Grenze International Journal of Engineering and Technology, Jan Issue

Precision Agriculture using Machine Learning and IoT for Optimal Crop Growth and Yield

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***Abstract*— This paper presents an innovative approach to improving agricultural practices using modern technologies such as machine learning, IoT, and image processing. The proposed system includes two main modules: fertilizer prediction and crop recommendation and crop disease detection. The first module utilizes machine learning algorithms to analyze data from various sources such as soil sensors, weather stations, and historical crop yield data to predict optimal fertilizer requirements and recommend suitable crops for the specific soil type and climate. The second module employs image processing and Convolutional Neural Network (CNN) algorithms to detect crop diseases by analyzing images captured by IoT devices such as drones and cameras. The proposed system aims to increase crop yield, reduce the cost of crop maintenance, and promote sustainable farming practices. The results of this research demonstrate the potential of smart agriculture technologies in improving food security and agricultural sustainability.**

***Index Terms*— Smart irrigation system, data analytics in agriculture, precision agriculture.**

I. INTRODUCTION

Agriculture plays a significant role in ensuring food security and is the backbone of many economies. However, traditional agricultural practices are often inefficient and labor-intensive, resulting in lower crop yields and higher maintenance costs. With the rapid advancements in technology, there is an opportunity to modernize agriculture and make it more efficient and sustainable. This project proposes a smart agriculture system that integrates machine learning, IoT, and image processing technologies for fertilizer prediction, crop recommendation, and crop disease detection.

The proposed system utilizes various sensors, including DHT11 for measuring temperature and humidity, and soil moisture sensors for collecting data on soil moisture levels. The collected data is uploaded to the cloud using the Blink platform, where it is analyzed using machine learning algorithms. The system then uses this data to predict optimal fertilizer requirements and recommend suitable crops for the specific soil type and climate.

In addition to fertilizer prediction and crop recommendation, the proposed system also includes a crop disease detection module. The system captures images of crops using IoT devices such as drones and cameras and analyzes them using image processing and Convolutional Neural Network (CNN) algorithms. This helps to detect crop diseases at an early stage, allowing farmers to take timely action to prevent their spread and minimize crop losses.

The integration of IoT technologies and machine learning algorithms in agriculture has the potential to revolutionize the sector by increasing crop yields and reducing maintenance costs. Furthermore, the use of sustainable agricultural practices will also help to conserve natural resources and promote a more environmentally

Grenze ID: 01.GIJET.10.1.79
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friendly approach to farming. The following sections provide a detailed description of the system architecture, data collection, and analysis methodology

II. HELPFUL HINTS

There have been several research papers published on the topic. Here are summaries of some of the notable research papers:

