ISSN 2277-2685
IJESR/June-2024/ Vol-14/Issue-2s/129—139
Ayesha Sultana *et. al.,* / International Journal of Engineering & Science Research

PLANT DISEASE DETECTION AND GROWTH ANALYSIS THROUGH MACHINE LEARNING AND IOT

[1] Ayesha Sultana, [2] Shaheen Fatima, [3] Md Safdar Hussain Khan, [4] Mohammed Abdul Rahman,

[5]Mohammad Yaser

[1, 2] Assistant Professor, [3, 4, 5] Student

Department Of ECE,

ISL ENGINEERING COLLEGE

ABSTRACT: - Smart agriculture is undergoing a transformative evolution through the integration of machine learning algorithms for the early identification of plant diseases. High-resolution images, facilitated by Internet of Things (IoT) devices, serve as the primary data source, meticulously analyzed by sophisticated ML models. This streamlined process allows for swift intervention, averting potential crop devastation. Complementing this imagery analysis, real-time environmental and soil data are continuously collected, offering valuable insights into the most favorable conditions for crop growth. Accessible via web or mobile applications, farmers benefit from instant access to this wealth of information, empowering them to make informed decisions and proactively mitigate risks. By leveraging this advanced system, the agricultural sector aims to enhance food production while simultaneously minimizing water and chemical usage, ushering in a more sustainable and efficient era in farming practices.

Index Terms – Machine Learning, Internet of Things (IoT), Node MCU, Plant Disease, Sensors.

I. INTRODUCTION: -

Climate change and urbanization are two of the leading causes of arable land reduction. Burrell et al [1]. Food production has a massive impact on the climate. It contributes to one-fourth of the global amount of greenhouse gas emission [2]. presented the application of weather station to monitor the environment surrounding the crops to perform weather forecasts, whereas Nakayama et al [3]. In India about 70% of the populace relies on agriculture. Identification of the plant diseases is important in order to prevent the losses within the yield. It's terribly troublesome to observe the plant diseases manually. It needs tremendous quantity of labor, expertise within the plant diseases, and conjointly need the excessive time interval. Hence, image processing and machine learning models can be employed for the detection of plant diseases. In this project, we have described the technique for the detection of plant diseases with the help of their leaf's pictures. Image processing is a branch of signal processing which can extract the image properties or useful information from the image. Machine learning is a subpart of artificial intelligence which works automatically or give instructions to do a particular task. The main aim of machine learning is to understand the training data and fit that training data into models that should be useful to the people. So it can assist in good decisions making and predicting the correct output using the large amount of training data. The color of leaves, amount of damage to leaves, area of the leaf, texture parameters are used for classification. In this project we have analyzed different image parameters or features to identifying different plant leaves diseases to achieve the best accuracy. Previously plant disease detection is done by visual inspection of the leaves or some chemical processes by experts. For doing so, a large team of experts as well as continuous observation of plant is needed, which costs high when we do with large farms. In such conditions, the recommended system proves to be helpful in monitoring large fields of crops. Automatic detection of the diseases by simply seeing the symptoms on the plant leaves makes it easier as well as cheaper. The proposed solution for plant disease detection is computationally less expensive and requires less time for prediction than other deep learning-based approaches since it uses statistical machine learning and image processing algorithm.

