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Detect Plant Disease and Recommend Fertilizer and Supplement Using CNN & Mobile Net Algorithm

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Abstract: Agriculture plays a crucial role in the Indian economy. Early detection of plant diseases is very much essential to prevent crop loss and further spread of diseases. Most plants such as apple, tomato, cherry, grapes show visible symptoms of the disease on the leaf. These visible patterns can be identified to correctly predict the disease and take early actions to prevent it. This can be overcome by the use of machine learning and deep learning algorithms. Hence, we are proposing a method that which is detecting the disease of a tomato plant from their leaf images. Here the process is performed with the deep learning algorithms Convolutional Neural Network (CNN), and MobileNet which is a one of the transfer learning method of CNN. Once after training the dataset with the algorithms, the accuracy of algorithms is compared and the images are classified. And the precautions are also provided for the classified plant.
Keywords: Plant diseases, machine learning, deep learning, CNN, MobileNet.

I. INTRODUCTION

Agriculture employs over 70% of India's population. Plant disease detection is very important to prevent yield loss. Manually monitoring plant diseases is very difficult. It requires considerable effort, plant disease expertise, and a long time. As a result, machine learning-based image processing and algorithms can be used to detect crop diseases. In this project, we described a method for detecting plant diseases from leaf images. Image processing is a subset of signal processing that extracts image attributes or useful information. Machine learning is a subset of artificial intelligence that functions autonomously or directs how to perform certain tasks. A fundamental goal of machine learning is to understand training data and combine that training data into predictions that are useful to humans. With a large amount of training data, it helps us make rational decisions and predict good performance. Leaf color, degree of leaf damage, leaf area, and structural criteria are used for classification. In this study, we analyzed a number of image metrics or traits to identify leaf diseases in different plants to achieve the highest accuracy. Previously, detection of plant diseases was done by visual inspection of leaves or by specific chemical procedures by specialists, requiring large teams of specialists and regular monitoring of plants. This is expensive on large farms. A variety of current technologies have arisen to reduce postharvest processing, strengthen the sustainability of agriculture, and increase production. For illness detection, based in laboratories techniques such as polymerase chain response, chromatography of gases, mass spectroscopy, thermography, and hyper spectral methods have been used. However, these techniques are inefficient and lengthy. In recent years, server-based and mobile-based approaches to illness identification have been used. Many aspects of these technologies, such as high resolution cameras, powerful processing, and deep built-in accessories, contribute to automatic disease recognition. To improve the identification rate and accuracy of the results, modern technologies such as machine learning and deep learning algorithms have been used. Several studies have been conducted in the application of artificial intelligence for identifying plant illnesses and diagnosis. Rural farmers sometimes have difficulty distinguishing between diseases that may be present in their crops. It is not reasonable for them to go to the farm office to find out what the infection is. The goal is to distinguish between plant-introduced diseases by observing plant shape using image processing and machine learning. Pests and diseases destroy crops and plant parts, leading to reduced food production and food poverty. In addition, many developing countries lack an understanding of pest and disease control. Virulent infectious diseases, poor disease control, and dramatic changes in the environment are some of the major causes of declining food production.

In such cases, recommendation systems are useful when monitoring large fields. The ability to automatically detect disease simply by observing signs on plant leaves makes it easy and cheap. Because it employs statistical machine learning and image processing algorithms, the suggested approach for identifying plant diseases is less computationally expensive and takes less time to predict than other deep learning-based approaches.

II. LITERATURE REVIEW

[1] P.R. Rothe and RV Kshirsagar published "Identification of cotton leaf diseases using pattern recognition techniques" using snake segmentation and Hu moments as features. Active contour models are used to limit survival within infected regions, and BPNN classifiers address different classes of problems. The average classification rate is 85.52%.

[2] "Detection and Classification of Leaf Diseases Using Computer Vision Techniques and Fuzzy Logic," Aakanksha Rastogi, Ritika Arora, and Shanu Sharma. Segment the defect regions using K-means clustering. GLCM is used to extract texture information. Fuzzy logic is used to rank diseases. They used an artificial neural network (ANN) as a classifier. This primarily helps determine the extent of leaf disease.

