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AUTOMATED HYDROPONICS WITH LEAF DISEASE DETECTION

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Abstract— The decline in the quantity and quality of farming output is primarily caused by plant diseases, presenting significant challenges for farmers. Identifying and managing plant illnesses in a timely manner is crucial to prevent further losses. To address this issue, an automatic hydroponic system with leaf disease monitoring has been developed, which also monitors real- time physical data such as pH and electrical conductivity. The use of this system has resulted in increased output while effectively controlling the hydroponic environment. The goal is to further increase output by implementing a plant-leaf disease detection system using image analysis. MobileNetV2 has been developed which is deep learning to identify tomato leaf diseases in real-time from a webcam stream. This approach is more effective than traditional methods, and it is also affordable and requires less space for irrigation. Early detection of leaf diseases promotes improved plant development
Keywords — automatic hydroponic system, plant-leaf disease detection, plant development, electrical conductivity

I. INTRODUCTION

An alternative to using soil for plant cultivation, hydroponics includes growing plants in nutrient-rich water solutions. Due to its many advantages over conventional soil-based farming, it is becoming more and more popular on a global scale. With hydroponics, gardeners may precisely regulate factors that affect plant development, such as temperature, light, and fertilizer levels. As a consequence, plants grow more quickly, produce more, and use less water. Hydroponics is more water-efficient than conventional soil-based farming, using up to 90% less water, and it may be used in a number of contexts, from small-scale indoor systems to large-scale commercial operations. To improve the development and productivity of tomato plants, automated hydroponics uses pH and electric conductivity sensors to regulate the nutrient delivery through water while simultaneously verifying the detection of leaf disease. Modern deep learning-based technology is used in the approach suggested in this study to automatically identify leaf diseases in tomato plants. The system divides leaf photos into 10 distinct classes of leaf illnesses using the MobileNetV2 architecture. The classifications we are detecting are spidermite, bacterial spot, early blight, leaf mold and yellow leaf curl virus.

The proposed system gives the user a real-time prognosis of the disease along with a likelihood score after receiving input from a camera. With precise and reliable findings, even in the early stages of disease development, this method does away with the need for human inspection, enabling quick action to stop the spread of disease and reduce crop losses. Additionally, it is simple to use and doesn't take a lot of skill to utilize, making it available to farmers and agricultural specialists everywhere. The suggested method, which offers a precise, effective, and user-friendly tool for farmers and agricultural specialists, illustrates the promise of computer vision and deep learning for the automated diagnosis of leaf diseases in tomato plants. Manual examination is a key component of traditional disease detection techniques, although it may be laborious and error-prone. The suggested system achieves excellent accuracy and real-time performance through the use of deep learning algorithms and transfer learning, making it a potential option for automated tomato leaf disease diagnosis in the field.

II. CONVOLUTIONAL NEURAL NETWORK

CNN is neural network architecture utilized extensively for image recognition, segmentation, and object detection tasks. It consists of different layers, they are fully connected, activation and convolutional layer. In this the layer which is responsible for feature extraction from an input image. It is given by a set of trainable filters and is called convolutional layer. In the activation layer, there is a non-linear activation function, the output of previous layer is passed through the non-linear function, with the Rectified Linear Unit (ReLU) function being a common choice. The Pooling layer down samples the output of the previous layer by selecting the maximum or minimum of non-overlapping regions. At last, the fully connected layer will take the output from the previous layer then applies a transformation and softmax function to obtain the class score. The architecture of the CNN, including the number and size of filters per layer, can be modified to suit the task at hand. Popular CNN designs include MobileNet, ResNet, Inception, VGG, and AlexNet. Figure 1 depicts CNN Architecture.They are frequently employed in fields including facial recognition, medicine, and the auto industry and have proven to be state-of-the-art performance on several tasks involving computer vision.