II. LITERATURE SURVEY: -

In 2015, S. Khirade et Al. tackled the problem of plant disease detection using digital image processing techniques and back propagation neural network (BPNN) [1]. Authors have elaborated different techniques for the detection of plant disease using the images of leaves. They have implemented Otsu’s thresholding followed by boundary detection and spot detection algorithm to segment the infected part in leaf. After that they have extracted the featuressuch as color, texture, morphology, edges etc. for classification of plant disease. BPNN is used for classification i.e. to detect the plant disease. Shiroop Madiwalar and Medha Wyawahare analyzed different image processing approaches for plant disease detection in their research [2]. Authors analyzed the color and texture features for the detection of plant disease. They have experimented their algorithms on the dataset of 110 RGB images. The features extracted for classification were mean and standard deviation of RGB and YCbCr channels, grey level cooccurrence matrix (GLCM) features, the mean and standard deviation of the image convolved with Gabor filter. Support vector machine classifier was used for classification. Authors concluded that GCLM features are effective to detect normal leaves. Whereas color features and Gabor filter features are considered as best for detecting anthracnose affected leaves and leaf spot respectively. They have achieved highest accuracy of 73.34% using all the extracted features. Peyman Moghadam et Al. demonstrated the application of hyperspectral imaging in plant disease detection task [3]. visible and near-infrared (VNIR) and short- wave infrared (SWIR) spectrums were used in this research. Authors have used k-means clustering algorithm in spectral domain for the segmentation of leaf. They have proposed a novelgrid removal algorithm to remove the grid from hyperspectral images. Authors have achieved the accuracy of 73% with vegetation indices in VNIR spectral range and 93% accuracy with full spectrum. Though the proposed method achieved higher accuracy, it requires the hyperspectral camera with 324 spectral bands so the solution becomes too costly. Sharath D. M. et Al. developed the Bacterial Blight detection system for Pomegranate plant by using featuressuch as color, mean, homogeneity, SD, variance, correlation, entropy, edges etc. Authors have implemented grab cutsegmentation for segmenting the region of interest in the image [4]. Canny edge detector was used to extract the edges from the images. Authors have successfully developed a system which can predict the infection level in the fruit. Garima Shrestha et Al. deployed the convolutional neural network to detect the plant disease [5]. Authors havesuccessfully classified 12 plant diseases with 88.80% accuracy. The dataset of 3000 high resolution RGB images were used for experimentation. The network has 3 blocks of convolution and pooling layers. This makes the network computationally expensive. Also, the F1 score of the model is 0.12 which is very low because of higher number of false negative predictions.

V. METHODOLOGY: -

This section details the integration of machine learning, neural networks, and IoT technologies used in our system. We discuss how these components work together to collect, process, and analyze data for effective remote monitoring and management of plant growth.

Our methodology integrates machine learning, neural networks, and IoT technologies to achieve effective remote monitoring and management of plant growth and disease detection. We create a Convolutional Neural Network (CNN) model, which is trained using a comprehensive training dataset to predict diseases in test images. For more robust training and validation, we further split the original training dataset into separate training, validation, and test sets. The model is trained on the training and validation sets, while the test set is used to evaluate the model's performance by measuring its accuracy and F1 score. This approach helps us compare actual and predicted diseases on specific test images, providing a clear understanding of the model's efficacy. Machine learning, specifically usingCNNs, allows us to analyze and interpret complex plant image data, identifying patterns and features indicative of various plant diseases. Neural networks, with their deep learning capabilities, enable the system to improve its diagnostic accuracy over time as more data is processed. The IoT devices play a crucial role in real-time data collection, providing continuous environmental monitoring through sensors for soil moisture and temperature as well as capturing periodic images of the plants. This data is transmitted to a cloud server via the Node MCU, whereit is stored and analyzed. The integration of these technologies results in a powerful system for plant health monitoring and diseases detection, leveraging advanced machine learning models and neural networks to make accurate predictions based on real-time data collected through IoT devices. This methodology ensures a comprehensive and efficient approach to managing plant health and detecting diseases early, ultimately aiding in maintaining optimal growing conditions.

IV.SYSTEM MODEL: -

The proposed system consists of two main components: plant disease detection and plant growth monitoring. Images of the subjects, i.e., plants, are captured using ESPCAM32 cameras and then forwarded to the system. These images undergo processing, and the resulting data is compared with large, trained datasets using machine learning algorithms to detect various diseases affecting the plants. Additionally, the system includes various sensors that measure parameters such as soil

moisture, temperature to assess environmental conditions conducive to optimal plant growth and yield. The data collected by these sensors are uploaded to cloud servers, allowing remote access by users.

