

# ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING BASED PLANT MONITORING

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## ABSTRACT

*One of the main kinds of life in the world is plant. By giving food to individuals and, what's more, untamed life, plants benefit the environment and human existence in the world in different ways. Plants lead to a country's beneficial farming creation. A convolutional neural network (CNN) can be utilized to future plant development and wellbeing through leaf assessment. AIML had played a fundamental impact on checking plants' wellbeing. AIML grants objects to be detected or controlled from a distance across the organization's foundation. The outcome further develops exactness, financial advantages and productivity. AIML framework is intended to gather information and give continuous input on the condition of the plant, soil, and climate factors. Acknowledgment of plant diseases utilizing Convolutional neural Networks (CNN) is an emerging field of exploration that expects to recognize and analyse plant infections naturally. This method utilizes picture based calculations in light of profound realizing, which take into consideration the extraction of complex highlights from pictures of plant leaves, natural products, or stems impacted by different diseases. via preparing the CNN on an enormous dataset of solid and sick plants, it can figure out how to recognize designs and recognize various kinds of diseases. The acknowledgment of plant infections involving CNN has huge consequences for plant diseases across the board, as it takes into consideration early discovery and exact analysis, which can prompt ideal interventions and decreased crop misfortunes. In this paper, we will give an outline of the idea of acknowledgment of plant diseases utilizing CNN, its expected applications, and some of the difficulties that should be addressed to work on the precision and versatility of this technology.*

## KEYWORDS

*Plant leaf disease detection, Visualization, Internet of Things (IoT), Convolutional neural networks, Image classification.*

## 1. INTRODUCTION

Rural efficiency, a foundation of worldwide food security and financial strength, faces huge difficulties because of biotic burdens, prompting significant yield misfortunes. The relationship between food handling, sustenance, and rural economy frames a complicated transaction, especially influencing creating an immature nation, compounding wellbeing and monetary emergencies. Remarkably, in locales like Africa, where roughly 80% of harvests are developed by smallholder farmers, assets requirement represents a huge danger to horticultural creation. Plant infections address an imposing hindrance to horticultural supportability. Convenient recognition and the board of these diseases are basic to moderate food weakness and monetary misfortunes. Generally, diseases-distinguishing proof has depended intensely on emotional evaluations by horticultural specialists or farmers, a strategy burden with shortcomings,

mistakes, and ecological dangers. To address these difficulties, there is a developing interest in utilizing mechanical progressions, especially in picture handling and the Web of Things (IoT), to upset plant diseases acknowledgment and observing. Picture handling methods offer a promising road for computerizing diseases as recognizable proof by breaking down obvious signs, for example, sores or stains on plant leaves. All the while, the expansion of IoT gadgets open new doors for continuous observing and information collection in farming settings. By using sensors to quantify boundaries like humidity, temperature, and moisture content, combined with cutting edge man-made reasoning and AI calculations, like Convolutional Neural Networks (CNNs), it becomes practical to precisely predict and analyze plant diseases. The union of these advancements in the proposed project, named "AIML Based Plant Monitoring," means to foster an exhaustive answer for checking and overseeing plant wellbeing. Through the coordination of sensor information procurement, picture handling, and man-made intelligence driven diseases detection, the undertaking tries to engage farmers with ideal and significant experiences, consequently improving horticultural efficiency, and adding to worldwide food security. In this paper, we outline the reasoning, system, and expected results of the undertaking, highlighting its importance in tending to basic rural difficulties and encouraging maintainable cultivating rehearsals.

## 2. LITERATURE REVIEW

In recent years, the utilization of artificial intelligence and machine learning practices in agriculture, notably in plant diseases detection and monitoring, has drawn a considerable amount of focus point. This review consolidates discoveries from four unique research documents, each adding valuable understandings into the realm of AIML - based plant monitoring. The first paper [1] accentuates using machine learning algorithms, predominantly Convolutional Neural Networking (CNN), for recognizing and sorting crop diseases. In addition, the success of hyperspectral sight and deep learning methods in plant disease detection is emphasized in this paper. Nevertheless, crucial shortcomings are spotted,

