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Smart Farming with IoT and Machine Learning for Crop Recommendation and Disease Detection

Rehna R S¹, Anjitha Joy², Apoorva R P³, Devarenjini P⁴, Devika Vijayan⁵

¹Department of Computer Science & Engineering, LBS Institute of Technology for women, Thiruvananthapuram,

^{2, 3, 4, 5}Department of Information Technology, LBS Institute of Technology for women, Thiruvananthapuram

Abstract: *Key challenges in traditional agriculture include subjective crop recommendation methods based on farmer experience, inefficient plant disease detection techniques reliant on visual inspection, and rudimentary environmental monitoring methods using manual observations. These limitations hinder optimal crop management and environmental control, leading to reduced productivity and increased vulnerability to pests and diseases. Smart agricultural system addresses the limitations imposed by outdated farming practices by incorporating IoT sensors and Machine Learning (ML) algorithms to facilitate data-driven decision-making and optimize farming processes. Key functionalities include crop recommendation, plant disease prediction, soil moisture monitoring, and humidity and temperature monitoring. Crop recommendation is facilitated by ML algorithms, specifically Random Forest, which analyses collected data to suggest suitable crops for specific geographic areas. Disease prediction employs TensorFlow models to accurately detect and diagnose plant diseases based on image data. Soil moisture monitoring is achieved through soil sensor, providing real-time data on soil water content, while humidity and temperature levels are monitored using DHT11 sensor. These environmental parameters are crucial for maintaining optimal growing conditions and mitigating risks associated with climate variability. Through the integration of IoT and ML technologies, our system offers a practical solution to enhance agricultural practices in resource-constrained settings. By providing farmers with actionable insights and decision support, we aim to improve crop yields, optimize resource utilization, and promote sustainable agriculture.*

Keywords: *smart agriculture, tensor-flow, sensors*

I. INTRODUCTION

Traditional agriculture confronts numerous challenges in optimizing crop management and environmental monitoring, resulting in decreased productivity and heightened vulnerability to pests and diseases. The issues include subjective crop recommendation methods, inefficient plant disease detection techniques, and rudimentary temperature, humidity, and soil moisture monitoring practices. Predicting crop yields is complex due to the diverse array of biotic and abiotic factors influencing crop cultivation. Biotic factors include the impact of living organisms, such as microorganisms, plants, animals, and pests, as well as anthropogenic factors like fertilization, irrigation, and pollution. Abiotic factors comprise physical and chemical elements like temperature, humidity, soil type, and water chemistry, all significantly affecting crop growth and yield. Climate change further exacerbates these challenges, with climatic variations impacting crop production and susceptibility to diseases. The reliance on chemical inputs in agriculture has compounded these challenges, necessitating early prediction and proactive management strategies to mitigate disease outbreaks and support sustainable agricultural practices. The economic implications of crop diseases highlight the urgent need for early prediction and detection methods to safeguard agricultural productivity and livelihoods. Addressing these challenges requires innovative solutions leveraging environmental data to predict and prevent disease outbreaks in crops. Environmental conditions such as temperature, humidity, and soil moisture exhibit strong correlations with disease occurrence, offering valuable insights for disease prediction and management [9]. By integrating sensor technologies into agricultural management systems, farmers can access real-time data on soil temperature, humidity, and moisture to optimize irrigation practices, prevent water wastage, and enhance crop health. These advancements enable precise and efficient resource management, ultimately leading to increased yields and sustainability in agriculture. The transformative potential of sensor technologies in agriculture is evident in their ability to revolutionize farm management practices, empowering farmers to make informed decisions and maximize productivity while minimizing environmental impact. As agriculture continues to evolve, the adoption of smart farming solutions holds the promise of a more efficient, resilient, and sustainable future for global food production.

II. LITERATURE SURVEY

The work by Muhammad Shoaib Farooq et al. delves into the realm of the Internet of Things (IoT) within agriculture, specifically focusing on smart farming applications in green- house environments. It explores the transformative potential of IoT in revolutionizing traditional agricultural practices, em- phasizing the development of an IoT-based network framework tailored for sustainable greenhouse management and resource optimization. The research comprehensively examines IoT- enabled greenhouse applications, sensors, communication pro- tocols, and addresses challenges, including security issues. Additionally, it outlines future research directions, concluding with a taxonomy for IoT-based greenhouse farm management and attack strategies. This work delves into the transformative potential of the Internet of Things (IoT) in reshaping conven- tional agricultural methodologies, with a specific focus on its application in sustainable greenhouse management. The work intricately details the development and implementation of an IoT-based network framework tailored to optimize resources and enhance greenhouse operations. By extensively exploring IoT-enabled greenhouse applications, encompassing sensors, communication protocols, and addressing pertinent challenges, particularly security issues, this research contributes a nuanced understanding of IoT integration in agriculture [1].