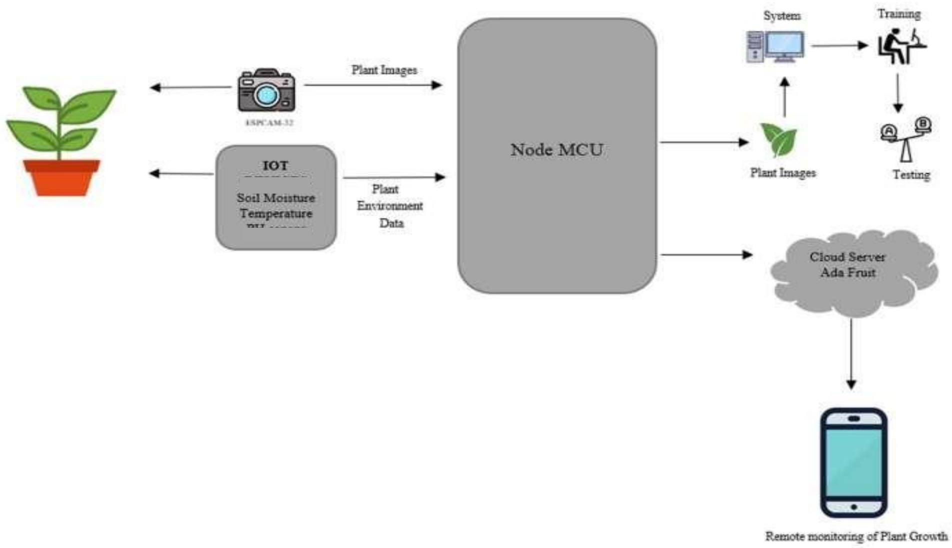


Figure-1 **BLOCK DIAGRAM**

The system for remote plant monitoring operates through a series of interconnected processes involving IoT devices, data transmission, cloud-based analysis, and user interface for remote monitoring. Initially, IoT devices collect real-time data on critical environmental parameters such as soil moisture, temperature, and pH levels. Additionally, an ESP32-CAM module captures periodic images of the plants, providing visual data to complement the environmental readings. This collected data is then transmitted to the Node MCU, which acts as an intermediary, packaging the information and forwarding it to a cloud server for processing and storage. Upon reaching the cloud server, the data undergoes analysis where it is compared against a pre-trained model developed from historical plant growth data and images. This analysis helps in assessing the current health and growth stage of the plants, identifying any patterns or potential issues, and predicting future growth trends. For remote monitoring, users access a dedicated interface connected to the cloud server. This interface displays real-time data and images, offering a comprehensive view of the plant's condition. Furthermore, the system can generate alerts if any of the monitored parameters deviate from the optimal range, enabling timely interventions to maintain ideal growing conditions. Through this integration of IoT devices, cloud computing, and user interface, the system provides an efficient and robust solution for remote plant care and monitoring.

The proposed system is an integration of several sensors and microcontroller such as,

1.NODE MCU

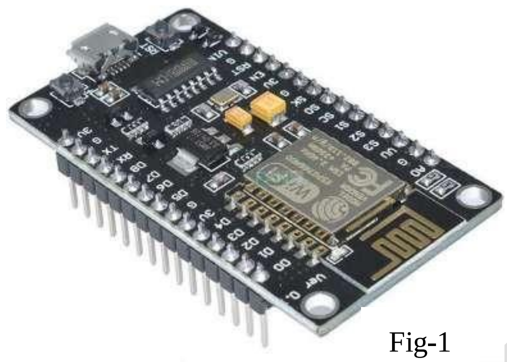


Fig-1

Node MCU is a versatile open-source development board based on the ESP8266 Wi-Fi module, with a built-in USB-to-serial converter and Lua scripting language support. It offers an easy-to-use platform for IoT (Internet of Things) projects, enabling rapid prototyping and development of connected devices. With its onboard Wi-Fi capability GPIO Pins and a wide range of community-supported libraries, Node MCU empowers developers to create innovative solutions for home automation, sensor networks, and more. Its compact size, affordability, and rich feature set make it a popular choice among hobbyists and professionals alike for building smart, interconnected systems**.** In our project it is used for sending sensors data on a web-based server i.e., adafruit all sensors' data like temperature humidity and growth i.e., height of the plant is sent on server, nodemcu also used for collecting sensors data and displaying on lcd