[3] "Visual-based automated diagnosis of banana bacterium and black sigatoka" was proposed by Godliver Owomugisha, John A. Quinn, Ernest Mwebaze, and James Lwasa. A color histogram is taken and converted from RGB to HSV and then to L*a*b. A max tree is constructed using peak components, 5 shape attributes are used for classification, and area under curve evaluation is used. They used nearest neighbors, decision trees, random forests, hyperrandom trees, naive Bayes, and SV classifiers. A highly random tree produces very high scores across seven classifiers, providing real-time information and adding versatility to the application.

[4] uan Tian, Chunjiang Zhao, Shenglian Lu and Xinyu Guo, "SVM-based Multiple Classifier System for Recognition of Wheat Leaf Diseases", Color features are encoded in HIS in RGB, and seven invariant moments are used as shape parameters Used by GLCM. They used his SVM classifier with MCS for offline disease detection in wheat plants.

III. EXISTING SYSTEM

The existing plant disease detection systems primarily depend on manual observation by experienced agricultural experts. Farmers identify diseases based on visible symptoms such as discoloration, leaf spots, wilting, or fungal growth. This traditional approach is often inaccurate due to similarities between disease symptoms and requires significant expertise. Some machine learning-based systems employ handcrafted image features combined with conventional classifiers such as Support Vector Machine (SVM), Decision Tree, or Random Forest, deep learning algorithms Convolutional Neural Network (CNN). These systems generally achieve moderate accuracy but struggle with complex backgrounds, varying illumination conditions, and multiple disease classes. Moreover, most existing solutions only detect diseases without providing fertilizer recommendations, nutrient suggestions, or preventive agricultural guidance.

A. Disadvantages

1) Less precision.
2) Less comfort characteristics.
3) We can't recommend a supplement

IV. PROPOSED METHOD

To overcome the problems of an existing system, the proposed method has evolved. The proposed system develops an intelligent plant disease diagnosis and recommendation platform using CNN and MobileNet deep learning architectures.

The uploaded plant leaf image undergoes preprocessing to enhance image quality and standardize dimensions. CNN extracts deep visual features from diseased leaf regions, while MobileNet performs efficient disease classification with reduced computational cost.

Once the disease is identified, the recommendation module retrieves appropriate fertilizer, micronutrient supplements, pesticides, organic treatments, and preventive farming practices from an agricultural database. The lightweight MobileNet architecture enables deployment on smartphones, allowing farmers to diagnose plant diseases directly in the field. The system supports multiple crop varieties and disease categories while maintaining high prediction accuracy.

V. METHODOLOGY

A. Modules

1) System

- Create Dataset: Here we use the pre prepared dataset which contains around 54305 images botanical leaf photographs of 38 different classes of the following fruits and vegetables like Apples, blueberries, cherries, corn, grapes, oranges, peaches, pepper bells, potatoes, raspberries, soybeans, strawberries, and tomatoes. In the total dataset 70% is used for training and 30% is used for testing, it is collected from kaggle plat village dataset.
- Pre-processing: Resizing and reshaping the images into appropriate format to train our model.
- Training: Use the pre-processed training dataset is used to train our model using deep learning (CNN, Mobile Net) algorithms
- Classification: The results of our model is predicted output along with the accuracy comparison.

2) User

- View training accuracy: User can check the trained algorithms accuracy
- Upload Image: The user has to upload an image which needs to be classified.
- View Results and precautions: The classified image results are viewed by user along with precautions.