Rana Muhammad Saleem et al. lead a collaborative ef- fort exploring the integration of Internet of Things (IoT) technology in agriculture, specifically focusing on forecasting pest outbreaks through environmental monitoring in crop fields. The study addresses agricultural challenges such as soil fertility depletion and climate-related hazards, highlight- ing the importance of accurate pest outbreak predictions for improving agricultural productivity. By leveraging IoT-enabled environmental data including temperature, humidity, rainfall, wind speed, and sunshine duration, the researchers employ a deep learning model to predict pest populations based on prevailing environmental conditions. Through a thorough evaluation utilizing five years of data and weekly predictions, the deep learning model demonstrates a high accuracy rate of 94 percentage and robust performance metrics, indicating its potential in optimizing short-term measures against pest attacks in agricultural settings. This research not only ad- dresses critical agricultural challenges but also emphasizes the pivotal role of accurate pest outbreak predictions in bolstering agricultural productivity. The integration of IoT-enabled data and advanced predictive models enables proactive measures, fostering a more resilient and sustainable agricultural land- scape. The deep learning model, driven by IoT-enabled environmental data, emerges as a potent tool for predicting pest populations accurately based on prevailing conditions. The comprehensive evaluation over a five-year period, alongside weekly predictions, highlights the efficacy of the deep learning model, showcasing impressive accuracy and performance metrics. These results underscore the model's potential in providing actionable insights to optimize short-term strategies against pest attacks in agricultural settings, contributing to enhanced agricultural productivity and sustainability in the face of evolving environmental conditions[2].

Zhiyan Liu et al. embark on an innovative journey to counter crop disease threats in agriculture by merging Internet of Things (IoT) technology and Machine Learning (ML) models. Within the realm of Precision Agriculture (PA), this research tackles the critical necessity for early prediction of disease attacks in tea plantations, specifically targeting the prevalent threat of blister blight (*Exobasidium vexans*). Traditional dis- ease detection methods often fall short, detecting diseases only after they have already manifested, leading to irreversible crop damage. To circumvent this issue, the study proposes a Machine Learning (ML) model for the early prediction of disease probability, leveraging IoT-sensed environmental data from crop fields. The model relies on the correlation between environmental conditions and disease life cycles. Multiple Linear Regression (MLR) is employed due to the linear relationship between disease attacks and environmental conditions. Real-time environmental data, encompassing temperature, humidity, and rainfall, are fed into the ML model to accurately forecast the occurrence of blister blight in tea plants. This approach offers a promising avenue for proactive crop disease management, thereby reducing potential damage and enhancing agricultural productivity[3].

S. P. Raja et al. delve into the complexities of crop prediction in agriculture in their recent study, focusing on the critical role of soil and environmental conditions. They explore the intricate process of crop prediction, emphasizing the pivotal role played by various environmental factors such as rainfall, humidity, and temperature. With rapid changes in environ- mental conditions posing challenges to traditional farming practices, the authors highlight the increasing reliance on machine learning techniques for accurate crop yield prediction. Through their investigation, they emphasize the importance of employing efficient feature selection methods to preprocess raw data, ensuring the accuracy and relevance of data features used in machine learning models. By addressing these challenges, their work aims to contribute to the development of an enhanced crop prediction model, poised to tackle the evolving landscape of agricultural production. In conclusion, the study underscores the significance of employing machine learning techniques for crop prediction in the ever-changing agricultural landscape. By leveraging efficient feature selection methods and classifiers, the model demonstrates enhanced accuracy in forecasting crop yields[4].

