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Disease Detection and Remote Monitoring in Chilli Crop Using Image Processing

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Abstract: Observations today have verified that the average crop yield in India is declining due to illnesses that have affected fully grown plants. Chilli plant production is tough due to the plant's vulnerability to a variety of microorganisms, infectious illnesses, and pests. Infections in the chilli plant impact areas such as the leaves and stems. In the early stages of diagnosing chilli illnesses, leaf characteristics are examined. The leaf image is taken and analyzed to determine the health of the chilli plant. Pesticides are currently being tested on chilli plants on a regular basis without first determining the needs of each plant. This ensures that pesticides are only used when diseased plants are discovered.

Keywords: Infections in the chilli plant, chilli illnesses, characteristics are examined, Pesticides are currently being tested on chilli plants.

I. INTRODUCTION

Climate change has negative consequences. In today's changing environment, timely and accurate identification of plant diseases, as well as early prevention, is critical in agriculture. Plant disorders can be identified in a variety of ways. Certain diseases have no obvious signs, or the effect is too late to be effective, necessitating a thorough investigation. However, because most diseases exhibit themselves in some way on the visible spectrum, qualified expert testing is the most effective method for detecting plant diseases. A plant pathologist must have great observational skills to make reliable diagnoses of plant diseases. abilities to recognize certain symptoms. Variations in all plant symptoms may lead to inaccurate diagnosis, as amateur and hobbyist pathologists may have a harder time determining the problem than expert pathologists. Amateurs in gardening and qualified experts alike can benefit from an automated system developed to determine the circumstances and visual symptoms of the plant as a verifier of disease diagnosis.

Plant disease identification is important in the agriculture sector since it has an indirect impact on a country's economy. The sickness of plants should be detected and identified as soon as possible. Plant diseases may now be detected with minimal human intervention thanks to advances in image processing technology. Effective plant disease protection is inextricably connected to sustainable agriculture and climate change. According to research, seasonal changes in climate can affect infections and the rate at which they evolve, causing host resistance to shift and host-pathogen interactions to change physiologically. It aggravates the situation now since diseases are more easily disseminated over the world than in the past. New infections may emerge in areas where they haven't been detected before and where local expertise isn't accessible to combat them. Through the unintentional use of pesticides, long-term diseases can develop resistance and severely reduce their fighting capacity. ‘One of the pillars of precision farming is the prompt and precise identification of plant diseases,' as mentioned in. Financial and other resources should not be squandered unnecessarily, and production should be prioritized by addressing the problem of long-term pathogenic resistance and lowering the cost of production.

II. LITERATURE SURVEY

The literature review is organized as introduction to domain terminology, the operation of an existing convolutional neutral network. A cognitive vision system with image processing, learning, and knowledge-based strategies was proposed. Using an SVM classifier, the author presents an automatic technique for classifying the primary agents that cause harm to chilli crops.

Convolutional neural networks (CNNs) are neural networks with one or more convolutional layers that are primarily utilized for image processing, classification, segmentation, and other auto-correlated data. Instead of looking at the full image at once to locate specific features, it may be more useful to look at discrete sections of the image. Around the 1980s, CNNs were developed and first deployed. A CNN could only recognize handwritten figures at the time. When we think about neural networks, we typically think of matrix multiplications, but this is not the case with ConvNet. Convolution is a unique technique that it employs. Convolution is a mathematical operation on two functions that yields a third function that explains how the shape of one is changed by the other. In comparison to other image classification methods, CNNs require very little pre-processing.

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This means that the network learns to optimize the filters (or kernels) by automatic learning, as opposed to hand-engineered filters in traditional techniques. This lack of reliance on prior information or human intervention in feature extraction is a significant benefit.

Multilayer perceptrons are regularized variants of CNNs. Multilayer perceptrons are typically completely connected networks, meaning that each neuron in one layer is linked to all neurons in the following layer. These networks' "complete connectedness" makes them vulnerable to data overfitting. Regularization, or preventing overfitting, can be accomplished in a variety of methods, including punishing parameters during training (such as weight loss) or reducing connectivity (skipped connections, dropout, etc.) CNNs use a different approach to regularization: they take advantage of the hierarchical pattern in data and use smaller and simpler patterns etched in its architecture to assemble patterns of increasing complexity. Therefore, on a scale of connectivity and complexity, CNNs are on the lower extreme.