Table 1: Gap Analysis

| Paper Title                                                                                                                  | Findings from Literature                                                                                                                                                                                                                                                                                                                                 | Gaps Identified                                                                                                                                                                                                                                                                                                                                        |
|------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Plant Disease Detection and Classification by Deep learning                                                                  | <ul style="list-style-type: none"> <li>- The system employs machine learning algorithms, particularly CNN (Convolutional Neural Network), for the detection and classification of crop diseases.</li> <li>- The use of hyperspectral imaging and deep learning techniques for plant disease detection.</li> </ul>                                        | <ul style="list-style-type: none"> <li>- The literature does not adequately address the detection and classification of plant diseases based on small sample data sets.</li> <li>- There is no mention of early disease detection methods.</li> </ul>                                                                                                  |
| Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks with Stepwise Transfer Learning | <ul style="list-style-type: none"> <li>- The potential of deploying the proposed system to mitigate losses in small farms and increase crop yield, indicating a practical application of the research.</li> <li>- Introduces a stepwise transfer learning approach to reduce the convergence time of any CNN architecture</li> </ul>                     | <ul style="list-style-type: none"> <li>- Detection of Diseases with Varying Symptoms.</li> </ul>                                                                                                                                                                                                                                                       |
| A Comparative study of IoT Technology in Precision Agriculture                                                               | <ul style="list-style-type: none"> <li>- The use of IoT and machine learning in agriculture for real-time monitoring of plant growth, health, and disease detection.</li> <li>- The role of data analytics in agriculture for efficient retrieval and manipulation of data from devices and machines deployed in the field.</li> </ul>                   | <ul style="list-style-type: none"> <li>- The challenges of implementing IoT in the agriculture sector, especially in developing countries due to high costs and the need for expertized farmers and workers.</li> </ul>                                                                                                                                |
| Crop Health Monitoring System                                                                                                | <ul style="list-style-type: none"> <li>- The development of a crop health monitoring system that utilizes sensors to collect data on environmental conditions and plant health.</li> <li>- The system employs machine learning algorithms, particularly CNN (Convolutional Neural Network), for the detection and classification of diseases.</li> </ul> | <ul style="list-style-type: none"> <li>- The integration of Google weather forecast to alert farmers in advance about unfavorable atmospheric parameters could enhance the system's predictive capabilities.</li> <li>- The addition of a feature to suggest remedies (pesticides) for curing diseases and obtaining feedback from experts.</li> </ul> |

compromising the insufficient managing of limited sample datasets and the lack of early diseases detection techniques. Upon building over that base, the paper [2] which introduces an incremental transfer education method targeted at reducing deficiencies in tiny farms and enhancing crop output. Not with standing its Nevertheless, difficulties in implementing IoT in the farming sector, particularly in under developing countries because of Internet of Things (IoT) technology and machine learning for immediate monitoring of plant growth, health, and disease detection. The paper reports a gap in sufficiently recognizing diseases with different symptoms, highlighting a necessity for more exploration in this space. Expanding on the scope, the paper [3] examines the merging of Internet of financial limitations and the necessity for particularized knowledge, are highlighted as issues needing focus. Finally [4] present a complete crop health monitoring system using sensors for collecting data and CNN for detecting and classifying diseases. The paper recommends to integrate Google weather forecast to improve predictive capacities and to include characteristics for recommend solutions and get expert feedback, deal with gaps identified in prior researches. The following papers present a varied outlook on AIML-based plant monitoring, highlighting changes and gaps for further research. Upcoming ventures in this area could revolutionize agricultural methods and improve harvest oversight by tackling acknowledged weaknesses and utilizing new innovations.

### 3. SYSTEM DESIGN

#### 3.1. Hardware Requirements

The sensor module includes three sensors which are temperature and humidity sensor (DHT11), Soil moisture sensor, PIR motion sensor and Rain detection module. A microcontroller to analyze the data from these sensors and interface sensors with a GSM module.