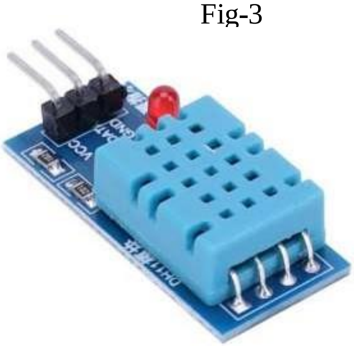
2. ESPCAM-32

Fig-2

The ESP32-CAM is a compact development board based on the ESP32 chip, featuring an integrated camera module. It combines the power and versatility of the ESP32 microcontroller with the convenience of a camera, making it ideal for projects involving image capture and processing in IoT and surveillance applications. With Wi-Fi and Bluetooth connectivity, GPIO pins, and support for various programming environments like Arduino and Micro Python, the ESP32-CAM offers a flexible platform for building projects such as video streaming, motion detection, and facial recognition. Its small form factor and affordability make it a popular choice for DIY enthusiasts and professionals alike in the realm of smart devices and visual applications. esp32 ai camera is used to record the images of the plant for feeding to ML algorithm for disease detection and also to get the prevention method needed.

3. HUMIDITY SENSOR

Fig-3



A humidity sensor, also known as a hygrometer, measures the amount of water vapor in the air. These sensors are essential in various applications, including weather forecasting, HVAC systems, and manufacturing processes where moisture levels are critical. They come in different types, such as capacitive, resistive, and thermal, each utilizing distinct principles to detect and measure humidity. Capacitive sensors, for instance, measure changes in electrical capacitance due to humidity levels, offering high accuracy and stability.

4. ULTRASONIC SENSOR

Fig-4

An ultrasonic sensor is a device that uses sound waves to measure distance to an object. It emits high-frequency sound waves, whichbounce off objects and return to the sensor. By calculating the time, it takes for the sound waves to return, the sensor can determine thedistance to the object. Ultrasonic sensors are widely used in applications such as robotics, automotive parking systems, andindustrial automation for their accuracy, reliability, and ability to operate in various environmental conditions. They are particularly effective for detecting transparent or shiny objects that might be challenging for optical sensors**.** This sensor is used to get the height of the plant in cm to measure the growth of the plants

5. SOIL SENSOR

To observe the moisture content of the soil a capacitive soil sensor is used this sensor collects the moisture contents and sends to node mcu controller to send it on the adafruit server for remote monitoring of soil data from the plant. To observe the moisture content of the soil a capacitive soil sensor is used this sensor collects the moisture contents and sends to nodemcu controller to send it on the adafruit server for remote monitoring of soil data from the plant.

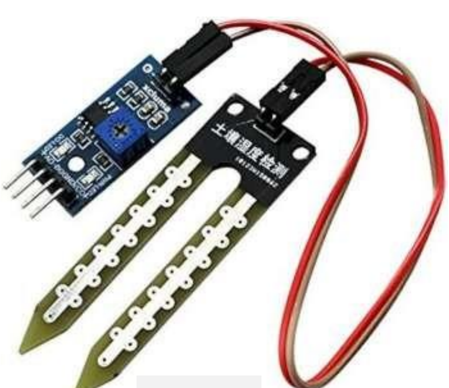
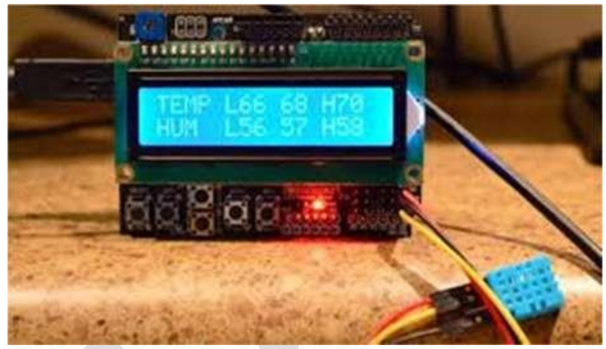


