TOMATO LEAF DETECTION AND REMEDY RECOMMENDATION SYSTEM USING MACHINE LEARNING AND IOT

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Abstract - *This project presents an innovative approach to tomato (biological name: Solanum lycopersicum) plant health monitoring, leveraging a synergy of image processing, IoT, and cloud technologies. The system centers around a Raspberry Pi equipped with a webcam and a DHT11 temperature sensor, enabling users to capture crucial leaf images and environmental data. Through secure transmission to a cloud-based infrastructure, the collected data undergoes comprehensive analysis. Initial image pre-processing enhances the quality of leaf images, followed by feature extraction and classification using a VGG19 deep learning model. The system adeptly identifies potential diseases affecting tomato plants, providing users with actionable insights. A unique feature of this project is its closed-loop functionality, as feedback, including disease classification and recommended pesticide options, is seamlessly relayed back to users via the Raspberry Pi. The cloud infrastructure, designed for scalability and reliability, ensures efficient data processing and model execution. By offering an accessible interface for farmers to monitor and address tomato plant health, this system contributes to improved crop management practices. The project's holistic integration of cutting-edge technologies is poised to empower agricultural stakeholders with timely, accurate, and actionable information, ultimately fostering sustainable farming practices and enhancing tomato crop yield.*

Key Words: **IoT, Cloud technologies, Raspberry Pi, DHT11 temperature sensor, Data analysis, Image pre-processing, Feature extraction, VGG19 deep learning model**

1.INTRODUCTION

In most African and Asian nations, agriculture has historically been the main source of wealth. The extensive commercialization of agriculture has had a profound effect on the environment. Identifying plant diseases is one of the most urgent problems related to agriculture. Early disease identification helps stop the illness from spreading to other plants, which could cause significant financial losses. Plant diseases can have a wide range of effects, from mild symptoms to the complete loss of plantations, which has a big effect on the agricultural economy.

This project addresses the pressing need for efficient and proactive monitoring of tomato plant health in agricultural settings. With the increasing challenges posed by plant diseases and the imperative to enhance crop yield, a comprehensive solution integrating cutting-edge technologies is proposed. The central components of the system include a Raspberry Pi equipped with a webcam and a DHT11 temperature sensor, providing a user-friendly platform for capturing vital leaf images and environmental data. Leveraging the Internet of Things (IoT), the collected information is securely transmitted to a cloud-based infrastructure, where a robust pipeline involving image processing and deep learning unfolds. The project's innovation lies in its utilization of a VGG19 deep learning model for disease classification, ensuring accurate and reliable identification of potential ailments affecting tomato plants. This integrated approach fosters a closed-loop system, as insights derived from the analysis, including disease categorization and recommended pesticide options, are promptly communicated back to users through the Raspberry Pi interface. By seamlessly merging IoT, image processing, and cloud computing, this project aims to empower farmers with timely, actionable information to make informed decisions about crop management. The overarching goal is to contribute to sustainable farming practices and optimize tomato crop yield in the face of evolving agricultural challenges.

2.PROBLEM STATEMENT

Given a dataset of tomato leaf images, the task is to develop a machine learning model that can accurately classify the images into different disease categories. The goal is to help farmers quickly identify and treat diseased tomato plants, thereby improving crop yield and reducing losses.

3.PROPOSED SYSTEM

The proposed system builds upon the foundation of the existing framework aiming to further enhance its capabilities and usability. It focuses on refining the image processing algorithms to improve disease detection accuracy, exploring additional IoT sensors for capturing more comprehensive environmental data, and optimizing the cloud infrastructure for scalability and efficiency this will incorporates a sophisticated approach to tomato leaf disease detection and remedy, leveraging image processing, IoT, and cloud computing. It utilizes a Raspberry Pi equipped with a webcam and a DHT11 temperature sensor to capture leaf images and environmental data, which are then securely transmitted to a cloud-based infrastructure. Through comprehensive analysis using a VGG19 deep learning model, potential diseases affecting tomato plants are accurately identified, and actionable insights, including disease classification and recommended pesticide options, are relayed back to users via the Raspberry Pi interface. This closed-loop system ensures timely and effective management of tomato plant health, contributing to sustainable farming practices and enhanced crop yield.

