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Smart Crop Monitoring Using IoT Sensors and Real-Time Image Analysis for Plant Disease Detection with Machine Learning

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Abstract: The integration of machine learning and Internet of Things (IoT) sensors has significantly advanced crop monitoring and disease detection methods. This study introduces an innovative approach that combines IoT sensors with live image capture to monitor crop health and identify plant diseases in real time. The proposed system utilizes high-resolution cameras to obtain live images of crops, while IoT sensors collect critical environmental and soil data. These images are then analyzed using enhanced machine learning algorithms trained on large datasets to accurately detect and classify plant diseases. By identifying early signs of disease, the system enables timely intervention, minimizing crop losses. Compared to traditional methods, the fusion of sensor data with image analysis greatly improves the precision of disease detection. The relevance of this research lies in its potential to transform agriculture by equipping farmers with real-time, actionable insights that support better crop management, increased yield, and sustainable farming practices.

Keywords: IoT sensors, crop monitoring, machine learning, disease detection, real-time monitoring, agricultural technology, live image capture, precision agriculture, smart farming, environmental data.

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I. INTRODUCTION

Agriculture is the backbone for most economies; it provides food, raw materials, and employment. Agriculture, however, is confronted with innumerable challenges, including unpredictable weather patterns, infestations by pests, and plant diseases. These factors can significantly bring down crop yields and affect food security. The monitoring and detection of disease in crops through traditional methods are often very time-consuming and labour-intensive, usually depending on the naked eye, which is quite erroneous. In the past years, there has been an increasing need for developing novel ways to improve crop management and mitigate the impacts of those challenges through the employment of advanced technologies.

The integration of IoT sensors and ML algorithms with farming practices offers a promising approach in responding to such problems. This paper dwells upon one state-of-the-art system that merges IoT sensors and live image capture technologies to observe the status of crops and detect plant diseases in real-time. The introduction below defines the importance of crop monitoring, the place of IoT and ML within agriculture, and the advantages of integrating these technologies. Crop monitoring is the effectual continuous assessment of the condition of the crop to detect any stress, pest, or disease. The effectual timing of intervention as and when required is important to avoid severe damage and loss. Traditional crop monitoring involves discontinuous field inspections by the farmer or the agricultural expert, which may be laborious and only restricted to a small scope. Such methods may also miss the early warning signs of diseases, and the reaction may be delayed to result in more intensive losses of the crop.

Modern crop monitoring systems, on the other hand, are based on the use of technology that provides continuous and exact assessment of crop health. Such automation can cover larger areas and deliver more frequent updates so that farmers are able to make informed decisions based on real-time data. IoT stands for the Internet of Things, which literally means a network of interconnected devices that collect and exchange data. Agricultural IoT devices can include any number of sensors that measure environmental and soil parameters such as temperature, humidity, soil moisture, and light. Such sensors could be mounted around fields and will continually sense the condition that may affect the health and growth of crops. Comparatively, there are several advantages of IoT sensors over the traditional

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ways of monitoring. They offer remotely accessible data in real-time, hence obviating the need for physical field inspections. The data obtained from this approach may also be used to determine trends and patterns and, consequently, manage crops proactively. Another advantage is that IoT sensors can operate autonomously and continuously so that critical information is always available at the exact time of need.

Machine Learning for Disease Detection

Machine Learning is a subset of artificial intelligence that deals with the training of algorithms to recognize patterns and make predictions based on data. Within the agriculture setting, ML can analyse data from IoT sensors and images taken from cameras to detect evidence of plant disease. These machine learning algorithms can be trained on enormous datasets of images of healthy and diseased plants. These algorithms learn characteristics of different diseases, which in turn help in the detection of symptoms in new images. It involves various steps, including pre-processing of images, feature extraction, and classification. Especially the application of advanced ML techniques, such as CNNs, can bring in a great effectiveness in image analysis, since they are able to automatically extract the appropriate features from the images. Combining IoT sensors with image capture and ML provides a powerful tool for disease detection. On top of the environmental and visual data being analysed, the system gives a fully-fledged assessment of crop health and identifies diseases at an early stage.

The Diseases on which we are working on:

1. Healthy Leaf:

The health of the leaf is very crucial to the plant's development and maintenance of its health. It is the key location of photosynthesis, whereby chlorophyll tackles daylight to convert carbon dioxide and water to glucose, the plants source of energy. A healthy leaf would normally be green in color, an indication of the presence of chlorophyll and, hence, active photosynthesis. It should not have discoloration or spots or any kind of growth that is abnormal, indicating a deficiency of disease, insects, or nutrient deficiencies.