Fig-5

Fig-6

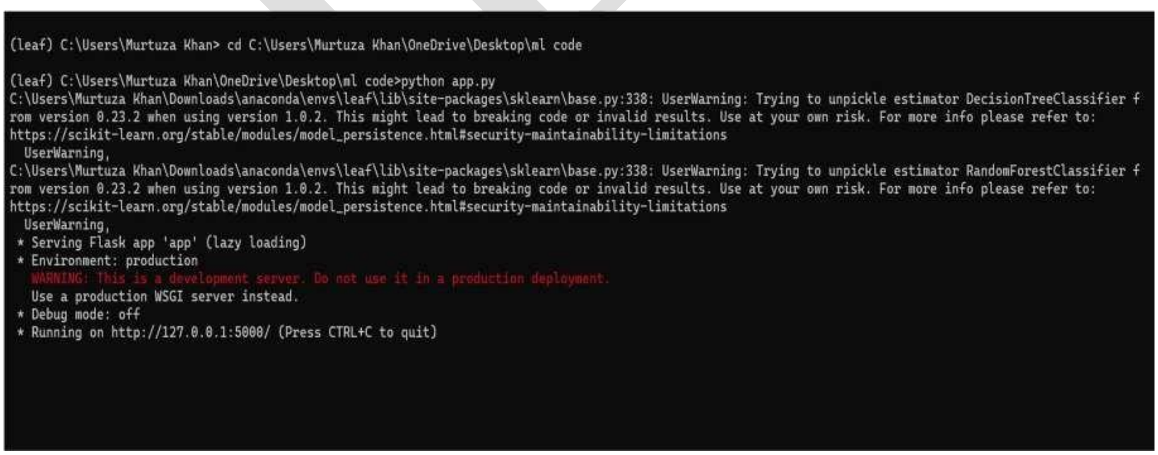
6. I2c-LCD DISPLAY

I2c lcd is used for monitoring sensors data, its connected with i2c module to make it less pins for easy interface with node MCU controller. this ld. have two rows and sixteen columns.it displays different numbers and characters. From the sensors.



RESULT: -

We have successfully implemented our project on plant disease detection and growth analysis using advanced machine learning algorithms and IoT technology. Through the collection and analysis of high-resolution images and real-time environmental data, our system has demonstrated its efficacy in early disease identification and optimal growth condition monitoring. The results obtained from various sampled plants validate the accuracy and reliability of our approach. Farmers now have instant access to actionable insights via web and mobile applications, enabling them to make informed decisions and proactively manage their crops. This project marks a significant step towards more sustainable and efficient farming practices, promising enhanced food production while reducing water and chemical usage.