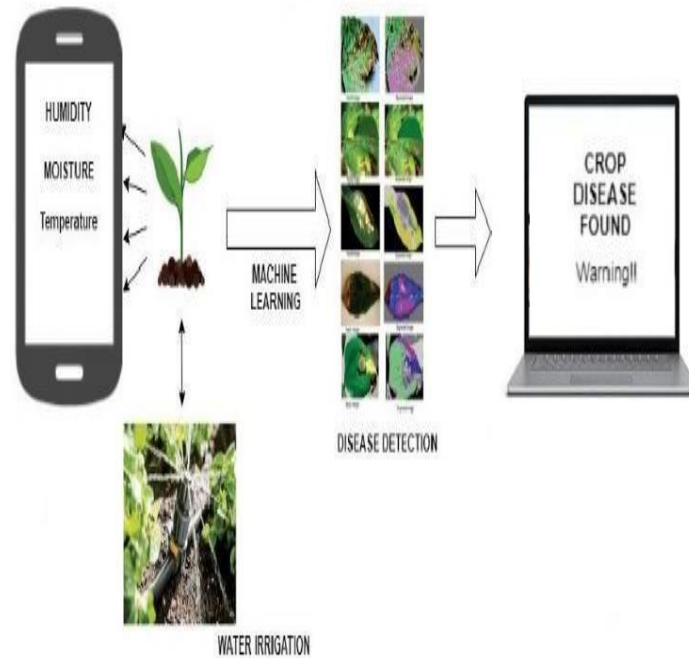


Fig 1. Overview of System

1. *Soil moisture sensor*: The dirt humidity sensor includes two tests used to gauge the volumetric substance of soil water. The current flows through these two tests, involving

soil as a channel, to get the obstruction worth of soil. The humidity content of soil is estimated utilizing this obstruction esteem. Contingent upon how much measure of humidity is expected for a specific sort of plant, we choose the opposition edge. As the humidity content of the dirt is contrarily relative to the opposition noticed, when the obstruction increments over a set edge, it implies that the dirt humidity has dipped under the expected levels and an alarm will be shipped off the farmer. The water system framework will be activated by the sensor esteem.

2. *Temperature and Humidity Sensor*: To identify temperature and humidity, a DHT11 sensor is utilized. Additionally, to gauge stickiness, the sensor utilizes two cathodes, which have humidity holding in the middle between them. As the humidity changes, substrate conductivity changes, and the obstruction between two terminals changes. This opposition change is estimated and handled by the IC.
3. *Rain sensor*: A board with lines of nickel coated on it is the raindrop sensor. It relies on resistance to function. Analog output pins in the Rain Sensor module measure moisture levels. The LM393 op amp is used in the module. The electronic module and a printed circuit board used to collect raindrops make up the module. Raindrops tend to form paths that serve as parallel resistance when they fall and saturate the circuit board. The op amp is used to measure this resistance. The sensor is essentially a resistive dipole with lower resistance when wet and higher resistance when dry. Because water is a good conductor of electricity and its presence connects parallel nickel lines to reduce resistance, raindrops on board reduce resistance.
4. *PIR sensor*: The Passive Infrared (PIR) sensing module seems out for shifts in the infrared emissions emitted by things within its seen range. This offers it the capacity to detect motion. It splits its sight area into recognition places and creates an end signal when recognizing movement. The reality that PIR sensors do not productively send signs makes them energy-effective and distinguishes them from another sorts of sensors. They are fit for a wide variety of purposes due to this aspect, like automated lighting structures and safety mechanisms.
5. *Node MCU (ESP8266) Wifi Module*: NodeMCU is a highlevel programming interface for equipment input/output gadgets, which emphatically decreases the work for designing manipulative equipment. It utilizes a code like Arduino yet rather is an intelligent content called Lua. It is an open source IoT stage. NodeMCU has 16 info/yield pins, and consequently 16 hubs can be associated with a solitary hub. "NodeMCU" imply in default to the firmware as opposed to the advancement units. ESP8266 is an inbuilt WiFi module that can likewise be utilized as a singular module as a WiFi module.

### 3.2. Software Requirements

To make a web application for the discovery of plant infections, a wide range of profound learning libraries have been utilized. The stage used to execute the code is a Jupyter notebook, utilized for the more profound preparation of the model and to acquire high exactness.