2. Bacterial Spot:

Bacterial spot is an infectious plant disease that manifests from several bacterial species but mainly Xanthomas. It is infectious to a variety of crops—tomatoes, peppers, and green leafy vegetables. This disease causes small, water soaked lesions on the leaves, fruits, and stems that turn dark or necrotic over time. Bacterial spot spreads when water splashes, in the wind, or in contaminated tools and grows in warm, humid conditions.

3. Mosaic Virus:

Mosaic spot is a plant disease typified by the appearance of irregular, mottled patterns on the leaves due to infection by viruses like tobacco mosaic virus and cucumber mosaic virus. Some viruses infect a large variety of plants, such as tobacco, tomatoes, peppers, and cucumbers. Typical symptoms include yellowing and distortion of leaves, which are often accompanied by puckering or blistering, and sometimes accompanied by stunted growth. Mosaic viruses are highly contagious and are normally spread from plant to plant by contact with the sap of infected plants through contaminated tools or by insect vectors.

4. Septoria Virus:

Septoria, a fungal disease, is quite common in plants, primarily tomatoes and other members of the Salicaceae family. It is caused by species of the Septoria genus, such as septoriaLycopersicon. Leaves of a plant infected with Septoria develop small, dark spots, which gradually become enlarged and coalesce to form large lesions with characteristic black specks in the centre. Such lesions may result in yellowing of the leaves, wilting, and premature defoliation, hence affecting the overall vigour and yield of the plants.

5. Leaf Mold:

Leaf mold is caused by many members of the genus Fulvia, of which Fulviafulva, formerly known as Cladosporiumfulvum, is the most common causal agent of this disease. It is mainly a tomato disease, although it Occasionally affects other solanaceous crops, such as peppers and egg plants. The first symptoms of leaf mold usually appear as yellowish or pale green areas on the top leaf surface, which may be accompanied by a fuzzy white to grayish mold growth on the leaf underside. Leaves often twist and wilt, then die.

6. Curl Virus:

The Curl virus is usually called Tomato yellow leaf curl virus, or just Tomato yellow leaf curl. It is a destructive viral disease that affects tomato plants and other members of the Solanaceae family. It is transmitted by the sweet potato

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whitefly, Bemisiatabaci, and can cause severe stunted growth, upward leaf curling, yellowing, and reduced fruit yield. Leaves of infected plants may thicken with swollen veins.

II. LITERATURE SURVEY

Divya J., Divya M., and Janani V. [1] Agriculture is critical to India's economy and people's survival. So, this paper will outline the development of an embedded soil monitoring and irrigation system that shall replace manual field monitoring and provide data through a mobile application. This will help farmers with enhancing their agricultural outputs. The soil is studied with a pH sensor, a temperature sensor, and a humidity sensor. The data gives which crop to sow as the best crop on their land. The data of the sensors is sent to the field manager through Wi-Fi. Crop advice is given with the help of a mobile application. An automated watering system is used when the soil temperature rises.

B. Sridhar and R. Nageswara Rao [2] In India and developing countries, agriculture is the primary source of economic development. The agricultural sector has always been a bottleneck to the development of the nation. No other solution is available to address the bottleneck except to modernize the existing agriculture systems with smart agriculture. Therefore, the proposed mechanism seeks to use automation and IoT to bring intelligence in agriculture. IoT realizes a host of purposes from decision support and monitor of irrigation to crop growth selection to mention a few. An IOT based autonomous irrigation mechanism based on Raspberry Pi has been proposed to modernize and increase crop yields. The main objective of the research is to produce crops using the minimum amount of water. Most of the farmer’s waste much time in the farms trying to observe when the plants need water. Improving the management of water and minimizing the complexity of the circuit of the system is also one of the objectives of the research. The proposed system determines the quantum of water required based on the data obtained from sensors. Two sensors used measure soil temperature, humidity, and temperature and sunshine hour variation for the day send data to the base station. The proposed systems have the task of determining the quantity of irrigation water depending on these features. The main merit of the system is the integration of cloud computing with PA which will increase the yield of crops and also help in estimating the weather condition of the field consuming lesser amount of water and fertilizer.