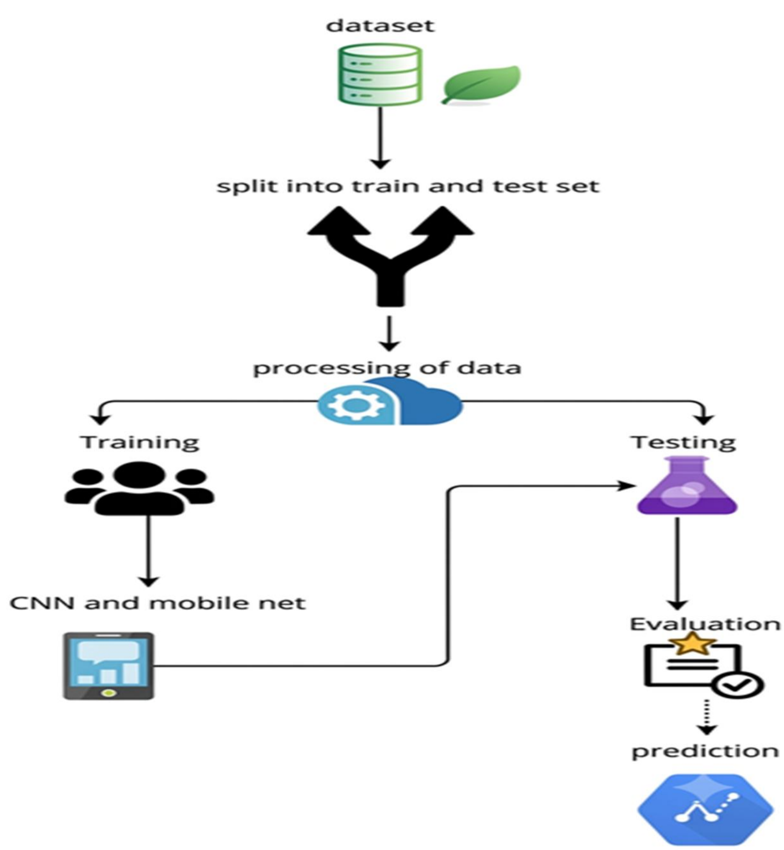


Figure1. System Architecture

VI. DEEP LEARNING ALGORITHMS

A. Convolutional Neural Network

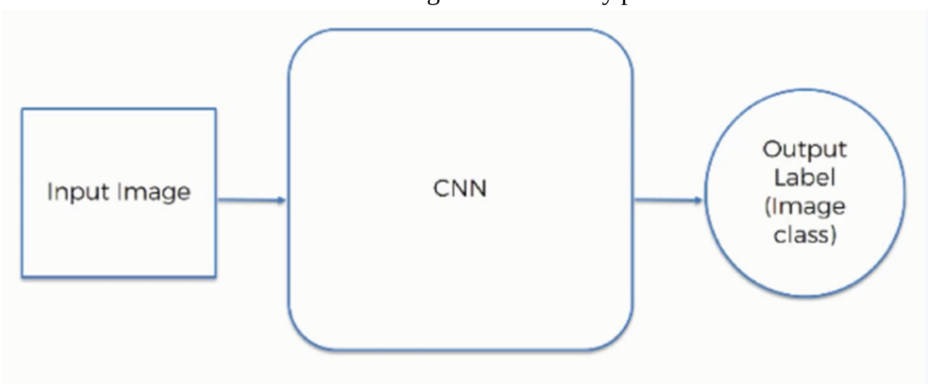
Step1: convolutional operation

Convolutional operations serve as the first stepping stone for our strategy. This phase provides a brief introduction to neural network filters or feature detectors. In addition, we discuss functional maps, their parameters, detection levels, how patterns are detected, and how results are presented.

Step 2: Pooling Layer
This section describes pooling and helps you understand how pooling usually works. However, in this case, a particular type of pooling (max pooling) plays a central role. However, consider different tactics, such as medium (or full) pooling. This part ends with a presentation using visual interactive tools.

Step 3: Flattening
Here, we provide an overview of the flattening process and how to move from pooling to flattened layers in convolutional neural networks.

Step 4: Full Connection
This part summarizes everything that was explained in the previous section. Understanding this helps us understand how a convolutional neural network works and how the "neurons" it generates classify photos.