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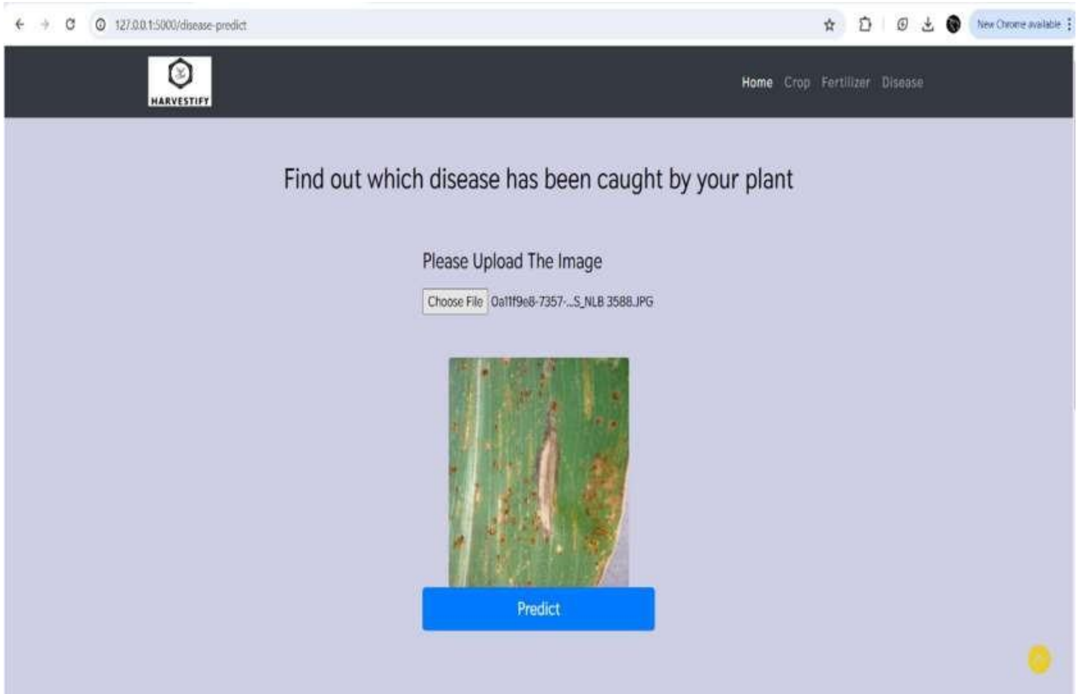

Disease: Northern Leaf Blight

Cause of disease:

Northern corn leaf blight (NCLB) is a foliar disease of corn (maize) caused by Exserohilum turcicum, the anamorph of the ascomycete Setosphaeria turcica. With its characteristic cigar-shaped lesions, this disease can cause significant yield loss in susceptible corn hybrids.

How to prevent/cure the disease

1. Management of NCLB can be achieved primarily by using hybrids with resistance, but because resistance may not be complete or may fail, it is advantageous to utilize an integrated approach with different cropping practices and fungicides.
2. Scouting fields and monitoring local conditions is vital to control this disease.

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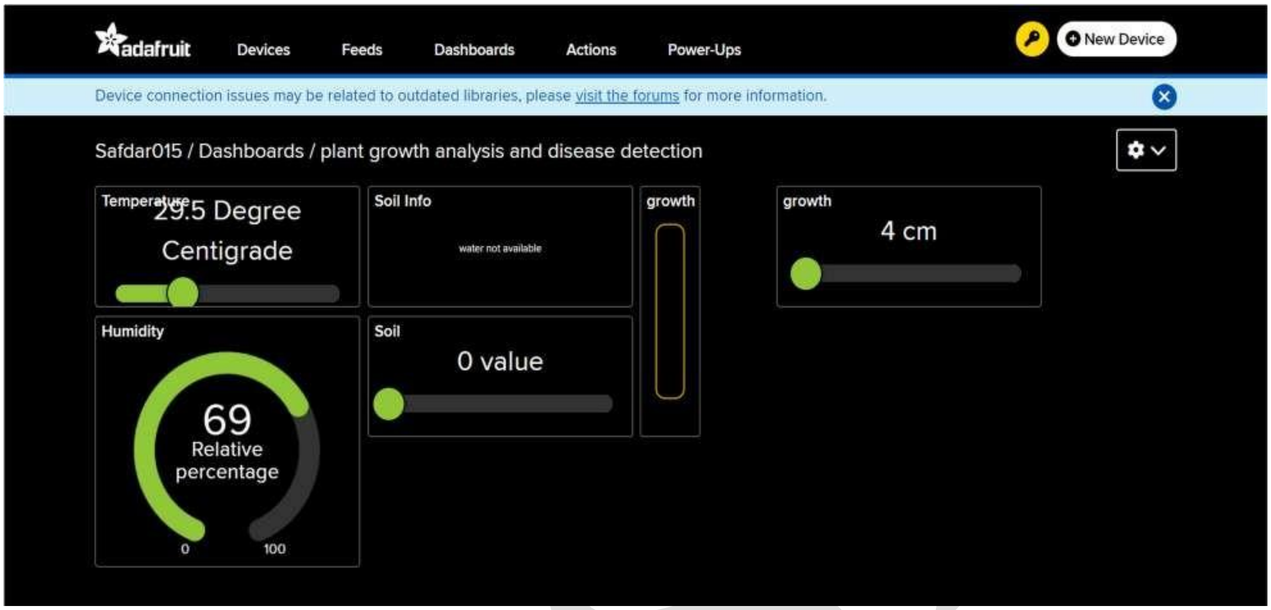