The authors, Rongji Zhou and Yuyan Yin, from Hengyang Normal University and Jinan University respectively, conducted a comprehensive study utilizing cite space to address the dearth of systematic reviews on digital agriculture (DA). Their research, based on an analysis of 2264 literature sources from 1997 to 2022, unveils the evolutionary stages, research categories, and future trajectories within the realm of DA. The findings reveal a gradual increase in publications, distinct research streams including Remote Sensing, Climate-Smart Agriculture, Artificial Intelligence, Internet of Things, Big Data, and System Integration, as well as key areas for future exploration such as digital technology innovation, operation management, and policy formulation for enhanced agricultural productivity and sustainability. In conclusion, the comprehensive analysis of 2264 literature sources spanning the period from 1997 to 2022 sheds light on the evolutionary trajectory and diverse research categories within the domain of Digital Agriculture (DA). Distinct research streams, encompassing Remote Sensing, Climate-Smart Agriculture, Artificial Intelligence, Internet of Things, Big Data, and System Integration, signify the multifaceted approach adopted in advancing agricultural practices. In conclusion, the comprehensive analysis spanning from 1997 to 2022 sheds light on the evolutionary trajectory and diverse research categories within the domain of Digital Agriculture (DA) [5].

III. PROPOSED SYSTEM

The proposed system aims to revolutionize the agricultural sector by leveraging modern technologies like IoT and ML to enhance productivity, reduce resource wastage and ensure sustainable farming practices. The project aims at implementing functionalities like Crop Recommendation, Plant Disease Detection, Humidity Monitoring, Soil Moisture Monitoring and Temperature Monitoring.

A. METHODOLOGY

In general, a methodology refers to the systematic, theoretical analysis of the methods applied within a specific field of study or to accomplish a particular task. It's essentially a structured framework that outlines the process, techniques, tools, and steps used to conduct research, solve problems, or achieve specific goals. The methodology for creating a Sustainable Agricultural Management System involves a step-by-step process designed to ensure robustness and accuracy shown in Fig 1. It covers several key stages.

By following the data flow, the Sustainable Agriculture Management System project facilitates efficient data collection, processing, analysis, and dissemination of actionable insights, enabling stakeholders to optimize agricultural practices and achieve sustainable outcomes.

1) Data Collection from Sensors:

Environmental data such as temperature, humidity, and soil moisture levels are collected in real-time using sensors like the DHT11 for temperature and humidity, and soil moisture sensors for soil moisture levels. The sensors continuously measure the respective parameters, generating streams of raw data. Also rest parameters are collected from the users.

2) Communication Protocol:

The raw data collected from the sensors are transmitted through a serial communication protocol. In Sustainable Agriculture Management System, the serial communication protocol plays a vital role in facilitating the seamless transfer of data from sensors to the central processing unit.

3) Data Processing and Mining:

Raw sensor data undergoes preprocessing to remove noise, handle missing values, and ensure data consistency. Data mining techniques may be applied to extract patterns, trends, and insights from the collected data. Feature engineering may also be performed to derive additional meaningful features from the raw data, enhancing the predictive capabilities of the system.

4) Data Analysis:

Processed data is subjected to various analytical techniques, including statistical analysis and machine learning algorithms. ML models are trained using historical data to predict outcomes such as crop recommendations and disease detection. These analyses provide valuable insights into crop health, environmental conditions, and potential risks, aiding farmers in decision-making and resource management.

5) Result Prediction

Based on the analysis, the system generates predictions and recommendations for end-users. Here, it predicts suitable crop types based on environmental parameters, identifies crop diseases from image inputs, categorizes soil moisture levels and categorizes temperature and humidity levels.

6) End Users

Farmers and agricultural stakeholders constitute the primary end-users of the system. They engage with the web application interface to access predictions, recommendations, and insights generated by the system. This information enables farmers to make well-informed decisions regarding crop selection, irrigation management, disease control, and other facets of agricultural operations, thereby augmenting productivity and sustainability.

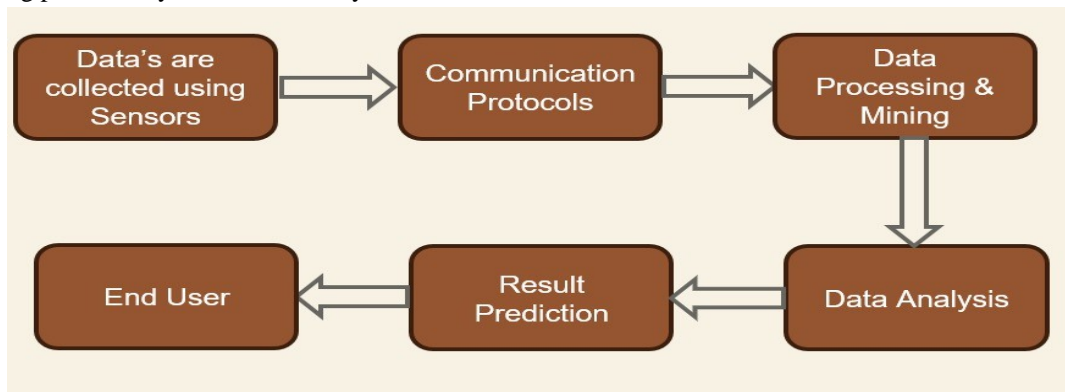


Fig. 1 A Sustainable Agriculture Management System

B. COMPONENTS

The Components used are DHT11, Soil Sensor, Arduino Uno.