A lot of studies with photographs, and some of them can find cancer cells or identify malady in leaves. Working using the Google Tensor Flow library, on the other hand, is more efficient and reliable. With less preparation information, it can appear to be an exact yield. This piqued my curiosity in working on it. CNN can be used to classify faces and non-faces, buildings and nature, dense and rational classification, and more. In their (ti be mentioned) classification, they employed 250 epochs. They achieved an accuracy of roughly 77 percent in forest and agricultural categorization and 91 percent in residential vs agricultural classification. Working with green zones yielded a 97 percent accuracy rate. They also demonstrated that CNN performs better in the green area than in the building scene. As a result, it works with nature and fruits as well as material or building pictures. As a result of this study, we can conclude that CNN is an excellent algorithm for working with nature and natural products such as fruits and vegetables.

III. PROPOSED SYSTEM

The full method of utilizing deep CNN to create a model for plant disease diagnosis is detailed here. The entire process is broken down into a few key phases, beginning with image acquisition for the deep neural network classification procedure. Here is the whole technique for using deep CNN to construct a model for plant disease diagnosis. Preprocessing techniques including Fourier filtering, edge detection, and morphological processes have historically been the focus of image processing. The image processing paradigm is extended by computer vision to incorporate scene content interpretation and object classification. As a result, this paper shows how image processing techniques can be used to detect plant chilli disease using a leaf image.

IV. FLOW CHART OF MACHINE TRANSLATION

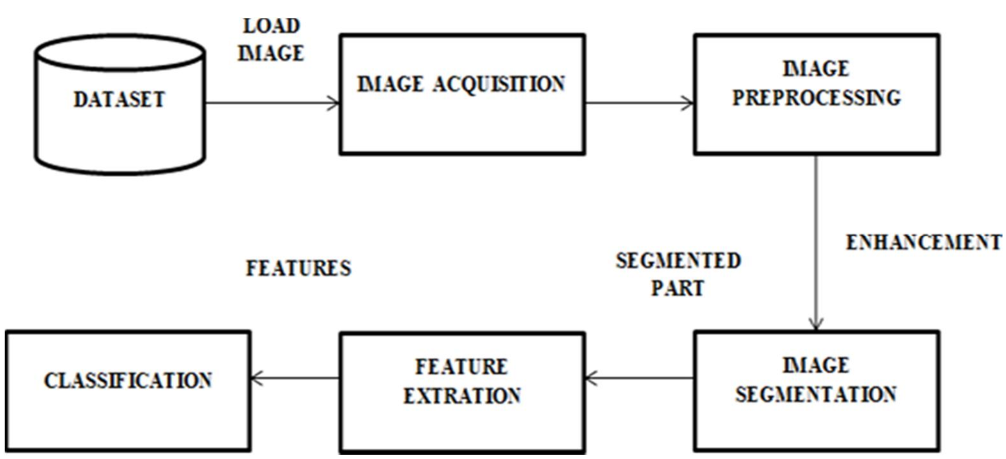

Fig 4.1 Picture showing block diagram of Chili crop disease prediction

The workflow of the entire project is depicted in the diagram above. The dataset was manually constructed by categorizing infected leaves into three disease classifications. Bacterial leaf blight, Brown spot, and Leaf smut are the three illnesses, each with 40 photos. Each image is in the.jpg format. Image augmentation was used to boost the dataset's size to 480. The photos were then converted into features using the Color Layout Filter image filtering, which added 35 characteristics to the dataset. The prominent features were then determined using a correlation-based attributes selection technique. The dataset was then divided into two parts: the training set, which contains 90% of the data, and the test set, which contains 10% of the data It is made up of the remaining 10%. Finally, four alternative categorization algorithms were employed, each yielding unique findings.

V. METHODOLOGY

1) *System Overview:* Our work aims to identify nine classes of diseases and pests that affect tomato plants using Deep Learning as the main body of the system. Following is the detail of each component of the proposed approach.

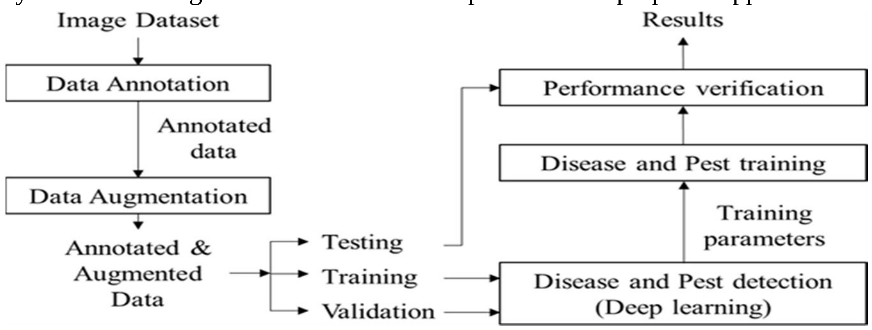

Fig 5.1 Picture showing System Overview.