1. *Arduino IDE*: The Atmega 328P is coded by utilizing the Arduino IDE. This product likewise upholds numerous other electronic modules and, furthermore, has an easy-to-use interface. The fundamental programming dialects utilized incorporate C/C++. The IC has an in-constructed boot loader to transfer and execute codes from the IDE.
2. *Jupyter Notebook*: Jupyter Notebook is an open-source web application that is utilized to run codes consecutively, and the result is created all the while. It very well may be utilized for different applications, which incorporate AI calculations, successive demonstrating, information recreation, and some more. It permits simple sharing of reports.
3. *Crop Disease Dataset*: The dataset being utilized for crop infection discovery comprises just about 15,000 pictures, which incorporate 14 different harvest species. There are

pictures of leaf diseases brought about by contagious, microscopic organisms, forms, viruses, and parasites. Likewise, pictures of 12 solid yields are available there. This dataset is taken from Plant Town, which is an internet-based stage to enable little ranchers by furnishing them with information about the yield diseaseses and different innovations accessible to fix them so they can develop more food.

## 4. METHODOLOGY

### 4.1. Sensor Module

Temperature and humidity sensors (DHT11), soil moisture sensors, and PIR motion sensors will collect data. Moisture values will be compared with its threshold, which is different according to the plant. According to the reading of a soil moisture sensor, the irrigation pump will be actuated to turn on or off the water supply. All the peripherals come together to water the plants to an optimum level.

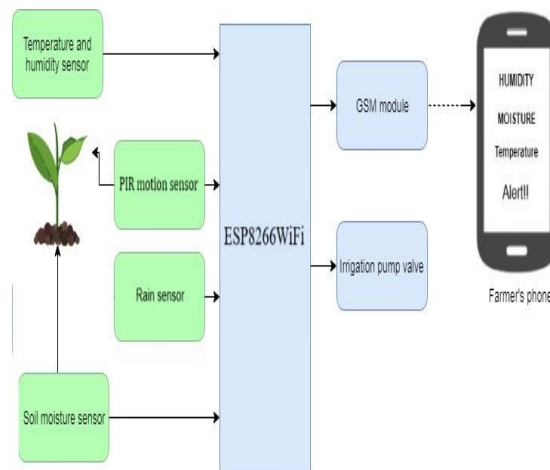


Fig. 2. Block diagram of sensor module

### 4.2. Software

#### 4.2.1. Creating Plant Disease Detection Model

First and foremost, a dataset was imported, out of which 80% of the dataset is being utilized as training and the rest for testing. After the dataset, every one of the libraries was imported, and the path for the dataset was defined. To get the labels of all the folder names, a Label Binarizer function was utilized. After this, the information was standardized according to imagenet boundaries. A model function was used to create a transfer model, and metrics were printed. After training the model for 15 epochs, we could achieve an accuracy of up to 99%. Ultimately, the model was saved and the trained data was interpreted by plotting graphs of loss vs. learning rate.

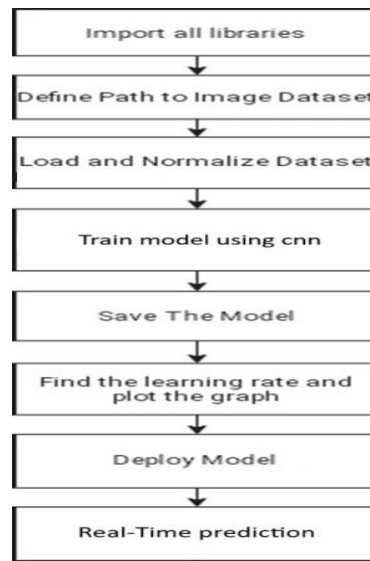


Fig. 3. Overview of Model

#### 4.2.2. Using Trained model for real-time prediction

Subsequent stage was to stack the model, which was prepared prior, and afterward utilize a web cam to catch the constant picture of the leaf and foresee whether it shows some symptoms of disease with the assistance of the trained model.