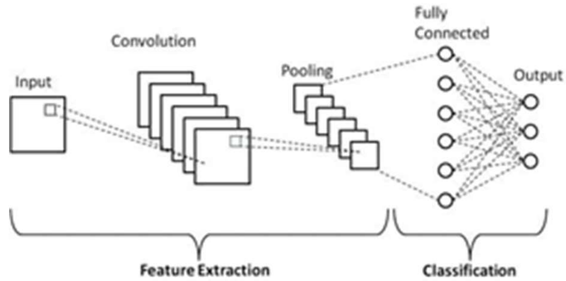

Fig. 1. CNN Architecture

III. PROPOSED SYSTEM

The proposed solution for detecting leaf diseases in tomato plants is a deep learning-based system. It uses a pre- trained MobileNetV2 model, developed from a large collection of photos, to identify different types of illnesses in tomato plants. The system records live video of the tomato plant leaves and then processes each frame with the trained model, using the MobileNetV2 preprocessor for preprocessing after downsizing the frames to 224x224. The pre-trained model provides a forecast, and a bounding box for the identified illness, along with its associated probability, is drawn using the anticipated class. A color-coded bounding box is used to show the type of illness detected, which can help farmers choose the right procedures for treating diseased plants. To reduce labor costs for farmers and ensure prompt treatment, the technology can be integrated with a robotic arm for autonomous spraying of the sick plants with necessary chemicals. This method can detect numerous ailments and accurately cure them in real-time. Additionally, the proposed system combines a leaf disease detection module with two sensors that monitor the pH and electrical conductivity levels of the nutrient solution, providing a complete hydroponic farming solution.

The microcontroller unit processes data fed from the sensors and a camera module that takes photos of the plant leaves. A deep learning model built on the MobileNetV2 architecture analyzes the images to detect any signs of sickness or infection. If the study identifies any illness symptoms, the system immediately notifies the farmer, allowing them to take necessary precautions. Remedial actions can be taken by modifying the nutrient solution's pH or electrical conductivity levels or by providing necessary therapy to diseased plants. The suggested system offers real- time monitoring of pH, electrical conductivity, and leaf diseases, enhancing the output and quality of hydroponic farming by identifying potential issues before they cause significant damage.

IV. BLOCK DIAGRAM

We are using the Python OpenCV package to capture frames of leaves from the webcam. First, we need to initialize a video capture object and set the default camera (i.e., webcam) as the video source using the cv2.VideoCapture(0) function. Inside a while loop, we can read the subsequent frame from the webcam using the cap.read() function and save the received image in the frame variable. o ensure that the frame size meets the input size specifications of the pre-trained model, we can scale the frame using the cv2.resize() function to 224x224 pixels. Next, we preprocess the enlarged frame using the preprocess input() method of the MobileNetV2 model in TensorFlow. This involves removing the mean RGB values and scaling the pixel values to be between -1 and 1. Finally, we apply the pre-trained model to the pre-processed picture to estimate the type of disease affecting the leaf. The TensorFlow Keras API's MobileNetV2 model includes the preprocess input() method, which is used as the preprocessing function. This method preprocesses the input image by scaling the pixel values to be within the range of -1 to 1 and subtracting the mean RGB values of the ImageNet dataset. This preprocessing step is essential in many deep learning models, as it ensures that the input data falls within the expected range and initializes the model's weights with suitable values. We use the preprocess input() method to make predictions about the type of disease affecting the tomato leaf. This method is applied to the enlarged frame obtained from the camera using OpenCV. For feature extraction, we use the MobileNetV2 pre-trained Keras model. For mobile and embedded vision applications, the MobileNetV2 model is an architecture called CNN. The image which is given is processed for the MobileNetV2 model using the preprocess input() function. The pre-trained MobileNetV2 model is then used to run the pre-processed image through. To get the anticipated probabilities for each class in the model's output, use the predict() method.