4.FLOW DIAGRAM

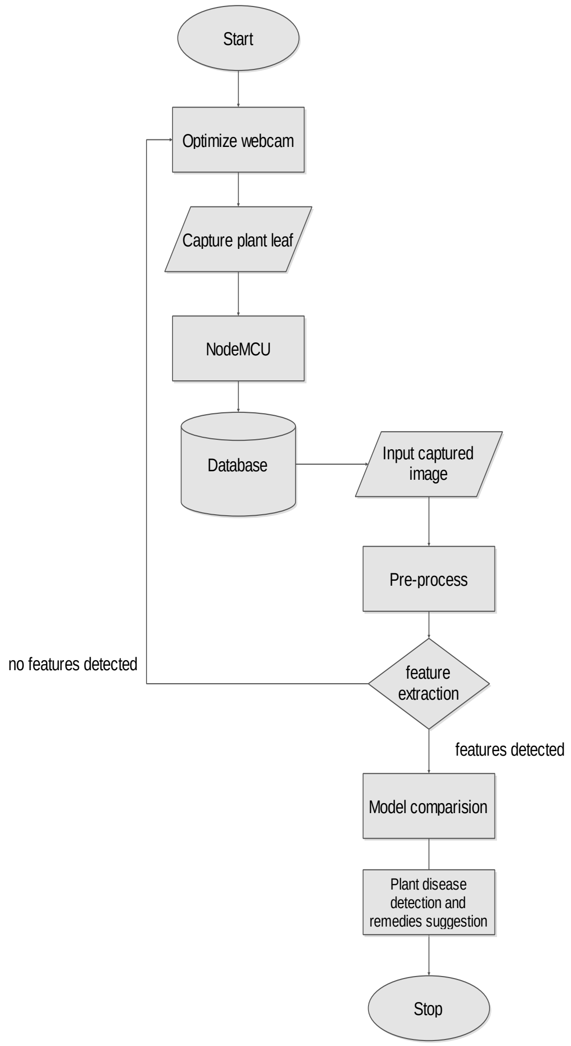

Fig -1: Flow chart of complete process

The system initiates with the activation trigger, leading to the webcam capturing an image of the plant leaf. This image data is seamlessly transmitted to the cloud through NodeMCU, establishing a crucial connection for further processing. In the cloud, a specialized VGG19 model processes the captured image to identify potential diseases affecting the plant. Upon disease identification, the system seamlessly suggests appropriate remedies based on a comprehensive database. The remedy suggestions aim to assist users in effectively addressing and mitigating the identified plant diseases. Users can provide feedback, creating a valuable loop for system improvement and enhancing accuracy over time. This automated plant health monitoring system integrates image capture, cloud computing, and machine learning to offer a comprehensive solution for plant disease identification and remedy suggestions. The feedback loop ensures continuous refinement, making the system adaptive and efficient in safeguarding plant health. The process concludes, providing users with actionable insights for maintaining the well-being of their plants.

5.RELATED WORK

K. Devi Priyanka approached a development of plant disease recognition model, based on leaf image classification, using deep networks. Novel way of training and the methodology used facilitate a quick and easy system implementation in practice. The developed model can recognize different types of plant diseases out of healthy leaves, with an ability to distinguish plant leaves from their surroundings. Beginning with acquiring photographs to build a database that is reviewed by agricultural professionals [1].

Laeeq Sana contributed the field by offering a practical solution for automating the detection of tomato leaf diseases, leading to enhanced disease management and more sustainable agricultural practices. The results underscore the potential of modern technology to revolutionize crop health monitoring and ensure food security [2].

Akshay Misal provided an overview of the use of deep learning in plant protection, specifically in the identification of crop leaf diseases. By applying deep learning to plant disease identification, it can provide more objective and efficient extraction of disease characteristics and improve research efficiency and technology transformation. our research aims to summarize recent advances in deep learning research related to crop leaf disease identification, highlighting current trends and challenges in this area, and serving as a useful resource for researchers studying plant pest detection. We are using CNN algorithm which provided 97% accuracy to detect disease [3].