## 5. RESULT

### 5.1. Hardware

As you can observe from Fig. 4. temperature, humidity and moisture content values can be seen on the mobile phone, where an alert is generated by the pir motion sensor if any motion is detected around the plant.

| Humidity | Temperature | Soil_Moisture | Motion_Status | Rain_Status | Timestamp           |
|----------|-------------|---------------|---------------|-------------|---------------------|
| 67.5     | 24          | 0             | 0             | 0           | 2024-04-21 20:28:28 |
| 67.5     | 24          | 0             | 0             | 0           | 2024-04-21 20:28:26 |
| 68.9     | 23.8        | 0             | 0             | 0           | 2024-04-21 20:28:24 |
| 68.9     | 23.8        | 0             | 0             | 0           | 2024-04-21 20:28:22 |
| 72.2     | 23.3        | 0             | 0             | 0           | 2024-04-21 20:28:21 |
| 75.2     | 22.9        | 0             | 0             | 0           | 2024-04-21 20:28:18 |
| 75.2     | 22.9        | 0             | 0             | 0           | 2024-04-21 20:28:16 |
| 77.9     | 22.5        | 0             | 0             | 0           | 2024-04-21 20:28:15 |
| 77.9     | 22.5        | 0             | 0             | 0           | 2024-04-21 20:28:13 |
| 80.6     | 22          | 0             | 0             | 0           | 2024-04-21 20:28:11 |
| 80.6     | 22          | 0             | 0             | 0           | 2024-04-21 20:28:09 |
| 83.4     | 21.5        | 0             | 0             | 0           | 2024-04-21 20:28:07 |
| 83.4     | 21.5        | 0             | 0             | 0           | 2024-04-21 20:28:05 |
| 86.2     | 21          | 0             | 0             | 0           | 2024-04-21 20:28:03 |

Fig. 4. Serial Monitor

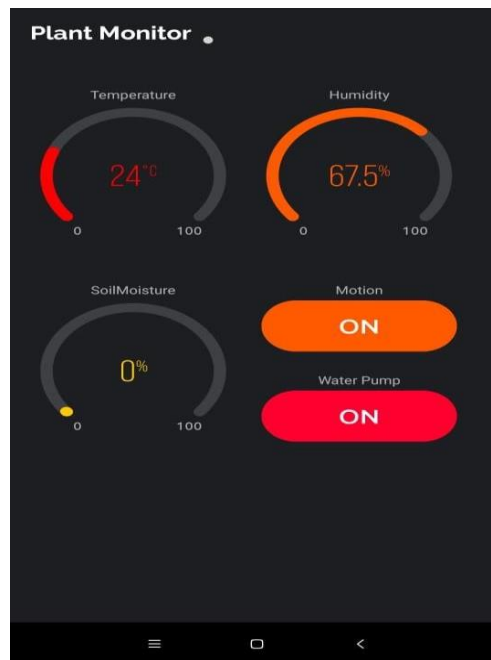


Fig. 5. User's Phone

## 5.2. Software

Learning rate is a significant element during the training of the model. Whenever kept less, it could result in dialing back and can set aside some margin to arrive at exact outcomes. Assuming it is kept high, it could not obtain an exact outcome by any stretch of the imagination. It very well may be seen from Fig. 6. that with every iteration of the model training, the loss is getting continuously diminished and the precision is expanded.

```
Epoch 1/5
78/78 ————— 194s 2s/step
- accuracy: 0.2231 - loss: 0.7874
- val_accuracy: 0.0634 - val_loss: 0.5545

Epoch 2/5
78/78 ————— 7s 68ms/step
- accuracy: 0.0938 - loss: 0.2026
- val_accuracy: 0.0824 - val_loss: 0.5236

Epoch 3/5
78/78 ————— 185s 2s/step
- accuracy: 0.3307 - loss: 0.3289
- val_accuracy: 0.0951 - val_loss: 0.3664

Epoch 4/5
78/78 ————— 8s 70ms/step
- accuracy: 0.5938 - loss: 0.0798
- val_accuracy: 0.0792 - val_loss: 0.3653

Epoch 5/5
78/78 ————— 204s 3s/step
- accuracy: 0.5465 - loss: 0.1701
- val_accuracy: 0.0903 - val_loss: 0.6585
```

Fig. 6. Analyzing the training model

You need to determine the acceptable error tolerance for your model first, and then iterate as much as needed until you either reach that threshold (i.e. until convergence), or your solver fails to make additional progress (keeps returning the same number for error over and over again). It can be observed from figure 7.1 and 7.2 that with every iteration of the model training, the loss is getting gradually decreased and the accuracy is getting increased.