The massive image dataset ImageNet, which comprises millions of labelled photos, served as the pre-training data for the MobileNetV2 model. The model has mastered the art of extracting from photos high-level traits that may be used to categorize various kinds of things, such as edges, textures, and forms. The MobileNetV2 model is utilized as a feature extractor to pull out high-level data from the input image

frame. The fully connected layers of the model are then given these characteristics to produce predictions about the type of disease afflicting the tomato leaf. A convolutional neural network architecture created for mobile and embedded vision applications, the MobileNetV2 model, is what we employ. The ImageNet dataset, which comprises millions of labelled photos, was used to train the model. By training on this dataset, the model has learned to extract high-level features from images that can be used for classification tasks. Using the Keras API in TensorFlow, the pre-trained MobileNetV2 model is loaded and used as a feature extractor for input images. The model's fully linked layers are then run through the retrieved data to generate predictions about the kind of illness afflicting the tomato leaf. Specifically, the code captures frames from a webcam and resizes them to 224x224 pixels, which is the expected input size for the MobileNetV2 model. The preprocessed frames are then fed into the model, and the model's predictions are used to draw bounding boxes and labels around any detected tomato leaves with disease. Overall, we are using a CNN-based approach for classifying tomato leaves into one of several disease categories, and is leveraging transfer learning by using a pre-trained MobileNetV2 model that has already learned to extract useful features from images. Figure 2 shows the block diagram of leaf disease detection .By CNN classification we can identify the leaf is healthy or not. Then the disease is classified.

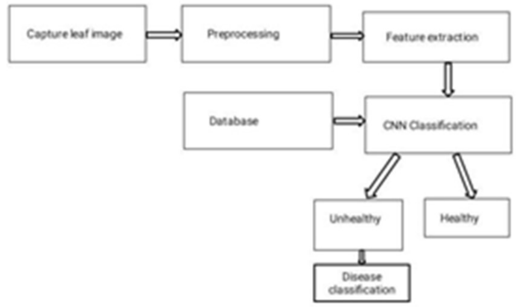

Fig. 2. Block Diagram of Leaf Disease Detection

Hydroponics farming is implemented and here EC sensor and pH sensor is integrated. In hydroponics, pH sensors are essential because they aid to maintain the proper pH level for plant growth. In hydroponics, plants are grown in a soilless environment with nutrient solutions that are directly absorbed by the roots of the plants. To keep the nutrient solution's pH level within the ideal range for plant growth, the pH level must be carefully checked and changed. The pH level impacts the nutrients that are available in the nutrition solution, and even little departures from the ideal pH range can result in toxicities or nutrient deficiencies, which can impair plant growth or even cause plant death. A pH sensor allows for real-time monitoring of the pH level, enabling growers to make timely adjustments to keep the pH range ideal for plant growth. This ensures that the plants receive the proper balance of nutrients, which is crucial for healthy growth and high yields. In summary, using a pH sensor to monitor and adjust the pH level of the nutrient solution is vital in hydroponics to maintain the optimal pH range for plant growth. This helps to ensure that the plants receive the right balance of nutrients, promoting healthy growth and successful harvests.

An EC (electrical conductivity) sensor is an essential tool that measures the concentration of dissolved salts or total ion concentration in the nutrient solution. Maintaining a specific balance of nutrients in the nutrient solution is critical for optimal plant growth, and the EC sensor plays a vital role in achieving this. By measuring the concentration of dissolved salts, the EC sensor provides information about the nutrient strength of the solution, allowing growers to adjust the nutrient concentration as needed to meet the plant's requirements. Imbalances in nutrient concentration can have negative effects on plant growth and yield, making it crucial to maintain the optimal nutrient concentration. EC sensor can also help growers identify potential problems, such as clogging or salt buildup, and take corrective actions promptly. Figure 3 shows the block diagram of hydroponics .Blynk cloud is used in hydroponics to link to microcontrollers that manage the system's different components, including pumps, fans, and sensors. We can use Blynk cloud to remotely monitor and manage their systems with a smartphone application that offers real-time data and notifications about the status of the system. Custom alerts and notifications, such as alerts when the pH or EC of the nutrient solution is out of range or when the water level is low, can be set up using the Blynk application. Finally, user get an alarm on the measurement.