2) *Data Collection:* Images of many diseases and pests in tomato plants can be found in our dataset. The photographs were obtained with simple camera devices under various situations based on the time (e.g., illumination), season (e.g., temperature, humidity), and location where they were taken (e.g., greenhouse). For that purpose, we have visited several chilli farms located in Korea and fed our dataset with various types of data, including:

a) Images with various resolutions.
b) Samples at early, medium, and last infection status.
c) Images containing different infected areas in the plant (e.g., stem, leaves, fruits, etc.).
d) Different plant sizes.
e) Objects surrounding the plant in the greenhouse, etc.

These factors aid in estimating the infection process and determining how a disease or pest affects a plant (origin or possible developing cause).

3) *Data Annotation:* Starting with the picture dataset, we manually mark the disease or pest-infested portions of each image using a bounding box and a class. Some diseases may appear similar based on the current infection status; consequently, professionals in the field have offered the knowledge for identifying the type of disease or pest.

4) *Data Augmentation:* Despite their superior performance as compared to standard machine learning or computer vision techniques, Deep Neural Network systems suffer from the overfitting problem. Hyper-parameter selection, system regularization, or many images utilized for training are all examples of overfitting.

5) *Image Preprocessing and Labelling:* The image was captured by the camera and downloaded from the internet in various sizes, formats, and resolutions. The final images that would be used as a data set for a deep neural network classifier were preprocessed to ensure consistency and improve feature extraction. After that, manually trim the photo to highlight the unhealthy jute leaves. We double-checked that the photographs contained all the information required for feature learning.

6) *Disease and Pest Detection:* Now we'll go through our primary way of detecting diseases and pests. Our goal is to detect and recognize disease and pest candidates in the image by class and location. To find our objective, we must first properly locate the box in which it is contained, as well as determine the class to which it belongs.

VI. IMPLEMENTATION

A. In this chapter dataset of 7000 images have been captured, out of which 225 chilli sectaries information is discussed. This chapter also covers research project tools, data collection, pre-processing, statistical analysis, and execution.
B. Grabbed 7000 images of chilli plant leaves as a source of information. The photos are divided into five categories:
C. Healthy images: 45 Images
D. Sick images: 45 Images - representing four diseases:
E. White flies (45 images)
F. Curved leaves (45 images)
G. Grey mould (45 images)
H. Yellowish (45 images).

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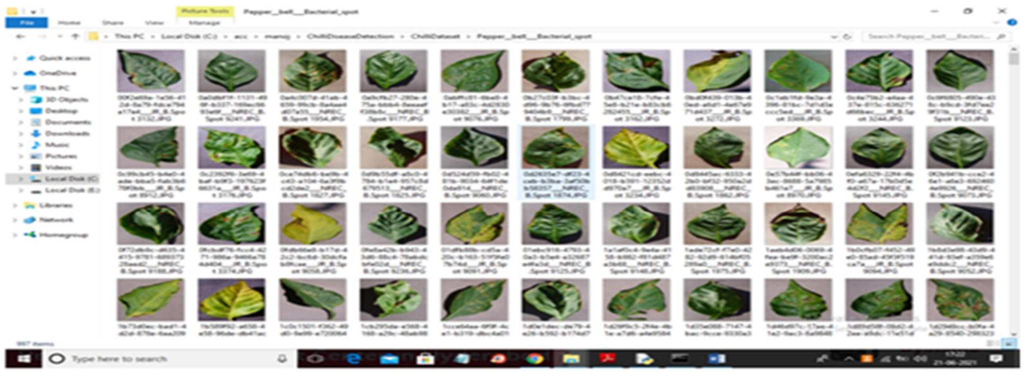
1) *Data Set:* Each data subset is then subdivided into four illness subsets for each of the four disease classifications. These statistics were taken from the Plant Village website. In the next part, we describe What are these symptoms, and how do we extract representative features.



Below code screen showing implementation of CNN model

2) *Data Pre-processing:* The pre-processing of datasets is referred to as data pre-processing. Raw data sets, in general, are unable to conduct operations and produce desired results. As a result, pre-processing of data is necessary. It is also regarded as one of the most crucial aspects of research. During this step, collected around 7000 images from various sources and eliminate any superfluous or noisy data.