1. "Integration of IoT and Machine Learning for Precision Agriculture" This paper proposes an integrated framework that combines IoT devices and ML algorithms to optimize resource management in precision agriculture, improving crop yield and minimizing environmental impact.
2. "Crop Yield Prediction using Machine Learning Techniques in Precision Agriculture" The study focuses on using ML techniques to predict crop yield based on historical data, weather conditions, soil quality, and other relevant factors. The results demonstrate the potential for precise yield estimation in agriculture.
3. "Smart Irrigation System for Precision Agriculture using IoT and ML" This paper presents a smart irrigation system that utilizes IoT sensors to collect data on soil moisture, temperature, and humidity. ML algorithms analyze the data to optimize irrigation scheduling, leading to efficient water usage and improved crop health.
4. "Weed Detection and Classification in Precision Agriculture using Machine Learning" The research focuses on developing ML-based algorithms for weed detection and classification in crop fields. The proposed approach enables precise and timely weed control, reducing the use of herbicides and minimizing yield loss.
5. "Disease Diagnosis in Crops using IoT and Machine Learning in Precision Agriculture" This study proposes a system that combines IoT sensors and ML techniques to diagnose diseases in crops. By monitoring environmental conditions and analyzing plant health data, the system enables early detection and targeted treatment of crop diseases.
6. "Optimal Fertilizer Recommendation using Machine Learning and IoT in Precision Agriculture" The paper presents a method for optimizing fertilizer application in precision agriculture by integrating ML algorithms with IoT data on soil nutrients and crop requirements. This approach ensures efficient nutrient management and minimizes environmental impact.
7. "Crop Monitoring and Yield Estimation using IoT and Machine Learning"This research focuses on developing a comprehensive crop monitoring system that utilizes IoT devices for data collection and ML algorithms for yield estimation. Accurate monitoring and prediction contribute to improved decision-making in precision agriculture.
8. "Real-time Pest Detection and Control using IoT and Machine Learning in Precision Agriculture"The study proposes an integrated system that combines IoT sensors and ML algorithms for real-time pest detection and control. By analyzing sensor data, the system provides early warnings and enables targeted pest management strategies.
9. "Energy-Efficient Sensing and Communication in IoT-based Precision Agriculture" This paper addresses energy efficiency challenges in IoT-based precision agriculture systems. It explores ML-based techniques to optimize energy consumption in sensor networks, prolonging battery life and reducing maintenance efforts.
10. "Predictive Maintenance in Precision Agriculture using Machine Learning and IoT" The research focuses on developing ML-based models to predict and prevent equipment failures in precision agriculture. By analyzing sensor data from agricultural machinery, proactive maintenance strategies can be implemented to minimize downtime.
11. "Automated Irrigation Control using ML and IoT in Precision Agriculture" This study presents an automated irrigation control system that utilizes ML algorithms and IoT sensors. By considering factors such as soil moisture, weather conditions, and plant water requirements, the system optimizes irrigation scheduling for improved water management.
12. "Drought Monitoring and Prediction using IoT and Machine Learning in Precision Agriculture" The paper proposes a system for drought monitoring and prediction in precision agriculture. By analyzing IoT data on soil moisture, weather patterns, and crop stress indicators, ML algorithms provide early warnings and inform water conservation strategies.
13. "Smart Pest Management in Precision Agriculture using IoT and ML" This research focuses on developing a smart pest
14. "Optimal Harvesting Time Prediction using Machine Learning in Precision Agriculture" This study proposes an ML-based approach to predict the optimal harvesting time for crops. By analyzing data on plant growth, weather conditions, and crop maturity indicators collected through IoT devices, farmers can make informed decisions to maximize yield and quality.

15. "Sensor Fusion Techniques for Data Integration in Precision Agriculture using IoT and ML" The paper investigates sensor fusion techniques for integrating data from multiple IoT devices in precision agriculture. ML algorithms are employed to process and combine data from different sensors, enhancing the accuracy and reliability of agricultural monitoring systems.
16. "Water Quality Monitoring in Precision Agriculture using IoT and Machine Learning" This research focuses on monitoring water quality in agricultural systems using IoT devices and ML techniques. By analyzing data on pH levels, nutrient concentrations, and contaminants, the system helps farmers maintain optimal water conditions for crop growth.
17. "Automated Crop Disease Identification using ML and IoT in Precision Agriculture" The study proposes an automated system for crop disease identification in precision agriculture. ML algorithms analyze data from IoT sensors, including images and plant health indicators, enabling early disease detection and targeted treatment.
18. "Smart Nutrient Management in Precision Agriculture using IoT and Machine Learning" This paper presents a smart nutrient management system that integrates IoT sensors and ML algorithms. By continuously monitoring soil nutrient levels and crop requirements, the system optimizes fertilizer application, ensuring balanced nutrient supply for improved crop health and productivity.
19. "Real-time Weather Monitoring and Prediction for Precision Agriculture using IoT and ML" The research focuses on real-time weather monitoring and prediction in precision agriculture. By collecting data from IoT weather stations and employing ML models, the system provides accurate and timely weather forecasts, enabling farmers to make informed decisions for crop management.
20. "Crop Growth Modeling and Yield Prediction using Machine Learning in Precision Agriculture" This study proposes a crop growth modeling framework that utilizes ML techniques to predict crop yield based on various factors such as historical data, weather conditions, and crop management practices. The model provides valuable insights for optimizing crop production and resource allocation.

Overall, these research papers demonstrate the potential of smart agriculture systems that leverage IoT and machine learning to improve crop production and promote sustainable agriculture. The papers highlight the importance of data analysis, sensor technology, and real-time recommendations for optimizing crop growth and minimizing waste.

III. METHODOLOGY

A. Hardware

The Project consists of following equipments :

1. Nodemcu

The NodeMCU comes with a firmware preloaded, which includes a Lua interpreter and a set of libraries for Wi-Fi, GPIO, and other functions. It can be programmed using Lua scripts, but it is also compatible with the Arduino IDE and can be programmed using the Arduino language. In addition to its built-in Wi-Fi capabilities, the NodeMCU can also be used with various sensors and actuators, making it a popular choice for IoT projects. It also supports the MQTT protocol for IoT messaging and has a built-in web server for creating web based user interfaces.