Anmol Sinha discussed a number of methods for identifying and categorizing plant diseases using image processing, including the extraction of texture-based features, machine learning algorithms, convolutional neural networks, and deep learning-based methods. These methods produce accurate findings in the detection and classification of many plant leaf diseases. The proposed methods' accuracy varies depending on the disease type, dataset, and experimental design used. By increasing crop productivity and lowering the usage of dangerous pesticides, these methods have the potential to completely transform the agricultural sector. The issues with image quality, lighting, and the intricacy of plant disease symptoms, however, still need to be addressed through additional research [4].

Venkatesh Shankar presented a method to detect the plant disease using machine learning under which using CNN algorithm can be found. The main focus is to develop a disease detection system for finding the disease. Therefore under CNN algorithm this paper have basically used MobileNet Architecture. Few parameters have been considered inorder to find the result. This paper have considered 38 different leaves to find the disease. By capturing the image and by extracting the features of it we get the disease. In this papers results shows the better accuracy than the other papers [5].

Jayashree Pasalkar presented an efficient approach to identify healthy and diseased or infected leaves using image processing and machine learning techniques. Various diseases damage leaf chlorophyll and cause brown or black spots on the leaf surface. These can be detected using image preprocessing, image segmentation, feature extraction, and classification using machine learning algorithms. A convolutional neural network (CNN) improved the accuracy of detection [6].

H Shiva reddy introduced the concept of internet of things and discusses the role of IOT in agricultural disease and insect pest control and gives thought regarding estimation of diverse climatic parameters of plant. The sensors integrated helps in detecting the moisture and humidity in soil and atmosphere. These factors helps in identifying the climatic conditions where the plant grows and the diseases that can be attacked for the plant. In this work we develop a user-friendly IOT architecture to provide on-field disease detection and spraying of recommended pesticides [7].

Gautam Lambe et al proposed a framework is to achieve more consistent execution in the detection of infections. In the middle of several plant diseases that affect leaves, such as Late scourge, bacterial, and viral infections, it has been chosen to separate contaminated leaves from healthy leaves, which includes Late scourge, bacterial, and viral infections. Using a large dataset, the proposed approach is designed to successfully discriminate specified illnesses that affect tomato plant leaves. We proposed using CNN techniques to predict tomato leaf disease [8].

Sanmati RM et al proposed the technique of Convolutional Neural Network using Keras which uses the concept of hidden layers to classify the different diseases that affect the plants. Their model is success fully able to classify the diseases mentioned in the Potato, Pepper and Tomato subsets of the Plant Village dataset with an accuracy rate of 95.8% [9].

Naresh K. Trivedi proposed the Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network uses the The Convolutional Neural Network (CNN) is used to effectively define and classify tomato diseases. Google Colab is used to conduct the complete experiment with a dataset containing 3000 images of tomato leaves affected by nine different diseases and a healthy leaf [10].

6. DATASET DESCRIPTION

The dataset assembled for training purposes in this project comprises 1000 high-resolution images for each of the following tomato plant diseases: Depending on the disease, fungi, bacteria, mold, viruses or mites can be blamed for it. There are four types of diseases: fungi cause early blight, late blight, leaf spot, and target spots, bacteria cause bacterial spot, mold causes leaf mold, viruses cause tomato mosaic and tomato yellow leaf curl, and mites cause spider mite disease.

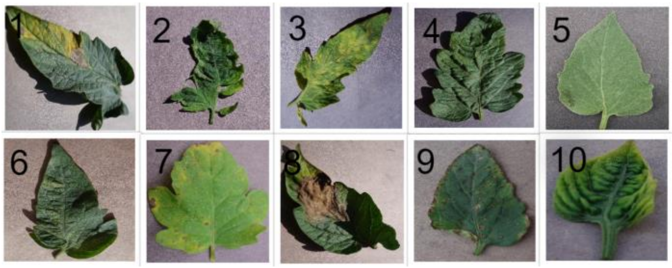

Fig -1: Dataset Images

Bacterial spots cause water-soaked patches on leaves, leading to necrotic areas and leaf loss, making fruit vulnerable to sunburn. Lesions can become translucent or oily, eventually drying up and falling out, leaving the plant with a blighted appearance.