Alan Mainwaring, A. Sivasankari and S. Gandhi Mathi [3] give a comprehensive analysis of the applicability of wireless sensor networks to real world habitat monitoring. A set of system design requirements defines the hardware design of the nodes, the sensor network design, and the ability to remotely access and manage data. We have set up a small pilot network at the James San Jacinto Mountains Reserve in Idyllwild, California to test its implementation. JMR is a 29-acre ecological reserve and is one of 34 properties owned by the University of California System Natural Reserve System. JMR has very different climate than GD, and the variation in weather patterns can persist for a very long period. Data collection from sources that were previously inaccessible can be made easier by using a micro measurement scale.

Joseph haule, et al [4] proposed an experiment to show how WSN is used to automate irrigation. WSN -based irrigation control and rescheduling are effective methods for optimum water management by automatically communicating the soil moisture conditions of irrigation design. The right frequency and timing of watering, which are important for ensuring that the procedure utilized here establishes effective water consumption, excellent crop detection quality, delay throughput, and load. OPNET simulates agriculture. The use of ZigBee protocol in an irrigation system may impact on battery life. There are a number of limitations because WSN is still at the research stage with inconsistent times in communication, fragility, high power consumption, and the likelihood of losing communication in the agricultural area. Consequently, the irrigation system and scheduling are carried out automatically by the use of wireless sensor networks. Energy efficiency is attained with WSN technology since it makes use of a minimal quantity of power and data rates. All gadgets and machinery are operated by using inputs attained from the sensors mixed with dirt. Through this, farmers can know whether the system is functioning or further actions are taken.

Internet of Things for Smart Water Management [5] This project can help to monitor the water levels and determine where they can be utilized in society. There is a sensor inside the tank to determine the level of water; it's recorded in the cloud via a mobile application. The user can see the level of water on their mobile phones; the motor will work both on auto and manual functions. If the water level is low, the motor will turn on automatically; if it is full, then it will shut down. In our proposed system, we might monitor and adjust the level of water by using mobile phones from any location and at any time. It can also be used in other industries to monitor the various types of liquids in the tank. Users can monitor and update information using a mobile application. Users can also receive alert notifications based on their specified criteria. It can also be implemented for flood propane by installing this equipment on dams and river banks etc.

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Problem Statement: IoT sensors in crop monitoring systems are currently in use for gathering environmental data on temperature, humidity, moisture, and light. These sensors are generally deployed at intervals in agricultural fields to get real-time insights from the growing environment. However, the integration of visual data through live image capture is not very frequent and is often of low order when used in conjunction with manual inspection or basic automated systems. When live image capture is used, the images usually have basic image processing techniques applied to them, which do not leverage advanced machine learning. Disease identification is usually reactive rather than proactive, based on periodic manual reviews or simple threshold-based alerts that are unlikely to accurately capture early-stage diseases or handle complicated disease symptoms with any level of proficiency.

III. PROPOSED ALGORITHM

The method proposed improves crop monitoring because it is fully integrated with IoT sensors and live image capture, coupled with sophisticated machine learning algorithms. In this approach, a network of high-resolution cameras is deployed across fields with IoT sensors. These high-resolution cameras capture continuous live images of the crops. All captured images are then transmitted in real time to a cloud-based platform for further processing. Then, the images are processed with state-of-the-art machine learning models, featuring convolutional neural networks. These models are trained with immense, cleaned-up databases of healthy and diseased plants, which allow them to identify and classify diseases according to their visual symptoms with high accuracy. Coupled with this image data, this system is in a position to make a more accurate and context-aware diagnosis correlated with the environmental conditions as captured by the IoT sensors. This proactive monitoring based on this system makes detection early and intervention timely, which greatly improves crop health management. The approach also incorporates a feedback mechanism where confirmed disease instances are used to retrain and update the machine learning models for continuous improvement and adaptation to new disease patterns. These bring about efficiency, accuracy, and sustainability in crop monitoring systems.