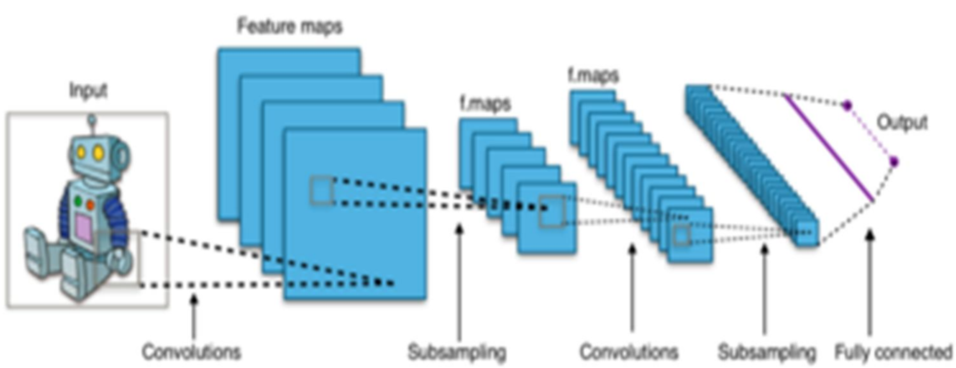


Figure2. CNN Architecture

B. Mobile Net

The utilization of Mobile Net algorithm in the detection of plant diseases through machine learning and deep learning is a groundbreaking approach. Mobile Net, known for its efficiency and lightweight architecture, proves to be instrumental in developing robust models for plant disease detection on mobile devices. By leveraging the power of convolutional neural networks (CNNs) within the Mobile Net framework, this technology enables real-time analysis of plant health through image processing. Mobile Net's capacity to efficiently handle computational tasks on resource-constrained platforms, such as smartphones, facilitates the deployment of portable and accessible plant disease detection solutions. The algorithm's ability to balance accuracy and computational efficiency is crucial in ensuring timely and accurate identification of diseases, empowering farmers and agricultural professionals to take swift corrective actions. Through the amalgamation of Mobile Net and advanced image recognition techniques, this research strives to enhance the efficacy and accessibility of plant disease detection, contributing to sustainable agriculture and food security.