Early blight first manifests as oval-shaped lesions with a yellow chlorotic area running the length of the lesion; infected leaves may also show concentric leaf lesions.

healthy tomato leaf appears vibrant green with no signs of discoloration or lesions. Its surface is smooth, firm, and free from any spots or blemishes.

Late blight, a fungal infection, affects all parts of the tomato plant, showing as water-soaked areas on leaves that turn brown rapidly. White fungal growth may appear on infected areas during wet weather.

Leaf mold fungus creates pale green-yellow spots on upper leaves with green-brown velvety growth below. Spots merge, turning brown, causing leaves to wither while staying attached.

Septoria leaf spot, a fungal disease, presents as small water-soaked or grayish-white spots on older tomato leaves. These spots develop gray centers and dark margins, often merging as the disease progresses.

Spider mites cause yellow stippling on leaves, often bronzing them and creating webbing. Infestation may be identified by tiny moving dots on webs or leaf undersides, leading to yellowing and leaf loss.

Target spot, a fungal infection, affects all parts of the plant, causing small water-soaked spots on leaves that enlarge into necrotic lesions with concentric circles. Fruits develop brown, slightly sunken flecks initially, later progressing to large, pitted lesions.

Tomato mosaic virus, a viral infection, causes dark green mosaic patterns on leaves, sometimes with yellow mottling. It can stunt growth, distort leaves, and create raised green areas, with necrotic streaks on petioles.

Tomato yellow leaf curl disease. The diseased leaves shrink in size, curl upward, resemble crumpled leaves, and have yellowed veins and leaf margins.

7. SYSTEM ARCHITECTURE

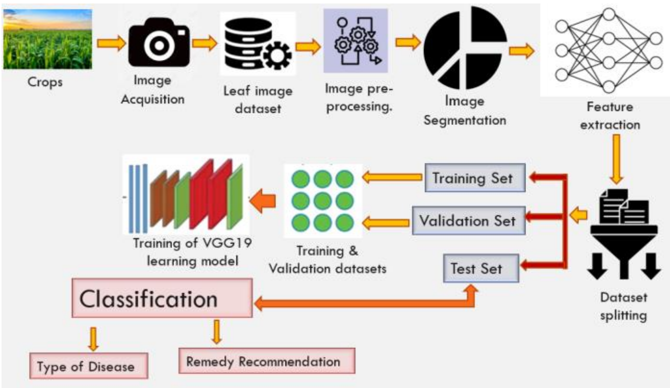

Fig -3: System Architecture Design

7.1. IMAGE ACQUISITION

The first step in plant disease detection using machine learning is to acquire images of plant leaves that are both healthy and diseased. Images can be captured using cameras, smart phones, or drones, and can be taken in a controlled environment, such as a greenhouse, or in the field. It is important to ensure that the images are of high quality, with good resolution and color accuracy, to ensure accurate disease detection.

7.2. DATASET PREPARTION

The Dataset collected from open source website “Kaggle”.

7.3. IMAGE PREPROCESSING

We load the dataset and preprocess the images to prepare them for training. This includes resizing the images to a consistent size and normalizing the pixel values. We also split the dataset into training and validation sets to evaluate the model's performance.

7.4. IMAGE SEGMENTATION

After preprocessing, the images are segmented to separate the plant leaves from the background. Image segmentation involves dividing the image into multiple regions, each of which contains pixels with similar properties.

7.5. FEATURE EXTRACTION

Once the plant leaves are segmented, the next step is to extract features from the image that can be used to train the machine learning model. These features might include color histograms, texture features, or shape descriptors.

7.6. DATA SPLITTING

The preprocessed images are labeled as healthy or diseased and used to create a dataset. The dataset is divided into training, validation, and testing sets.

7.7. TESTING AND VALIDATION

Fitting the model with the data and finding out the accuracy at each epoch to see how our model is learning. The trained model is then tested on a separate dataset of images to evaluate its accuracy in detecting plant diseases.