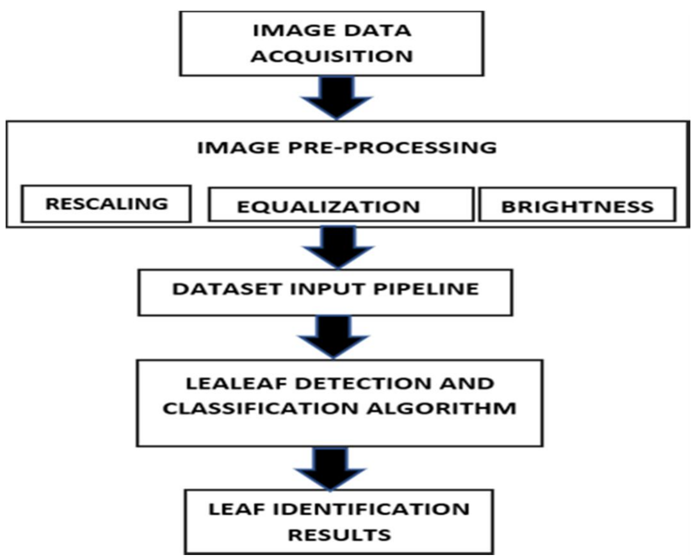


Fig 6.1 Picture showing data preprocessing.

VII. RESULTS AND DISCUSSIONS

A deep learning neural network-based approach to the identification and placement of targets is used in this study and presents an enhanced CNN model. As a pretrained model of this model, the trained CNN network. The parameters of the pretrained model optimize the model parameters of this convolution layer by improving its transfer learning technique and solving the Chili leaf disease detection classification issue. CNN parameters are focused in three layers of FC. Therefore, the three completely connected CNN layers are suggested to be replaced with one Flatten layer and two fully connected layers. The convolution layer cannot be linked directly to the Flatten layer is added to the Dense completely linked layer. The improved model training framework primarily employs fine-tuning transfer learning to transfer the CNN pretrained model parameters to the convolution layer, pooling layer, and fully connected layer of the Chili disease detection model and replaces the original with a 2-label SoftMax classification layer, sparse features via Dropout, Max pooling, and fit a detection model.