VII. RESULTS

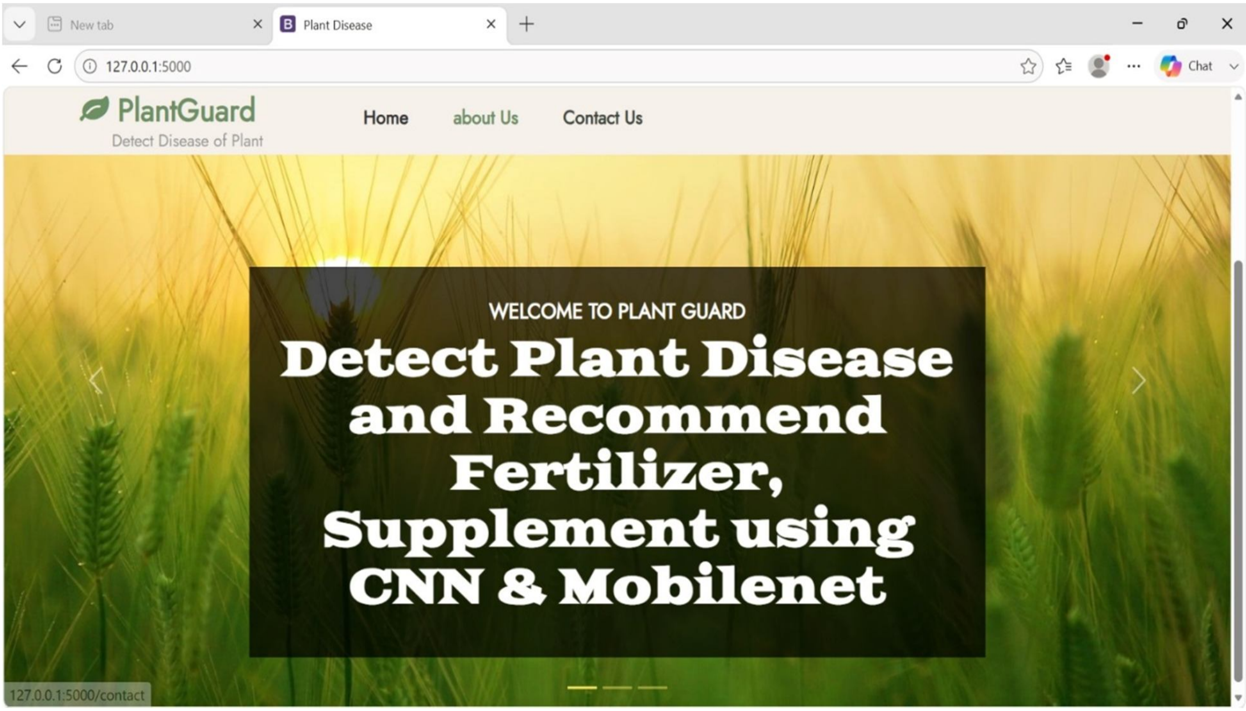


Figure3: Home Page

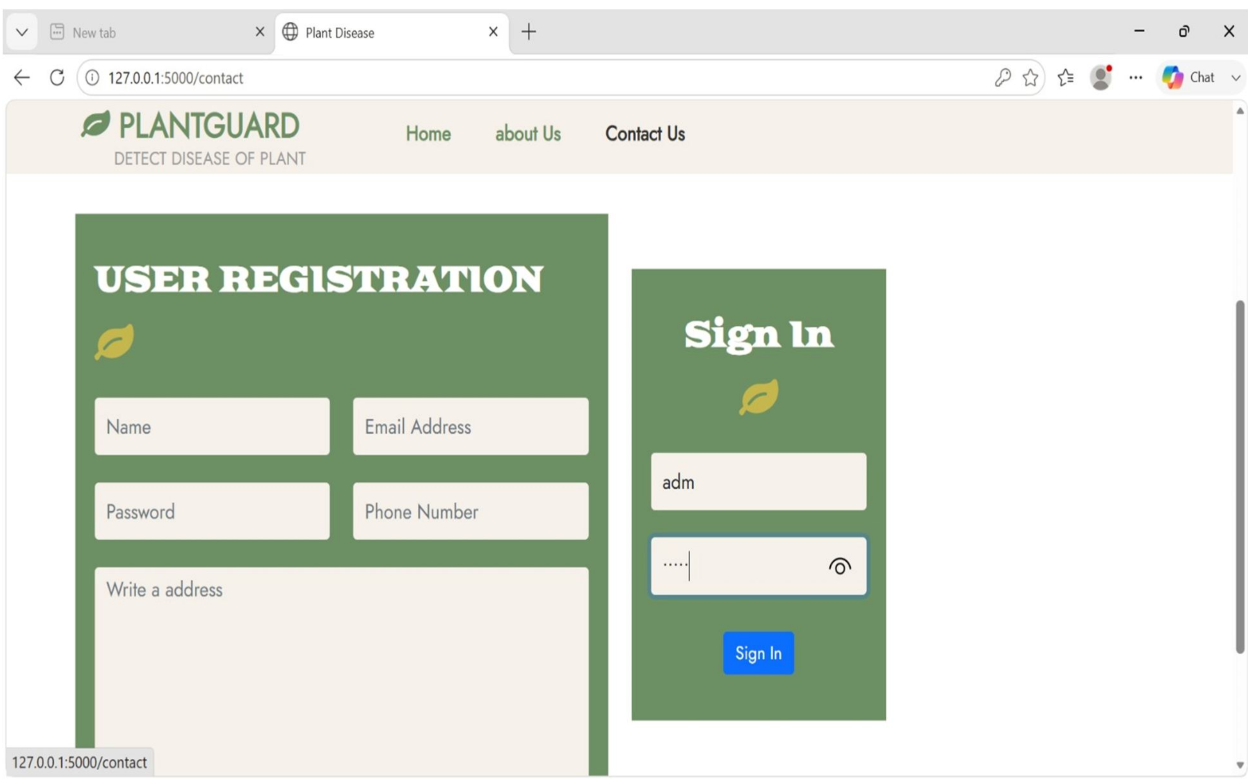


Figure4: Registration & Sign In Page

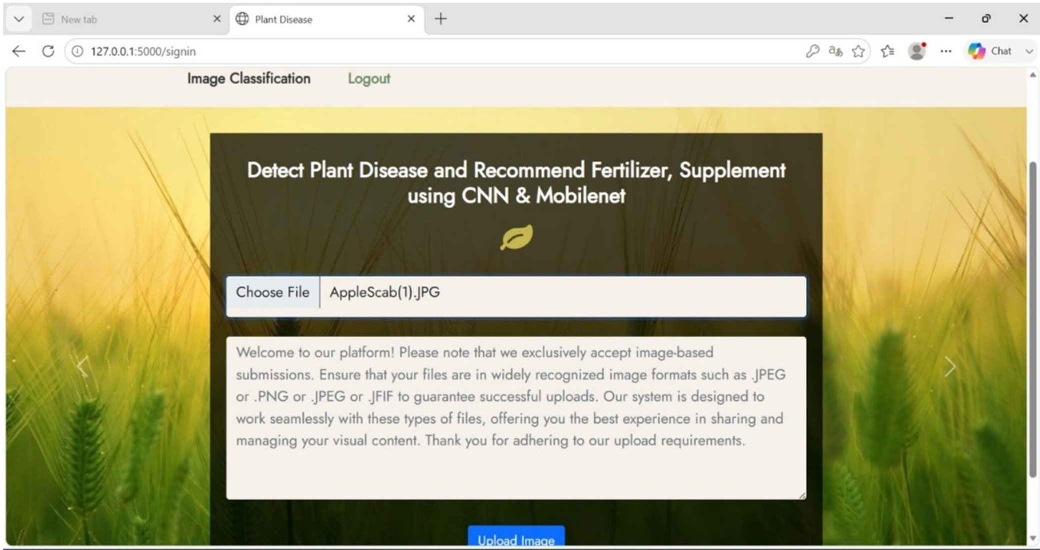


Figure5:Upload Leaf Image

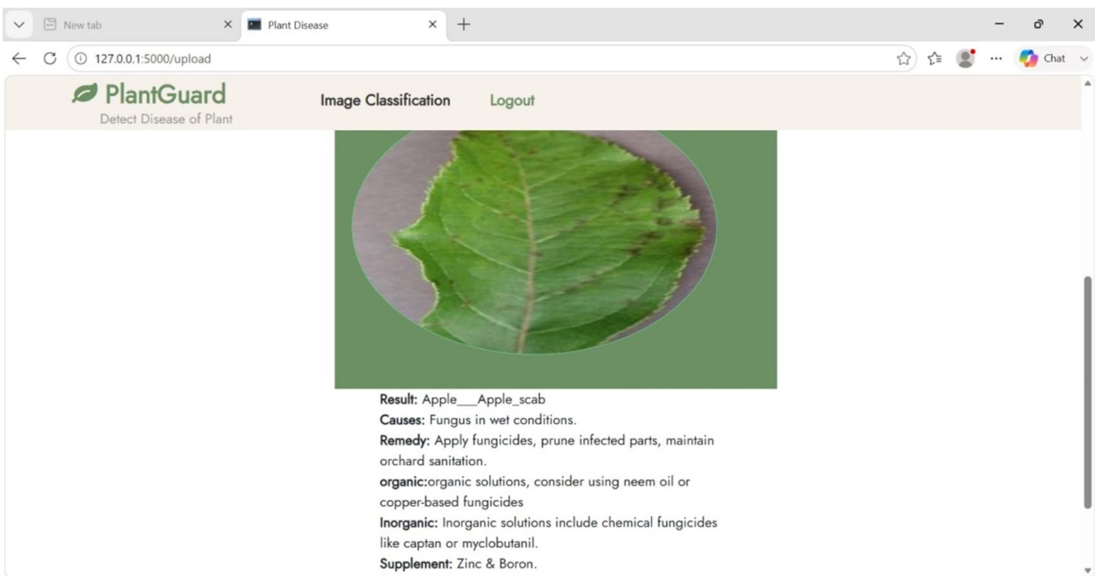


Figure6: Result Prediction

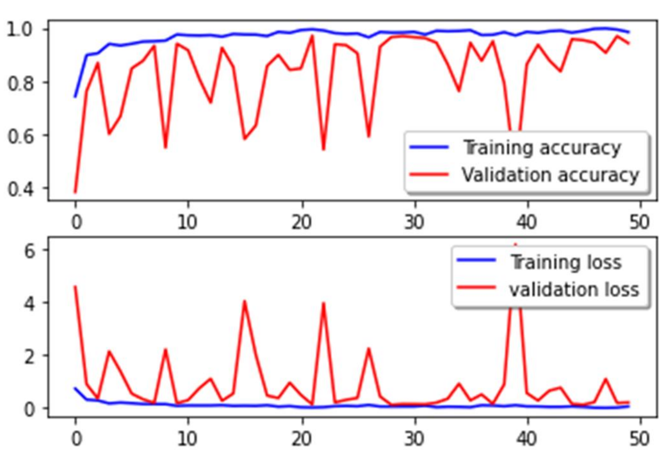


Figure7: Mobile Net Training Accuracy

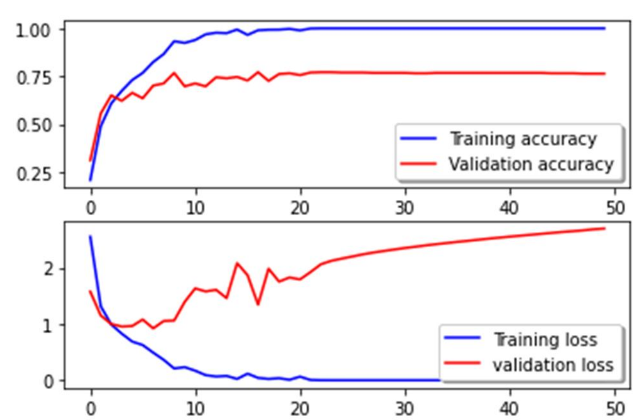


Figure8: CNN Training Accuracy

VIII. CONCLUSION

In this project we have successfully implemented the machine learning and deep learning algorithms to build a model that which can predict the plant leaf images, either the leaf is effected with which type of disease or not along with organic, inorganic fertilizer and supplement. Here we mainly used CNN, MobileNet, for the process of training image dataset. Once after training, we have checked the classified results for the provided input image and then the precautions are provided for the diseased leaf.

REFERENCES