A. ARCHITECTURE:

The architecture for an edit observatory system using IoT sensors and live image capture to identify plant diseases with the use of machine learning will consist of some basic modules cooperating with each other in the collection of information, handling, and giving significant bits of knowledge. The taking after are point by point components in this framework and what each of these parts does to incorporate:

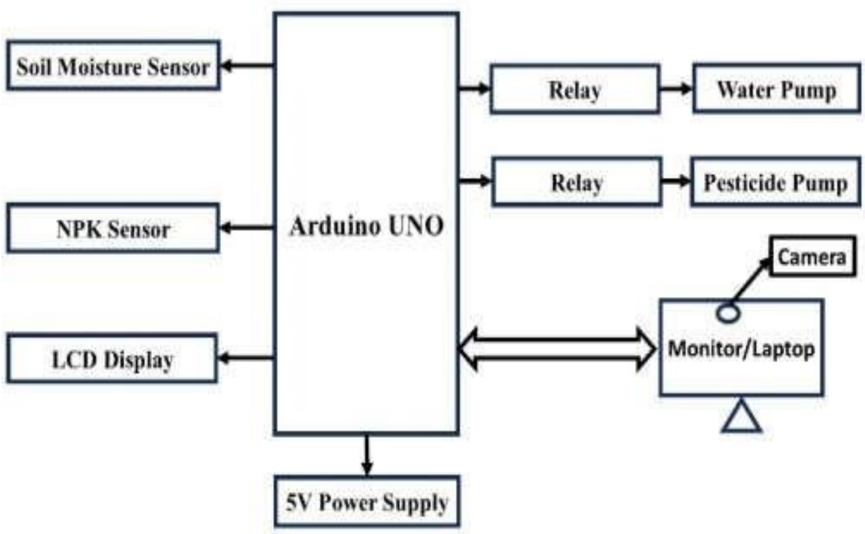

Fig. 1 Block Diagram

i. **Arduino UNO:** The Arduino UNO acts as the most controller for the coordination of information collection by different sensors and the actuator. The system's brain is dependable for handling inputs and commanding based on the gotten sensor inputs.

ii. **Soil Dampness Sensor:** This sensor gauges the level of dampness within the soil and sends the data to Arduino UNO. It makes a difference screen the level of water within the soil for ideal watering conditions of the crops.

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iii. Soil NPK Sensor: This sensor gauges the level of supplement within the soil, which incorporates the level of nitrogen, phosphorus, and potassium. It transmits information to Arduino UNO and gives basic data approximately soil ripeness that leads to focused on fertilization.

iv. DHT22 Stickiness Sensor: This sensor gauges both temperature and stickiness of the discuss. It makes a difference give natural setting that can influence plant wellbeing and illness predominance. The sensor information will be sent to Arduino UNO for preparing.

v. Water Pump: This is worked by Arduino UNO through a 2-channel hand-off. The water pump is utilized to inundate crops based on the soil dampness level. It guarantees plants get satisfactory water without overwatering them.

vi. Pesticide Pump: Also worked by Arduino UNO through the transfer, the pesticide pump discharges pesticide at whatever point an illness is recognized in a plant. It gives a mechanized reaction in overseeing infections instantly and productively.

vii. Power Supply: This provides the electric power needed to keep the entire system up and running.

viii. 2-Channel Relay: The relay module allows the Arduino UNO to drive the high-power devices (water and pesticide pumps) based on low power output from the Arduino. It acts as a switch to these devices for turning them on or off based on the sensor inputs.

ix. LCD Monitor 16x2: It displays real-time messages and data readings from the sensors on the soil moisture level, temperature, humidity, and nutrient content. It makes the system status available for immediate review in user-friendly form.

B. ALGORITHM

i. Data Collection:

The soil dampness sensor, soil NPK sensor, and DHT22 humidity sensor continuously collect information and send it over to the Arduino UNO.

ii. Data Handling:

The Arduino UNO processes the sensor information. In the event that the soil dampness is low, it acts on the water pump through the relay. Low levels of supplements can also indicate the need for fertilization.

iii. Disease Detection:

The high-resolution cameras click live images of crops, which they capture independently. Images are sent to the cloud-based platform for processing by machine learning models, looking for signs of diseases. If disease is detected, the information is passed back to an Arduino UNO.

iv. Automated Response:

Receiving infection location signals, the Arduino UNO activates the pesticide pump via the relay, thus helping to treat the infected plants.

v. User Interface:

The LCD displays current sensor readings and system status so that users can monitor conditions and system responses in real-time.