8. METHODOLOGY

The methodology for tomato leaf disease detection and remedy encompasses a systematic process involving image processing, IoT, and cloud computing. Users initiate the system by capturing leaf images through a webcam connected to a Raspberry Pi, simultaneously recording temperature data with a DHT11 sensor. This data is securely transmitted to a cloud server, where the central processing unit executes a series of steps. Upon arrival at the cloud, the input images undergo pre-processing, optimizing them for subsequent analysis. Relevant features are then extracted from the pre-processed images, and a VGG19 deep learning model is utilized to compare and classify these features, identifying the specific disease affecting the tomato plant. This phase ensures accurate and reliable disease detection. Subsequently, a database mapping disease to suitable pesticides is consulted, and the system suggests tailored remedies based on the identified disease.

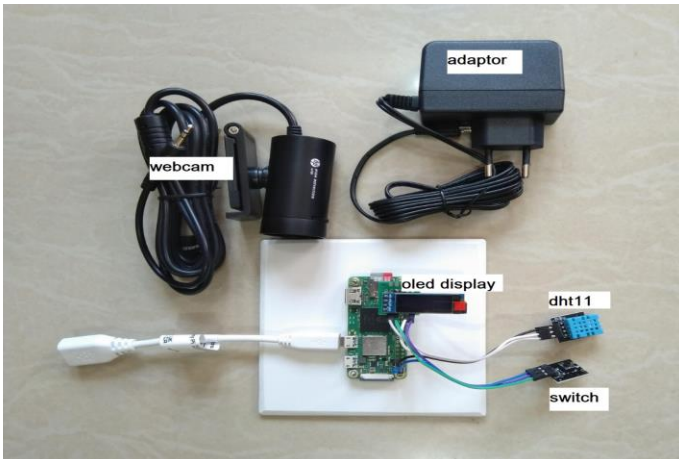

Fig -4: Hardware Device

8.1. MODEL BUILDING

We use VGG19 deep-learning neural network with 19 Connection layers, including 16 convolution layers and 3 fully connected layers to learn features from the images and classify them into disease categories.

8.2. TRAINING THE MODEL

We train the model using the training dataset, adjusting the model's weights based on the difference between predicted and actual disease categories During training, we monitor the model's performance on the validation set to avoid overfitting.

8.3. MODEL EVALUATION

After training, we evaluate the model's performance on the validation set to assess its ability to generalize to new, unseen data. we use metrics such as accuracy to measure the model's performance.

9. DISCUSSION

The experiment involved training and evaluating the performance of the integrated tomato leaf disease detection and remedy system. The VGG19 model was trained on the curated dataset containing 1000 images for each of the targeted diseases. The training process utilized a balanced dataset with careful splits for training, validation, and testing. During experimentation, the system processed real-world data captured by users using a webcam and DHT11 sensor on the Raspberry Pi. The cloud infrastructure executed image pre-processing, feature extraction, and VGG19 model comparison for disease identification. Pesticide suggestions based on disease classification were then relayed to users via the Raspberry Pi interface.

Discussion revolved around the system's accuracy, efficiency, and practical usability. Key points included the model's ability to accurately identify various diseases, the impact of dataset diversity on generalization, and the effectiveness of the closed-loop system for real-time feedback to users. Considerations were made for system scalability and potential improvements, fostering an insightful discourse on the system's overall effectiveness in contributing to timely and accurate tomato plant health management.