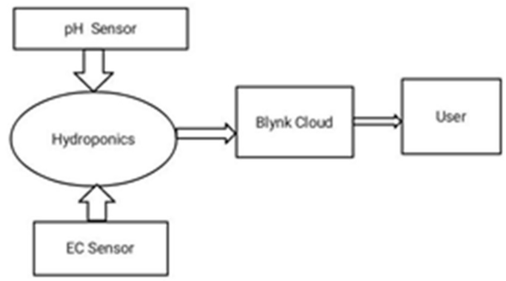

Fig. 3. Block Diagram of Hydroponics

V. WORKING PRINCIPLE

To start, we import the necessary libraries for our program, including OpenCV, NumPy, and TensorFlow. We then load our pre-trained deep learning model, which is based on the MobileNetV2 architecture, using the load_model() method from the TensorFlow Keras library. Next, we define the class names and colors for bounding boxes, which will be used to predict and display the classes. We then open the default camera using the VideoCapture() method and begin capturing frames. Each frame is captured using the read() method and then resized and preprocessed using the resize() and preprocess_input() methods, respectively. The preprocessed frame is then passed through the pre-trained model to make a prediction. We retrieve the predicted class and its corresponding probability using the argmax() and indexing methods. After obtaining the predicted class and probability, we retrieve the color associated with the predicted class from the list of colors defined earlier. We then obtain the predicted class's bounding box from the output of the model and draw the bounding box on the captured frame using the rectangle() method.

Using the putText() method, we display the predicted class and its corresponding probability on the captured frame. We then use the imshow() method to display the final output frame, which includes the predicted class, probability, and bounding box. The program stops when the user presses the 'q' key. To ensure proper termination, we release the camera using the release() method and close all windows using the destroy AllWindows() method. In general, the program takes pictures with the default camera, uses a trained deep learning model to predict outcomes, and shows the results. Real-time predictions of bounding box, class, and probability for the collected frame. The program ends and releases the camera after the user is done.

A deep learning model built on the MobileNetV2 architecture is used by the leaf disease detection system. The model's goal is to correctly identify the type of illness present in a given leaf image by examining visual markers of damage such as lesions or discoloration. The model was trained on a dataset comprising photographs of both healthy and diseased leaves. The model is combined with pre-processing methods like resizing and normalization to detect these properties, and it receives data from a live webcam video feed. Each video frame is pre-processed and sent through the model, which generates a probability distribution over different classes of leaf illnesses. The resulting output includes a bounding box around the affected portion of the leaf, which is labeled with the type of illness and its likelihood. This approach has several advantages over traditional methods of leaf disease identification, such as physical examination or chemical treatments. It is faster, more accurate, and can be used in real- time. Additionally, it is non-invasive and does not require physical alteration of the plants or the use of harmful chemicals, making it a safer and more environmentally friendly option. Hydroponic gardening is a method of plant cultivation that involves growing plants in nutrient-rich water solutions instead of soil. The underlying principle of hydroponics is that plants obtain nutrients from water in the soil, rather than the soil itself. With this method, the plant's environment including its temperature, humidity, and nutritional levels can be precisely controlled.

Plants are often grown in pots filled with inert media like perlite, rockwool, or coco coir, and a properly balanced fertilizer solution is given to meet their individual needs. To ensure optimal plant growth, the solution is often circulated through the growing media and supplemented with additional oxygen. Hydroponic systems can be open or closed; in open systems, the fertilizer solution is periodically replenished as the plants consume the nutrients, while in closed systems, the solution is recycled continuously throughout the system. Compared to traditional soil-based growing methods, hydroponic systems offer greater control over the growth environment and more efficient use of resources like water and fertilizer They are also versatile and sustainable, making them a viable option for growing plants in a variety of settings, including urban areas and indoors.

