Confluence). IEEE, 2020.

[14] Khirade, Sachin D., and A. B. Patil. "Plant disease detection using image processing." 2015 International conference on computing communication control and automation. IEEE, 2015.

[15] Camargo, A., and J. S. Smith. "An image-processing based algorithm to automatically identify plant disease visual symptoms." Biosystems engineering 102.1 (2009): 9-21.

[16] Al-Hiary, Heba, et al. "Fast and accurate detection and classification of plant diseases." International Journal of Computer Applications 17.1 (2011): 31-38.

[17] S. Albawi, T. A. Mohammed and S. Al-Zawi, "Understanding of a convolutional neural network," 2017 International Conference on Engineering and Technology (ICET), 2017, pp. 1-6, doi: 10.1109/ICEngTechnol.2017.8308186.

[18] Alzubaidi, L., Zhang, J., Humaidi, A.J. et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. J Big Data 8, 53 (2021).

[19] Greenleaf, James F., Mostafa Fatemi, and Michael Insana. "Selected methods for imaging elastic properties of biological tissues." Annual review of biomedical engineering 5.1 (2003): 57- 78.

[20] Rathod, Arti N., Bhavesh Tanawal, and Vatsal Shah. "Image processing techniques for detection of leaf disease." International Journal of Advanced Research in Computer Science and Software Engineering 3.11 (2013).

[21] Gavhale, Kiran R., and Ujwalla Gawande. "An overview of the research on plant leaves disease detection using image processing techniques." IOSR Journal of Computer Engineering (IOSR-JCE) 16.1 (2014): 10-16. VIII SEM, DEPT. OF TCE, Dr. AIT Page | 53 Greenleaf Disease Detection and Identification using Raspberry Pi 2021-22

[22] Jagtap, Sachin B., and Mr Shailesh M. Hambarde. "Agricultural plant leaf disease detection and diagnosis using image processing based on morphological feature extraction." IOSR J. VLSI Signal Process 4.5 (2014): 24-30.

[23] 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.

[24] Ganatra, Nilay, and Atul Patel. "A multiclass plant leaf disease detection using image processing and machine learning techniques." Int. J. Emerg. Technol 11.2 (2020): 1082-1086.

[25] Singh, Vijai, and A. K. Misra. "Detection of unhealthy region of plant leaves using image processing and genetic algorithm." 2015 International Conference on Advances in Computer Engineering and Applications. IEEE, 2015.

[26] Jasim, Marwan Adnan, and Jamal Mustafa Al-Tuwaijari. "Plant leaf diseases detection and classification using image processing and deep learning techniques." 2020

International Conference on Computer Science and Software Engineering (CSASE). IEEE, 2020.

[27] Pooja, V., Rahul Das, and V. Kanchana. "Identification of plant leaf diseases using image processing techniques." 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR). IEEE, 2017.

[28] Kumar, Santhosh S., and B. K. Raghavendra. "Diseases detection of various plant leaf using image processing techniques: a review." 2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS). IEEE, 2019.

[29] Shire, Atul, Umesh Jawarkar, and Manoj Manmode. "A review paper on: agricultural plant leaf disease detection using image processing." Int J Innov Sci Eng Technol 2.1 (2015): 282-285.

[30] Kamlapurkar, Sushil R. "Detection of plant leaf disease using image processing approach." International Journal of Scientific and Research Publications 6.2 (2016): 73-76.