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```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 3)                 75267
=================================================================
Total params: 20,099,651
Trainable params: 75,267
Non-trainable params: 20,024,384
```

Fig 7.6 Screenshot showing the training process.

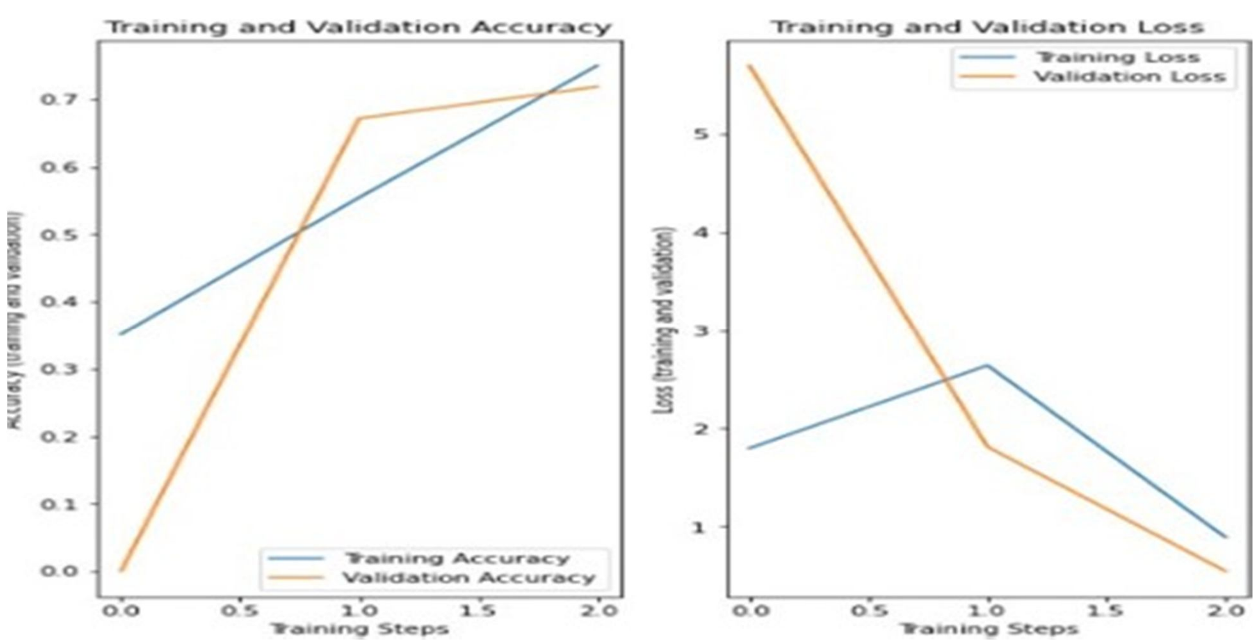
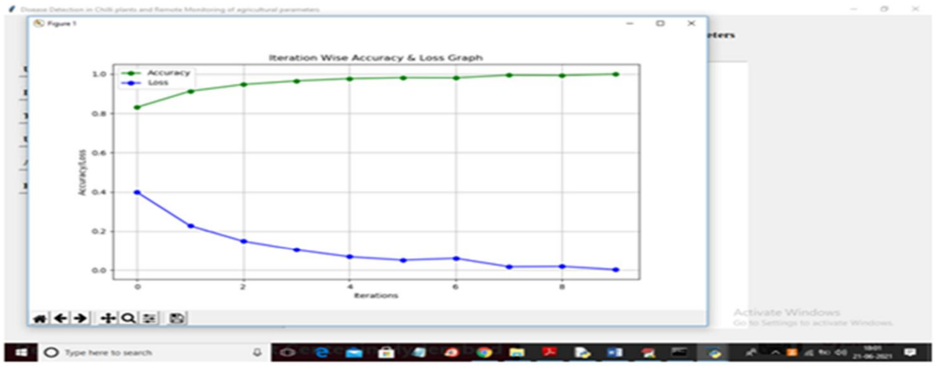
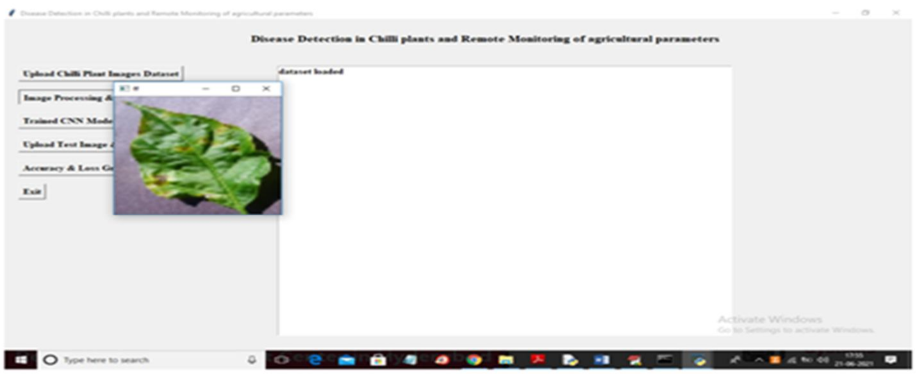


Fig 7.1: Screenshot showing training accuracy vs. Validation accuracy.



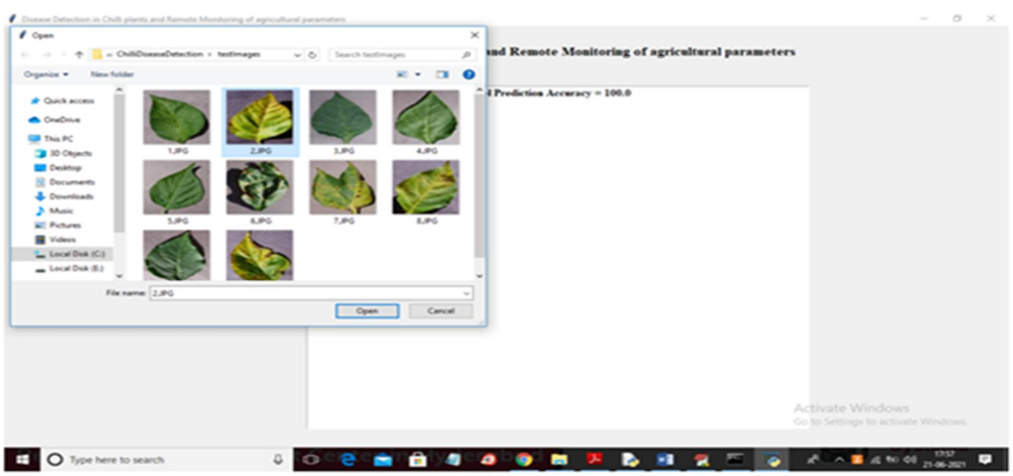
In above graph x-axis represents CNN EPOCH and I took 10 EPOCH and in above graph y-axis represents accuracy and LOSS value and in above graph green line represents accuracy and blue line represents LOSS and in above graph we can see with each increasing EPOCH accuracy is getting increase and loss getting decrease. This increasing accuracy will consider model as accurate.

Fig 7.2 Screenshot showing Training loss vs. validation loss.



In above screen all images are normalized and to check all Images are processed successfully I am displaying one sample image and now close above image to get below screen

Fig 7.3 Screenshot Showing Display of Sample Image.



In above screen selecting and uploading '2.JPG' file and then click on 'Open' button to get below prediction result

Fig 7.4 Screenshot showing General Images Selection.

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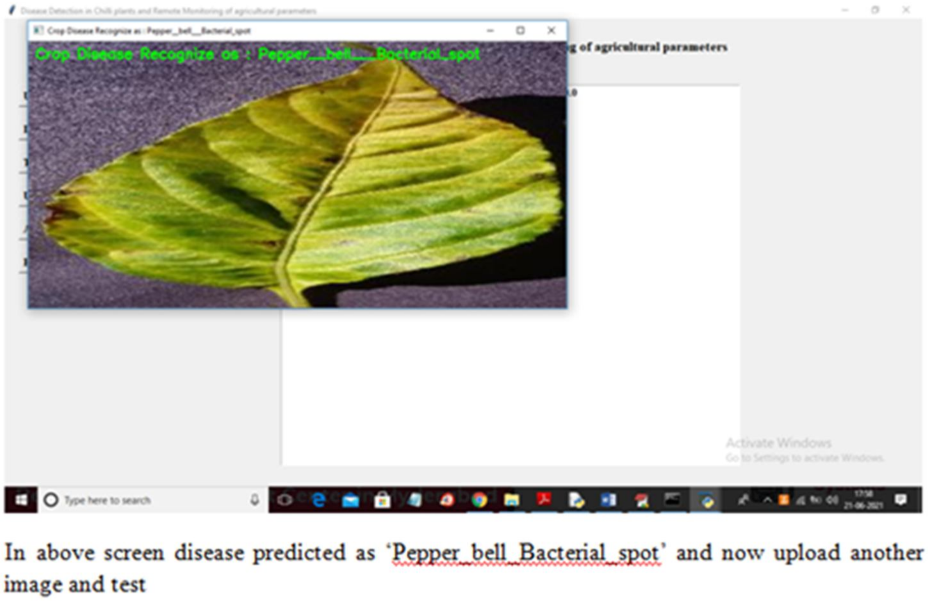

Fig 7.5 Screenshot showing display of Sample Image.

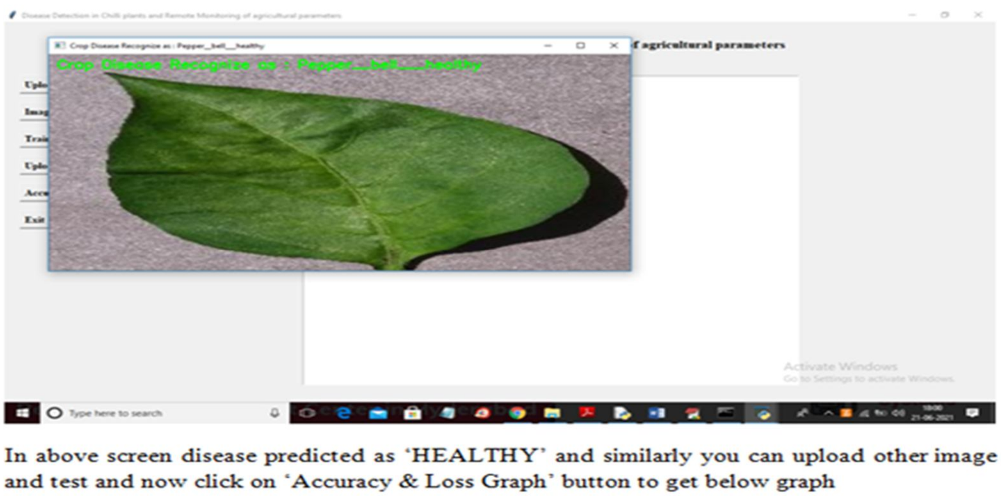

Fig 7.6 Screenshot showing Healthy Leaf.

VIII. CONCLUSION