VI. RESULT AND ANALYSIS

The tomato plant's leaf disease has been found by the suggested system. Several illnesses, like Bacterial spot, Early blight, Late blight, Leaf Mold, Yellow Leaf Curl Virus, Spider Mites and Septoria Leaf Spot.Based on photographs of healthy and diseased tomato leaves, the suggested system was trained to categorize tomato leaves into these ten classifications. The model learns to identify patterns and features in the images that distinguish between healthy and diseased leaves for each class. During the prediction stage, the model takes a new image of a tomato leaf and predicts its most likely class based on the learned patterns and features. They are detected using MobileNetV2. It is a suitable architecture for leaf disease detection due to its efficiency and accuracy. Thereby the farmers can have high yield and better productivity by using less soil.

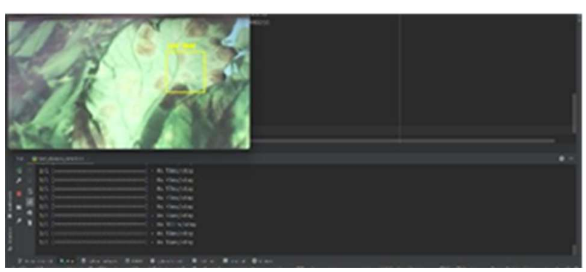

Fig. 4. Leaf Mold

The Figure 4 depict the disease called leaf mold. Leaf mold is a common fungal disease that affects tomato plants. It is caused by the pathogen known as Fulvia fulva (previously called Cladosporium fulvum). Leaf mold primarily affects the foliage of tomato plants and can lead to significant damage if not managed properly.

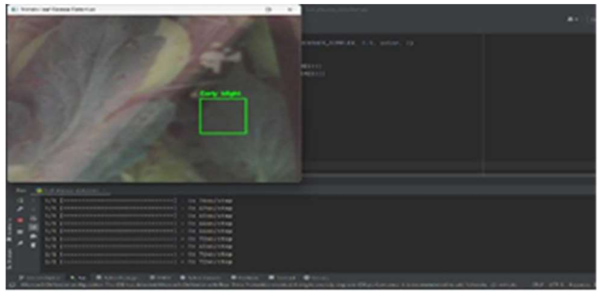

Fig. 5. Early Blight

The Figure 5 shows the disease named early blight. Early blight is a common fungal disease that affects tomato plants. It is caused by the fungus Alternaria solani and can lead to significant damage if not properly managed. Early blight typically affects the leaves, stems, and fruit of tomato plants.

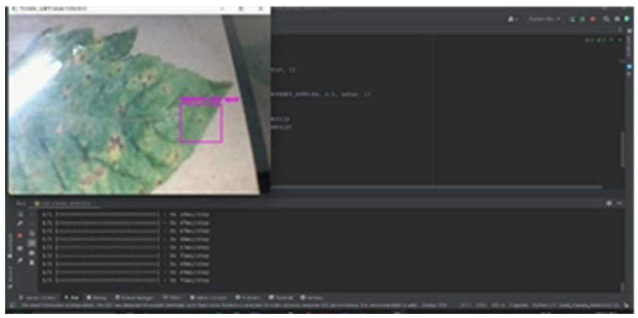

Fig. 6. Septoria Leaf Spot

The Figure 6 shows Septoria Leaf Spot. It also known as septoria leaf blight, is a common foliar disease that affects tomato plants. It is caused by the fungus Septoria lycopersici and can cause significant damage if not managed properly.

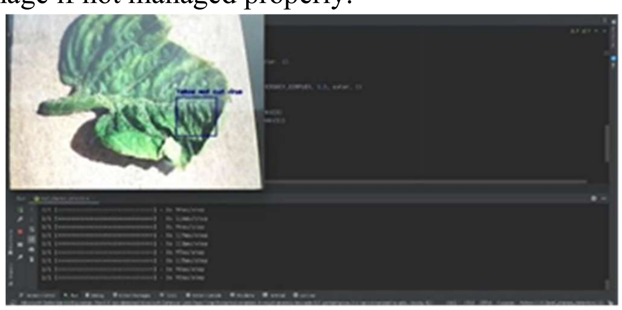

Fig. 7. Yellow Leaf Curl Virus

The Figure 7 shows Yellow Leaf Curl Virus on the tomato plant. It is a devastating viral disease that affects tomato plants and belongs to the Begomovirus genus. It is transmitted by the whitefly Bemisia tabaci and can cause significant yield losses if not managed effectively.