[1] Rothe, P.R. and Kshirsagar, R.V., "Identifying Cotton Leaf Diseases Using Pattern Recognition Techniques", International Conference on Pervasive Computing (ICPC), 2015.

[2] Aakanksha Rastogi, Ritika Arora and Shanu Sharma, “Detection and grading of leaf diseases using computer vision techniques and fuzzy logic,” 2nd International Conference on Signal Processing and Integration Networks (SPIN) 2015.

[3] Godliver Owomugisha, John A. Quinn, Ernest Mwebaze und James Lwasa, ``Automated Vision-Based Diagnosis of Banana Bacterial Welt Disease and Black Sigatoka Disease“, Proceedings of the First International Conference on Mobile ICT in Africa, 2014.

[4] uan Tian, Chunjiang Zhao, Shenglian Lu und Xinyu Guo, "SVM-based Multiple Classifier System for Recognition of Wheat Leaf Diseases", CDC'2010 Proceedings, 20.-22. November 2010.

[5] S. Yun, W. Xianfeng, Z. Shanwen und Z. Chuanlei (2015), "Pnn-based detection of plant diseases using leaf image characteristics and meteorological data," International Journal of Agricultural and Biological Engineering, vol. 8, No.4, p. 60.

[6] J. G. A. Barbedo (2013), "Digital Image Processing Techniques for Detection, Quantification and Classification of Plant Diseases," Springer Plus, vol. 2, No. 660, pp. 1-12.

[7] Caglayan, A., Guclu, O., and Can, AB. (September 2013)."Methods for Recognizing Plants Based on Shape and Color Features of Leaf Images" International Conference on Image Analysis and Processing (pp. 161-170). Heidelberg and Berlin:jumper.

[8] X. Zheng, Z. Wang, A. Islam, I. Chan and S.Li, 2014d. "Regression Forest for Direct Estimation of Cardiac Biventricular Volumes." MICCAI 2014, Medical Image Computing and Computer-Assisted Intervention. Accepted.

[9] Wang P, Chen K, Yao L, Hu B, Wu X, Zhang J, et al.

[10] Monica Jhuria, Ashwini Kumar, Rushikesh Borse “Image Processing for Smart Farming: Detection of Disease and Fruit Grading” Proceeding of the 2013 IEEE Second International Conference on Image Processing.