The approach now in use for detecting plant chilli disease is both effective and quick. It is strongly suggested for use in the early identification of plant chilli illness via chilli inspection. The chilli images captured are processed to determine the healthiness of each plant. By using this recognition technique, it will identify the potential problems to the chilli plants before it goes seriously damage for all chilli plants. With this method, the use of harmful chemicals on plants can be reduced and hence ensure a healthier environment and may be even lowering the production cost of the maintenance and producing a high quality of chilli.

In short, the technique presented integrates new technology like CNNs for improving traditional farming practices. New technologies are part of the technique. The farmer may monitor and assess chilli plants in his field remotely using specific sensors and Deep Learning algorithms. With very easy implementation, the idea of illness detection has been accomplished. The steps utilized to detect the plant disease are described in this publication. It demonstrates how plant disease detection is implemented. It improves the accuracy of plant disease detection. Because manually detecting plant illness is difficult, image processing is used.

IX. ACKNOWLEDGEMENT

While bringing out this thesis to its final form, I came across a few people whose contributions in various ways helped my field of research and they deserve special thanks. It is a pleasure to convey my gratitude to all of them.

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REFERENCES

[1] K. Singh, M. &. Chetia, S. &. Singh and Malti, "Detection and Classification of Plant Leaf Diseases in Image Processing using MATLAB," International Journal of Life sciences Research, vol. 5, no. 1, pp. 120-124, 2017.