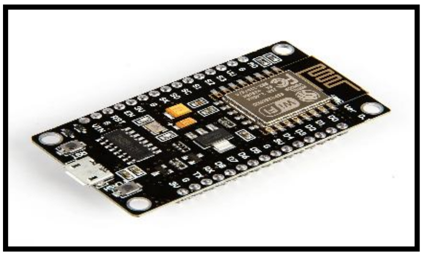

Fig 1: Node MCU

2. DHT

DHT stands for Digital Humidity and Temperature sensor. It is a type of sensor that can measure both humidity and temperature levels in the surrounding environment. There are various types of DHT sensors available, but the most common ones are the DHT11 and DHT22 sensors. The DHT sensors use a capacitive humidity sensor and a thermistor to measure humidity and temperature, respectively. The sensor outputs a digital signal that can be read by a microcontroller or other electronic device.

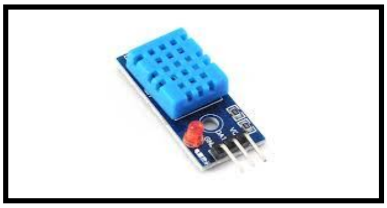

Fig 2: DHT sensor

The DHT11 is a low-cost sensor that can measure humidity levels between 20% and 90% with an accuracy of ±5%. It can also measure temperature between 0°C and 50°C with an accuracy of ±2°C.
The DHT22 is a higher-end sensor that can measure humidity levels between 0% and 100% with an accuracy of ±2-5%, depending on the temperature and humidity range. It can also measure temperature between -40°C and 80°C with an accuracy of ±0.5°C. The DHT11 is a low-cost sensor that can measure humidity levels between 20% and 90% with an accuracy of ±5%. It can also measure temperature between 0°C and 50°C with an accuracy of ±2°C. The DHT22 is a higher-end sensor that can measure humidity levels between 0% and 100% with an accuracy of ±2-5%, depending on the temperature and humidity range. It can also measure temperature between -40°C and 80°C with an accuracy of ±0.5°C.
Both the DHT11 and DHT22 sensors are commonly used in various IoT projects, such as weather monitoring systems, indoor climate control, and smart home automation. They can be interfaced with microcontrollers like Arduino or NodeMCU to collect and analyze data, and can be programmed to trigger certain actions based on the measured values. Both the DHT11 and DHT22 sensors are commonly used in various IoT projects, such as weather monitoring systems, indoor climate control, and smart home automation. They can be interfaced with microcontrollers like Arduino or NodeMCU to collect and analyze data, and can be programmed to trigger certain actions based on the measured values.

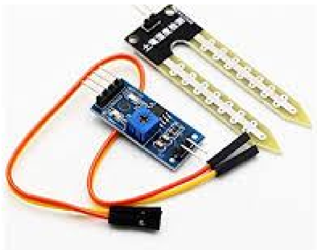

Fig 3: NodeMcu : Esp8266

3. Moisture Sensor

A moisture sensor is a type of sensor that is used to detect the moisture content of soil or other substances. There are several types of moisture sensors available, but the most common ones are resistive, capacitive, and Time Domain Reflectometry (TDR) sensors.
Here are some technical details about moisture sensors:

a. Resistance Range

The resistance range of the sensor determines the accuracy of moisture detection. A typical resistive moisture sensor has a resistance range between 100 kΩ to 100 MΩ.

b. Sensitivity

The sensitivity of the sensor determines how much the resistance or capacitance changes for a given amount of moisture. Sensitivity is usually expressed as a percentage change per unit of moisture.

c. Operating Voltage

The operating voltage of a moisture sensor varies depending on the type of sensor. For resistive moisture sensors, the operating voltage is typically between 3 to 5 volts DC. For capacitive sensors, the operating voltage is usually between 3.3 to 5 volts DC.

d. Measurement Range

The measurement range of the sensor determines the minimum and maximum moisture levels that can be detected. This range can vary depending on the type of sensor and the environment in which it is used.

e. Output Signal

The output signal of a moisture sensor can be analog or digital. Analog sensors output a voltage or current that changes with the moisture level, while digital sensors output a binary signal indicating whether the moisture level is above or below a certain threshold.

f. Calibration

Moisture sensors need to be calibrated for accurate readings. Calibration involves determining the relationship between moisture content and sensor output, and can be done using a known moisture source or by comparing readings to a reference sensor.