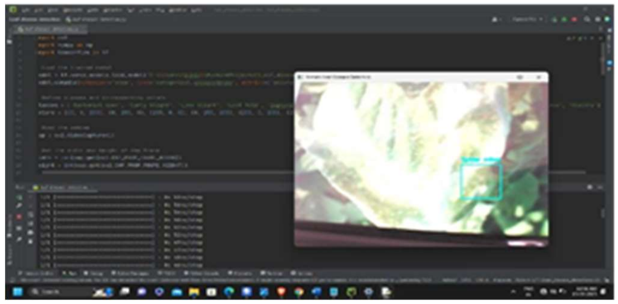

Fig. 8. Spider Mites

We are detecting the spider mite to make more benefit for the farmers and for better life for leaf, spider mite can make direct damage to the plant. Figure 8 shows spider mite on tomato plant.We are also identifying other diseases which gets spread in the leaf and cause reduction in the health of a leaf. The detection of spider bites on leaves plays a vital role in agriculture as it helps farmers and agricultural experts to identify the presence of spider mites on their crops. Spider mites are tiny arachnids that feed on plant sap, leading to a decrease in crop output and damaging the leaves. Moreover, they can also transmit viruses and diseases, posing a threat to the overall health of the plant. By detecting spider bites early on, farmers can take necessary steps to control the infestation and prevent further damage. This can involve using pesticides or natural predators to eliminate the mites and adjusting the environmental conditions, such as temperature and humidity, to make them unfavorable for the growth of spider mites. Identifying spider bites is a crucial aspect of managing plant health and can lead to the production of healthy crops with high yields.

Fig. 9. Hydroponics Setup

We implemented a hydroponics system with leaf disease detection .The figure 9 shows the hydroponics setup.The system has a 90mm PVC pipe with a 50mm hole. We put the 50mm hole using drill chuck. We have four motors. The first two motors control the pH in the reservoir. When the pH drops below 6.0, the pH up motor turns on to add pH up solution to the reservoir. When the pH goes above 7.5, the pH down motor turns on to add pH down solution. The third motor turns on when the EC (electrical conductivity) value is 1.2, and it adds NPK solution to the reservoir. The fourth motor turns on when the EC value is 1.4, and it adds nutrient solution to the reservoir. In Traditional Farming the accuracy relies on visual observation and farmer expertise, which may result in moderate to low accuracy in disease detection whereas in hydroponics, with advanced technologies such as machine learning algorithms and computer vision, achieves higher accuracy in disease detection. Time of Detection in traditional farming is relatively slow as it depends on human observation and may lead to delayed detection of diseases where as in hydroponics enables faster detection of diseases, thanks to automated systems and real-time or near real-time monitoring. Detection speed due to manual observation, the speed of disease detection is delayed in traditional farming where as in hydroponics with automated systems and advanced technology, hydroponics enables real-time or near real-time disease detection. In traditional farming methods are prone to human error in disease identification, as it relies on visual recognition and farmer expertise but in hydroponics reduces the risk of human error in disease identification, as it relies on advanced technologies rather than human visual recognition.