[2] K. Simonyan and A. Zisserman, Very Deep Convolutional Networks for Large-Scale Image Recognition, arXiv: 1409.1556v6 [cs.CV], 2014.

[3] J. Redmon, S. Divvala and R. G. a. A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," J. Redmon, S. Divvala and R. G. a. A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, 2016.

[4] Y. Lecun, L. Bottou and Y. B. a. P. Haffner, "Gradient-based learning applied to document recognition," Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, Nov 1998.

[5] S. Ren, K. He and R. G. a. J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 2017.

[6] R. Girshick, "Fast R-CNN," in 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015.

[7] Sufola Das Chagas Silva Araujo, Meenakshi Sundaram Karuppaswamy, "Comparative Analysis of K-Means and K-Nearest Neighbor Image Segmentation Techniques" in IEEE 6th International Conference on Advanced Computing (IACC)Year: February2016, DOI: 10.1109/IACC.2016.27, IEEE Conference Publications.

[8] Coakley, S.M.; Scherm, H.; Chakraborty, S. Climate Change and Plant Disease Management. Annu. Rev. Phytopathol. 1999, 37, 399–426. [CrossRef] [PubMed].

[9] Food and Agriculture Organization of the United Nations. Plant Pests and Diseases. 2017. Available online: http:// www. fao. org/emergencies/emergency-types/plant-pests-and-diseases/ en/ (accessed on 20 June 2017).

[10] Zulkifli Bin Husin,Ali Yeon Bin , Abdul Hallis Bin Abdul Aziz,Rohani Binti S Mohamed Farook "Feasibility Study on Plant Chilli Disease Detection Using Image Processing Techniques", 3rd International Conference on Intelligent Systems Modelling and Simulation, 2012

[11] J. L. González-Pérez1, M. C. Espino-Gudiño2, J. Gudiño-Bazaldúa3, J. L. Rojas-Rentería4, V. Rodríguez-Hernández5 and V.M. Castaño6 "Colour image segmentation using perceptual spaces through applets for determining and preventing diseases in chili peppers" African Journal of Biotechnology Vol. 12(7), pp. 679-688, 13 February 2013