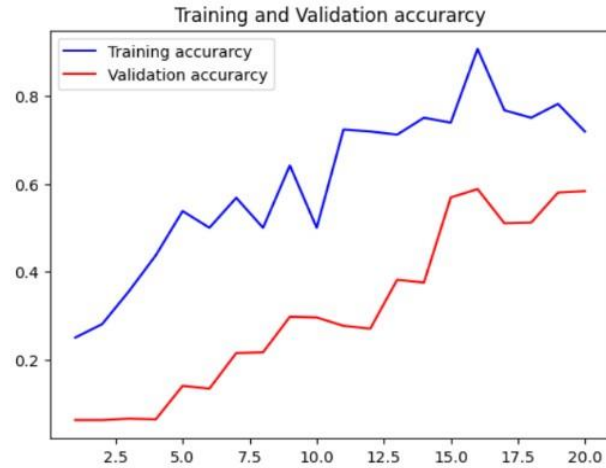


Fig. 7.1. Training and Validation Accuracy

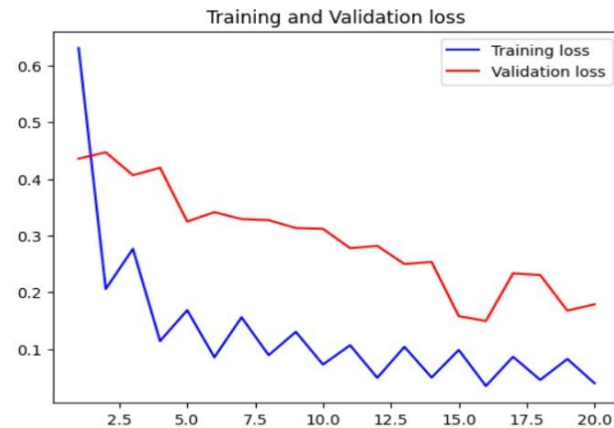


Fig. 7.2. Training and Validation Loss

The dataset used to train and test the CNN model comprises two indexes: healthy and disease. In the event of real-time testing, a Webcam catches the picture of the leaf that we have given and will be stored inside another directory, and the model uses this image to predict whether it is healthy or diseased. The leaf in Fig. 8.1. has bacterial spot disease, and the model predicts the named disease by recognizing the obvious signs with the given likelihood. The leaf in Fig. 9.1. is healthy and the model predicts by recognizing the obvious signs with the given likelihood.





Fig. 8.1. Real-time image capturing

```
1/1 ————— 0s 47ms/step  
Probability: 0.9739018  
_Bacterial_spot
```

Fig. 8.2. Prediction Probability



Fig. 9.1. Real-time image capturing

```
1/1 ————— 0s 47ms/step  
Probability: 0.9645038  
healthy
```

Fig. 9.2. Prediction Probability

## 6. CONCLUSION

The discovery of plant leaf diseases by utilizing machine learning is done effectively. The machine learning algorithm CNN is utilized for crop disease recognition and classification via training the datasets. The framework is carried out for early detection of crop diseases and precautionary measures. The temperature and humidity sensor DHT11 and the soil moisture sensor are effectively aligned. The unit for temperature value is degree Celsius, humidity and soil moisture content are given in rate. Alert messages for rain and motion detection were sent effectively, utilizing the GSM module. Analysis and detection of various crop diseases through the photo are carried out successfully, along with monitoring soil parameters.

## 7. FUTURE ENHANCEMENT

For future scope, our mobile application can be converted into a web application, making it vaster and more reachable to audiences for monitoring and detection. An additional feature can

be added to this mobile application, which will suggest remedies (pesticides) to cure the diseases, and they can also take feedback from the experts. Also, the Google Weather Forecast can be used to alert the farmers in advance about the mishaps, and he can take the necessary steps. Detection of plant diseases can also be extended from leaves to stem, root and other parts, assuring complete recognition of diseases. Our model can be powered up using either solar power or hydro power saving energy.

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