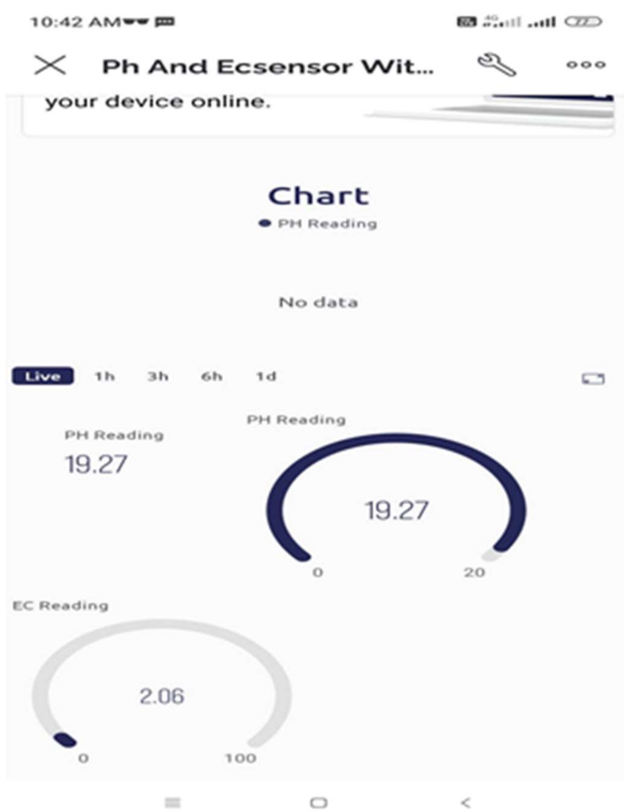

Fig. 10. Blynk App View

The Figure 10 shows blynk app view.The pH and EC values are monitored through a mobile app (Blynk) on a mobile device. The pH and EC sensors using are from a company called "Groove." We done hydroponics coding is done using the Arduino IDE. For leaf disease detection, we are using PyCharm as the software development environment. With a normal webcam (iBall) we are using as the camera for the leaf disease detection. The dataset for leaf disease detection was obtained from Kaggle. The dataset are trained using Google Teachable Machine.

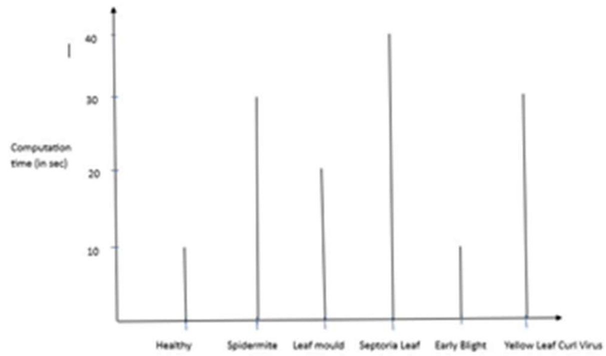

Fig. 11. Computational Analysis of the Proposed System

The computational analysis of the proposed system is depicted in Fig 11.Computational analysis offers early detection, accuracy, efficiency, scalability, and real-time monitoring in hydroponics with leaf disease detection. These benefits empower growers to effectively manage diseases, enhance plant health, and improve overall productivity in hydroponic systems. By leveraging computational analysis techniques, growers can optimize their cultivation practices and contribute to sustainable agriculture.

VII. CONCLUSION

In conclusion, the suggested system for leaf disease identification has demonstrated good results in precisely detecting the type of disease affecting tomato leaves using a deep learning model based on the MobileNetV2 architecture. The model was able to reach a high degree of accuracy in a short period of time by utilizing transfer learning strategies and pre-trained weights. In addition, by integrating the pH sensor and electrical conductivity sensor, our proposed hydroponic system can effectively monitor the pH level and nutrient concentration in the water, ensuring that the plants receive the required nutrients to grow and develop optimally. Developed an automatic system to diagnose the disease of tomato plant. Automated hydroponics will be also implemented. Helps to reduce soil as well as space for cultivation. pH and EC sensors are used to monitor the solution for efficient growth of plant which help in better yield of tomato. Help farmers to save crops in early stage. Manual work is reduced and large scale production of tomatoes can be achieved. The integration of the leaf disease detection model allows for early identification and intervention of potential diseases, preventing extensive damage to the crops and ultimately improving yield. Healthy leaf and Early blight takes 10seconds for computation, Spider Mite and yellow leaf curl virus takes 30 seconds and Leaf mold takes 20 seconds Septoria leaf took 40seconds.

Overall, the system that is suggested can be a useful tool for farmers and agricultural researchers, enabling them to more effectively and efficiently monitor the health of their crops and ultimately contributing to profitable and sustainable agriculture. More investigation can be done to increase the model's accuracy in detecting leaf diseases and to look into the possibility of adding other sensors and technologies to the system.

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