[12] Jyoti A Kodagali. S Balaji "Computer Vision and Image Analysis based Techniques for Automatic Characterization of Fruits", International Journal of Computer Applications (0975 – 8887) Volume 50 – No.6, July 2012.

[13] Shiv Ram Dubey1, Pushkar Dixit2, Nishant Singh3, Jay Prakash Gupta4"Infected Fruit Part Detection using K-Means Clustering Segmentation Technique", International Journal of Artificial Intelligence and Interactive Multimedia, Vol. 2, Nº 2

[14] Erick SALDAÑA, Raúl SICHE "Computer vision applied to the inspection and quality control of fruits and vegetables", Campinas, v. 16, n. 4, p. 254-272, out. /dez. 2013.

[15] Erick SALDAÑA, Raúl SICHE "Computer vision applied to the inspection and quality control of fruits and vegetables", Campinas, v. 16, n. 4, p. 254-272, out. /dez. 2013.

[16] S. Thomas et al., "Benefits of hyperspectral imaging for plant disease detection and p

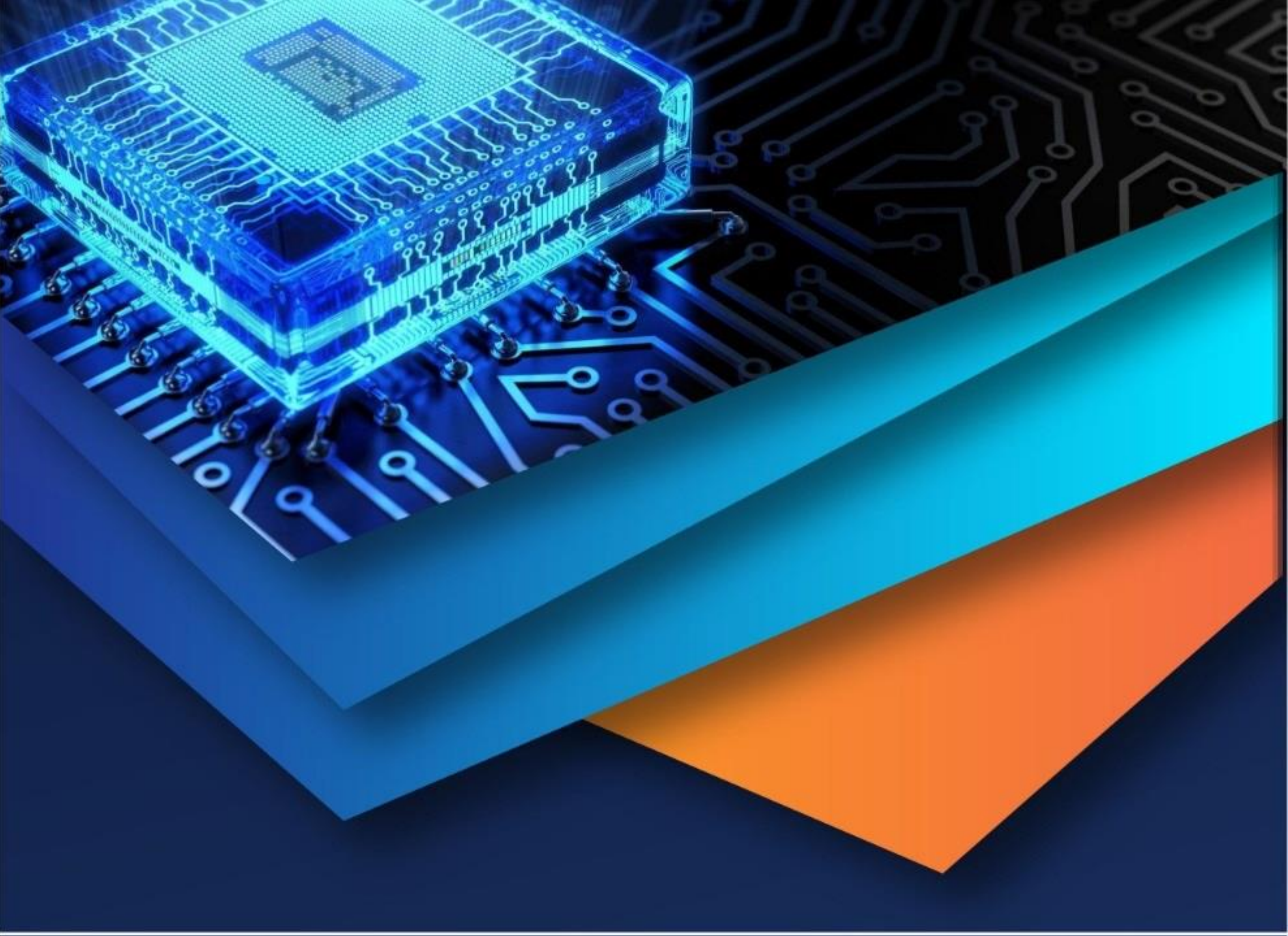
[17] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Comput. Electron. Agric., vol. 145, no. January, pp. 311–318, 2018.

[18] V. Singh and A. K. Misra, "Detection of Plant Leaf Diseases Using Image Segmentation and Soft Computing Techniques," Inf. Process. Agric., 2016.

[19] S. D. Khirade, "Plant Disease Detection Using Image Processing," pp. 1–4, 2015.

[20] F. Martinelli et al., "Advanced methods of plant disease detection. A review," 2014.

[21] Z. Bin Husin, A. Hallis, and B. Abdul, "Feasibility Study on Plant Chili Disease Detection Using Image Processing Techniques," pp. 291–296, 2012.



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