B. Software

The Software part of project consists of an application that is integrated with 3 Machine Learning models that are helping to for prediction of different parameters and the app act as the interface between
User and the models. The application is made using Flutter and uses dart as its programming language. We have divided the whole structure of application into 4 parts namely:

1. Crop Recommendation.
2. Fertilizer Prediction.
3. Disease Prediction
4. Farm status

Fig. Application Interface

1. Crop Recommendation

The model used for Fertilizers prediction is developed using Deep Neural Networks (DNN). Dataset which is used for training and testing purposes is obtained from Kaggle.

Working of the model

1. DNN model processes the input data through the network.
2. Then each hidden layer extracts and transforms features to generate meaningful representations.
3. The model is trained using the ReLu Function.

4. Trained model is scaled using the MinMaxscaler function.
5. And a scaled array of values is used for prediction.

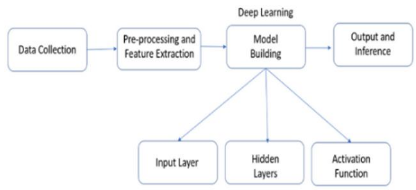

Fig. Workflow of the model

Crop is recommend for a particular field by taking various input parameters such as

- Nitrogen
- Phosphorus
- Potassium
- Rainfall
- Temperature
- Humidity
- PH

The values are given to model and the prediction is obtained after which user is given respective information about the crop and can also choose to get more information through the buttons available. The dataset used for the model is taken from Kaggle website and is divided as 80% of data for training and 20% for testing.

2. Fertilizer Detection

The model used for Fertilizers prediction is developed using Deep Neural Networks (DNN). Dataset which is used for training and testing purposes is obtained from Kaggle. The dataset used comprises various features such as soil temperature, soil moisture, Nitrogen, Phosphorous, Potassium Values, Humidity, Crop Type, Soil Type.
Working of the model:

1. DNN model processes the input data through the network.
2. Then each hidden layer extracts and transforms features to generate meaningful representations.
3. The model is trained using the ReLu Function.
4. Trained model is scaled using the MinMaxscaler function.
5. And a scaled array of values is used for prediction.

So by utilizing a DNN architecture, which consists of multiple hidden layers, the model is capable of learning complex patterns and relationships within the dataset and more accurate results are delivered to farmers.

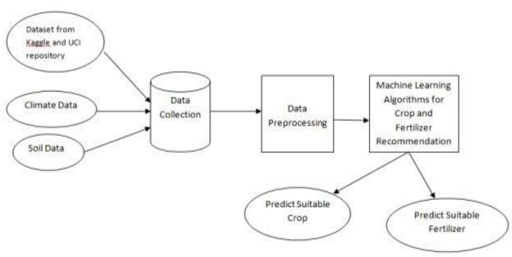

Fig. Workflow of the model

3. Disease Detection

Convolutional Neural Network (CNN) model is employed for leaf disease detection. The model is trained and tested using the Plant Village dataset, a widely used dataset specifically designed for plant disease classification.

The dataset provides a diverse range of leaf images, including both healthy leaves and leaves affected by different diseases.
Below flowchart explains the working of CNN:

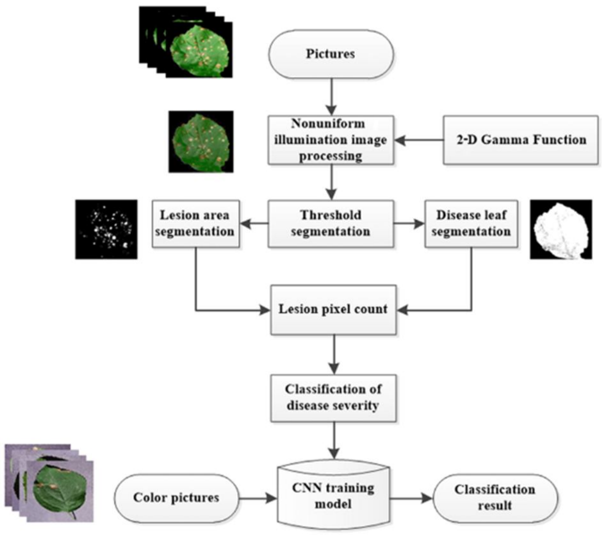

Fig. Working of CNN

Steps to be followed before deployment of the model
1. Train CNN model to learn and distinguish patterns and features indicative of specific plant diseases.
2. Trained model is then evaluated on a separate testing set from the same dataset
3. Assess its performance and accuracy in detecting and classifying leaf diseases.