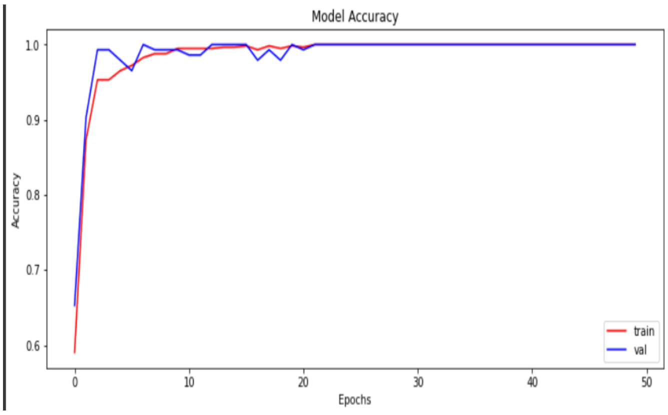

Chart -1: Showing the Model Accuracy

10. CONCLUSION

In conclusion, the integrated system for tomato leaf disease detection and remedy, utilizing image processing, IoT. and cloud computing, presents a promising solution for modern agriculture. The robust methodology, incorporating a VGG19 deep learning model trained on a diverse dataset, demonstrated accurate disease identification. The closed-loop system, from data capture to real-time feedback via the Raspberry Pi interface, enhances its practicality for farmers. The experiment showcased the system's proficiency in processing real-world data, leveraging cloud resources for efficient image analysis and classification. The discussion highlighted the importance of dataset diversity, model generalization, and the effectiveness of the proposed closed-loop architecture. The system's ability to suggest targeted pesticide remedies based on disease classification signifies a valuable tool for crop management. While achieving commendable results, continuous updates to the dataset and model fine-tuning can further optimize its performance. In essence, this project offers a comprehensive approach to address tomato plant health issues, empowering farmers with timely insights for effective disease management. The successful integration of emerging technologies reflects a positive stride towards sustainable and efficient agricultural practices. As technology evolves, this system provides a foundation for future enhancements in crop health monitoring and contributes to the ongoing advancement of precision agriculture.

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REFERENCES

[1] Zaagueri, T.; Mnari-Hattab, M.; Moussaoui, N.; Accotto, G.P.; Noris, E.; Marian, D.; Vaira, A.M. Chickpea Chlorotic Dwarf Virus Infecting Tomato Crop in Tunisia. Eur. J. Plant Pathol. **2019**, 154, 1159–1164. [Google Scholar] [CrossRef]

[2] Bai, Y.; Im, P.; In, L.; Ut, D.O. Domestication and Breeding of Tomatoes: What Have We Gained and What Can We Gain in the Future? Ann. Bot. **2007**, 100, 1085–1094. [Google Scholar] [CrossRef]

[3] Blanca, J.; Montero-Pau, J.; Sauvage, C.; Bauchet, G.; Illa, E.; Díez, M.J.; Francis, D.; Causse, M.; van der Knaap, E.; Cañizares, J. Genomic Variation in Tomato, from Wild Ancestors to Contemporary Breeding Accessions. BMC Genom. **2015**, 16, 257. [Google Scholar] [CrossRef] [Green Version]

[4] Sladojevic, S.; Arsenovic, M.; Anderla, A.; Culibrk, D.; Stefanovic, D. Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Comput. Intell. Neurosci. **2016**, 2016, 1–11. [Google Scholar] [CrossRef] [Green Version]

[5] Panno, S.; Davino, S.; Caruso, A.G.; Bertacca, S.; Crnogorac, A.; Mandić, A.; Noris, E.; Matić, S. A Review of the Most Common and Economically Important Diseases That Undermine the Cultivation of Tomato Crop in the Mediterranean Basin. Agronomy **2021**, 11, 2188. [Google Scholar] [CrossRef]

[6] Gilardi, G.; Matic, S.; Guarnaccia, V.; Garibaldi, A.; Gullino, M.L. First Report of Fusarium Clavum Causing Leaf Spot and Fruit Rot on Tomato in Italy. Plant Dis. **2021**, 105, 2250. [Google Scholar] [CrossRef]

[7] Durmus, H.; Gunes, E.O.; Kirci, M. Disease Detection on the Leaves of the Tomato Plants by Using Deep Learning. In Proceedings of the 2017 6th International Conference on Agro-Geoinformatics, Fairfax, VA, USA, 7–10 August 2017; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5. [Google Scholar] [CrossRef]

[8] Hu, J.; Shen, L.; Sun, G. Squeeze-and-Excitation Networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 7132–7141. [Google Scholar] [CrossRef] [Green Version]

[9] Rangarajan, A.K.; Purushothaman, R.; Ramesh, A. Tomato Crop Disease Classification Using Pre-Trained Deep Learning Algorithm. Procedia Comput. Sci. **2018**, 133, 1040–1047. [Google Scholar] [CrossRef]

[10] Karthik, R.; Hariharan, M.; Anand, S.; Mathikshara, P.; Johnson, A.; Menaka, R. Attention Embedded Residual CNN for Disease Detection in Tomato Leaves. Appl. Soft Comput. **2020**, 86, 105933. [Google Scholar] [CrossRef]