IV. RESULTS AND DISCUSSION

Accuracy and Prediction of the Model		
Diseases	Accuracy (%)	Prediction (%)
Healthy	35.294118	32
Bacterial Spot	6.666667	15
Mosaic Virus	14.285714	12
Septoria	7.692308	14
Leaf mold	6.666667	17
Curl virus	22.222222	10

Table. 1 Accuracy and Prediction

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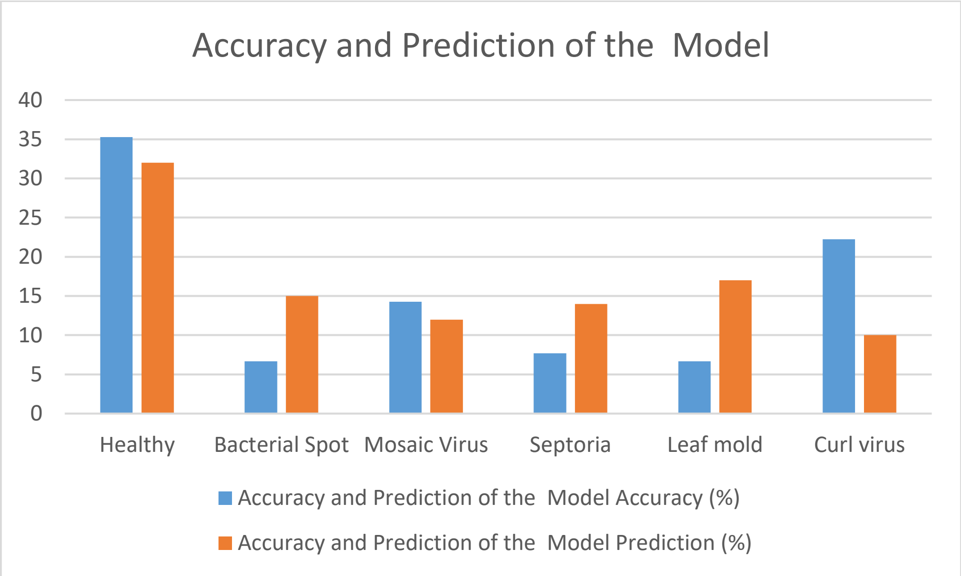

Fig. 3. Graphical representation of the Result

The model is quite good at identifying healthy plants, as it correctly does so about 35% of the time. The prediction percentage indicates that the model identified 32% of the samples as healthy, which is close to its accuracy-strongly indicating consistency in this area. The execution appears to be almost perfect in precision in regard to recognizing bacterial spot, with a 6.67%-win rate. In any case, it predicts this infection 15% of the time, which seems like a huge disparity and possible misclassification problems. The model for mosaic virus was 14.29% accurate, insinuating moderate difficulty in properly identifying diseases. Prediction was 12%, meaning it's a bit cautious but still misclassifies other conditions as **mosaic virus.**

Detection for Septoria is very low, at 7.69%, while the prediction percentage is 14.0%, hence showing over prediction tendency of the disease against its actual occurrence. Compared to bacterial spot, the show features a lower accuracy, at 6.67%, for leaf shape, but covers a larger expectation rate at 17.0%. This suggests misidentification of other conditions as a visit for leaf shape. The model performed much better in detecting twist infection at an accuracy of 22.22%. With a lower expectation rate of 10%, the model was conservative within the expectation of this disease and hence may lead to fewer false positives. In the graph above, key issues regarding the current state of the machine learning model used in crop monitoring are highlighted.

Variation in Performance: There are wide variations in the accuracy of different diseases, where the plants were more correctly identified as healthy and curl virus compared to bacterial spot, Septoria and leaf mold Over-prediction: The model overestimates certain diseases, such as bacterial spot, Septoria, and leaf mold, with higher prediction percentage values than the real accuracy of each.

Area for Improvement: The accuracy rates for many of the diseases are relatively low, so further refinement of the models is required. This is further corroborated by the fact that enhancements can be made through an increased diversity and size of the training dataset, improvement in the quality of image capture, and integration of additional data from sensors to further build context.

V. CONCLUSION

In conclusion, the integration of IoT sensors with algorithms of machine learning and live image capture is a great solution in agriculture for efficient monitoring of the crops and identification of diseases. The data can be collected and analyzed in real-time to ensure the detection and prevention of plant diseases at an early stage. Therefore, it eventually results in better health of crops, enhanced yields, and reduced losses. The technology permits timely intervention in an efficient manner, uses minimal resources, and limits the use of chemical treatments. Besides this, these systems are both adaptable and scalable, so they can be deployed on a wide variety of crops and within varied farming environments. Such advanced monitoring techniques could offer considerable potential to improve the sustainability and resilience of food production systems, as challenges continue to evolve in agriculture

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