Working of the model
1. Input the leaf image
2. Pre-process the image
3. Feature Extraction
4. NN classification
5. Result

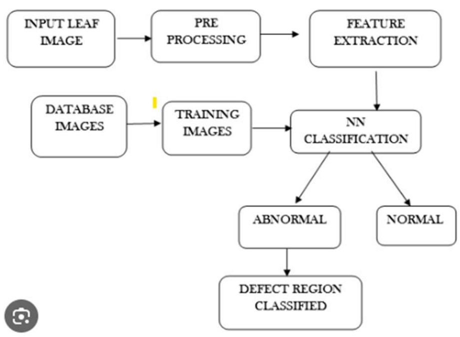

Fig. Working of the model

4. Min-Max scaling

The Min-Max scaling technique, also known as Min-Max normalization, scales numerical features to a specific range, typically between 0 and 1. The mathematical formula for Min-Max scaling is as follows:
For each feature, the scaled value (S) is calculated for each data point (x) as:
S = (x - min(X))/(max(X) - min(X)
Where:
1. s the scaled value of the feature.
2. s the original value of the feature for a specific data point.
3. min(X) is the minimum value of the feature across all data points.

4. max(X) is the maximum value of the feature across all data points.

Here's a step-by-step explanation of the process:

Find the minimum (min(X)) and maximum (max(X)) values of the feature across all data points in the dataset.

For each data point, subtract the minimum value (min(X)) from the original feature value x). This operation ensures that the minimum value of the scaled feature is 0.

Divide the result from step 2 by the range of the feature, which is the difference between the maximum value (max(X)) and the minimum value (min(X)). This step scales the feature to fit within the range [0, 1].

The result of Min-Max scaling is that all values of the feature are transformed to a range between 0 and 1, with 0 corresponding to the minimum value in the original data and 1 corresponding to the maximum value. Values between 0 and 1 represent the relative position of a data point within the range of the feature.

This scaling technique is useful when working with algorithms or models that are sensitive to the scale of the input features, as it ensures that all features have a consistent and comparable impact on the model regardless of their original scales.

IV. Results And Conclusion

1. Crop Prediction

Crop prediction model developed using Deep Neural Networks (DNN) has yielded remarkable results, achieving an impressive accuracy of 94.6%.

This accuracy of 94.6% showcases its potential as a reliable tool for crop prediction, enhancing agricultural productivity, and aiding in sustainable agricultural practices.

2. Fertilizer Prediction

Fertilizer prediction model developed using Deep Neural Networks (DNN) has also demonstrated outstanding performance, achieving an impressive accuracy rate of 94.6%.

With an accuracy of 94.6%, the developed fertilizer prediction model holds significant potential in assisting farmers, agronomists, and fertilizer manufacturers. By providing precise and tailored fertilizer recommendations, the model can help optimize plant nutrition, minimize environmental impact, and improve crop yields.

3. Leaf Disease Detection

Convolutional Neural Network (CNN) model developed for leaf disease detection has demonstrated outstanding performance, achieving an impressive accuracy rate of 95%. This high level of accuracy indicates the model's capability to effectively classify and identify various leaf diseases.

Overall, we have developed a robust application which can

- detect soil moisture.
- detect humidity and soil moisture
- recommend suitable crop
- recommend fertilizers
- detect plant disease and recommend pesticide

thus helping the farmer to increase his income and efficiency in agricultural practices.

V. Future Scope And Acknowledgement

Here are several potential future scopes for the smart agriculture IoT-based project:

1. Expansion of the system

The current project can be expanded to cover more crops and regions, providing farmers with a comprehensive solution for optimizing crop growth and minimizing waste.

2. Integration with drones and robotics

The integration of drones and robotics with the smart agriculture system can automate certain farming tasks such as planting, irrigation, and pest control, reducing labor costs and increasing efficiency.

3. Sustainability and Environmental Impact

The project can further emphasize sustainability by incorporating environmental impact assessments and promoting eco-friendly farming practices.

Overall, the future scope for the smart agriculture IoT-based project is vast, and there are numerous opportunities for innovation and growth.

We would like to extend our heartfelt acknowledgement to our project guide Prof. Mukund Kulkarni for his guidance and support towards the project.

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