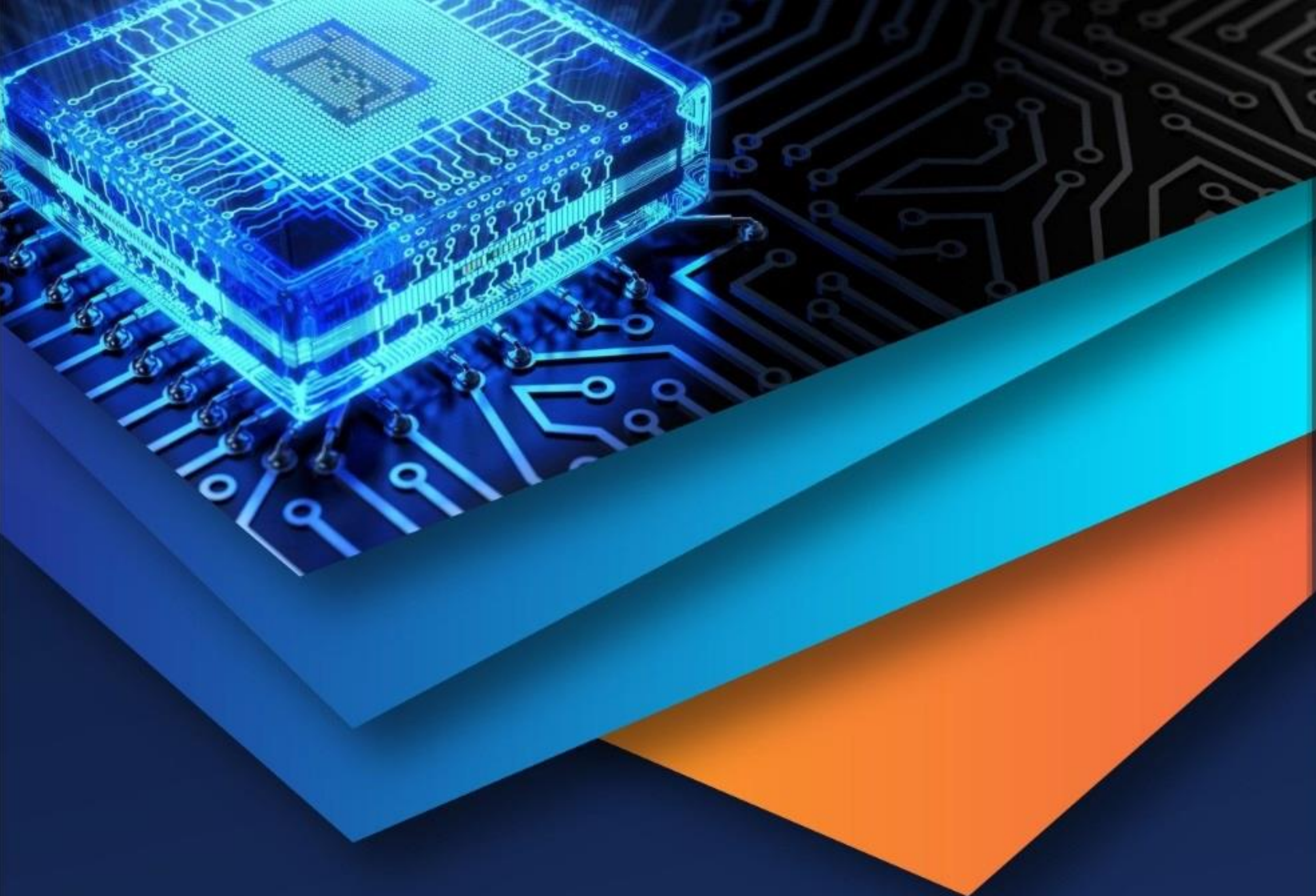
[11] Sudhir Rao Rupanagudi, Ranjani B.S., Prathik Nagaraj, Varsha G. Bhat “A Cost Effective Tomato Maturity Grading System using Image Processing for 974 2015 International Conference on Green Computing and Internet of Things (ICGCIoT) Farmers” International Conference on Contemporary Computing and Information, 2014.

[12] Dhaka, V. S., Meena, S. V., Rani, G., Sinwar, D., Kavita, K., Ijaz, M. F., & Woźniak, M. (2021). A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases. *Sensors*, *21*(14), 4749. https://doi.org/10.3390/s21144749 Cited by: 503

[13] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using Deep Learning for Image-Based Plant Disease Detection. *Frontiers in Plant Science*, *7*, 1419. https://doi.org/10.3389/fpls.2016.01419 Cited by: 6776.

[14] Shafay, M. (2024). Recent advances in plant disease detection: challenges and opportunities. *Plant Methods* / *PMC*. Cited by: 92

[15] Sheneamer, A. (2024). Early detection of plant leaf diseases using stacking hybrid learning. *PLOS ONE*, *19*(11), e0313607. https://doi.org/10.1371/journal.pone.0313607 Cited by: 14



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