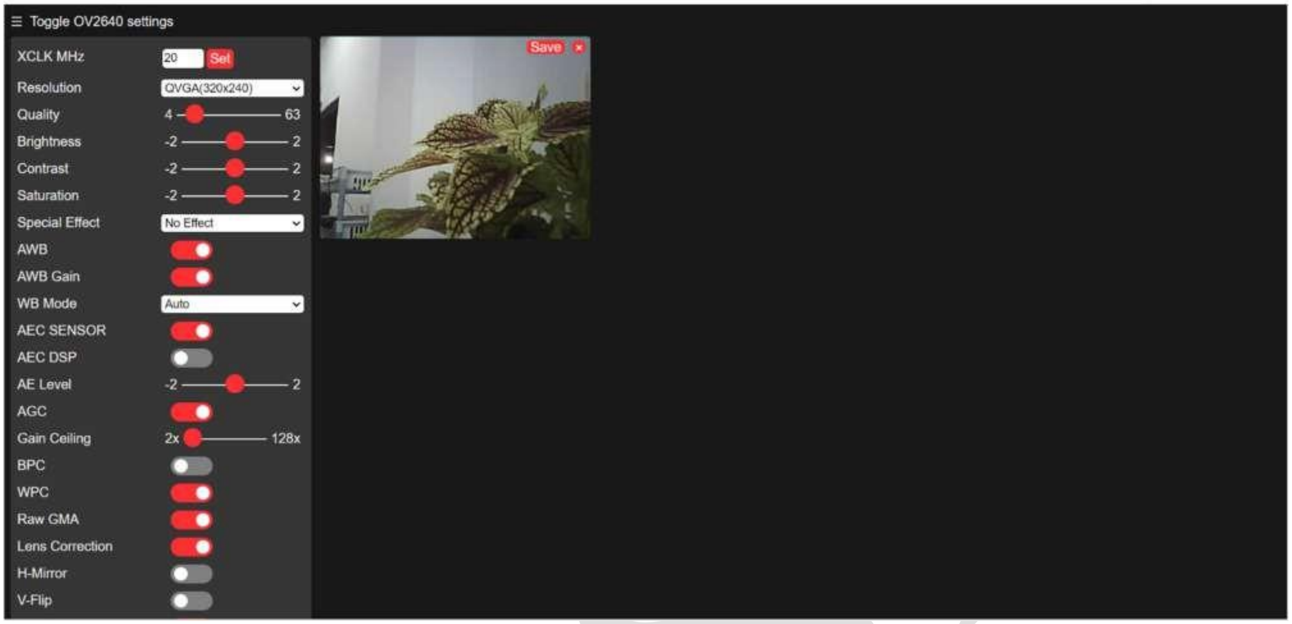

CONCLUSION: -

In this paper, we propose a synergy between Machine Learning (ML) and Internet of Things (IoT) technologies that offers a revolutionary approach to plant disease detection and growth analysis in agriculture. By leveraging high-resolution imaging, real-time environmental monitoring, and advanced ML algorithms, farmers can detect diseases early, optimize growth conditions, and improve crop yields. The integration of IoT devices enables seamless data collection and analysis, empowering farmers with actionable insights for informed decision-making. However, while these innovations hold immense promise, challenges such as data accuracy, scalability, and interoperability remain. Continued research and development efforts are crucial to address these challenges and refine the effectiveness of ML and IoT solutions in agriculture. Ultimately, the adoption of ML and IoT in plant disease detection and growth analysis signifies a pivotal step towards building resilient and sustainable agricultural systems capable of meeting the food demands of a growing population while mitigating the impact of environmental stressors on crop health and productivity.

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