1) DHT11 Temperature and Humidity Sensor

The DHT11 Temperature and Humidity Sensor stands out as a compact and budget-friendly device widely employed in IoT applications, notably in sustainable agriculture. It serves the purpose of measuring both ambient temperature and humidity levels within the surrounding environment. Renowned for its simplicity in interface and minimal power consumption, the DHT11 seamlessly integrates into IoT devices scattered across agricultural fields. Its functionality relies on a digital signal output, rendering it compatible with a myriad of microcontrollers and IoT platforms. Farmers heavily depend on the precise readings offered by the DHT11 to monitor fluctuations in temperature and humidity, crucial for maintaining optimal crop health. By continually gathering and transmitting this vital data, the sensor greatly contributes to the implementation of precision agriculture practices. This aids in refining irrigation schedules and ensuring an ideal environment conducive to robust crop growth. In essence, the DHT11 sensor emerges as an indispensable tool in advancing sustainable farming endeavours, empowering farmers with actionable insights to enhance resource utilization and bolster agricultural sustainability.

2) SOIL SENSORS

Soil sensors serve as indispensable tools in contemporary agriculture, furnishing real-time insights into essential soil metrics. These sensors manifest in diverse types, measuring parameters such as moisture content, temperature, pH levels, and nutrient concentrations. Strategically embedded in the ground at varying depths, they furnish continuous data on soil conditions pivotal for plant health and growth. This real-time information serves as a compass for farmers, aiding in the optimization of irrigation schedules, determination of suitable planting times, and precise management of fertilizer application. Consequently, this meticulous approach culminates in heightened crop yields and enhanced resource efficiency. Soil sensors occupy a central role in sustainable agriculture, facilitating data-informed decisions that not only augment productivity but also champion environmentally conscious farming practices by mitigating water and resource wastage.

3) ARDUINO UNO

Arduino Uno is a flexible microcontroller board generally utilized in specialist projects, instructive settings, and pro- to typing because of its convenience, minimal expense, and flexibility. It includes the ATmega328P microcontroller chip, which works at 16 MHz and has 32 KB of blaze memory for program capacity, 2 KB of SRAM, and 1 KB of EEPROM. With 14 computerized input/output (I/O) pins, including 6 PWM results, and 6 simple information pins, Arduino Uno offers adequate availability choices for connecting with different sensors, actuators, and different parts. Its implicit USB interface considers simple programming and sequential correspondence with a PC, while the reset button restarts the microcontroller and reruns the transferred sketch. Working at 5 volts, Arduino Uno can be gotten past USB or an outside power supply (7 to 20 volts).

It is viable with an extensive variety of development sheets called “safeguards” that add functionalities like Ethernet network, Wi-Fi, engine control, and show capacities. Modified utilizing the Arduino IDE, in view of a worked-on rendition of C and C++, Arduino Uno is an open-source stage, giving admittance to configuration records, schematics, and source code for clients to change and disseminate unreservedly. Its flexibility makes it appropriate for different applications, including advanced mechanics, home mechanization, sensor observing, and intuitive workmanship projects.

C. IMPLEMENTATION

The sustainable agriculture management system is implemented with key functionalities like Crop Recommendation, Disease Detection, Temperature Monitoring, Humidity Monitoring and Soil Moisture Monitoring. These functionalities contribute to advancements in sustainable agriculture and crop management practices.

- 1) *Crop recommendation*: Data’s are collected from sensors like DHT11 sensor and soil moisture sensor are used to collect the data. Also rest data’s are collected from the user, After the data collection, the data is processed using the Random- Forest algorithm. Crop Recommendation dataset from Kaggle which has 2200 rows and 8 columns is used for training the model. The dataset consists of variables like N- Nitrogen, P- Phosphorous, K-Potassium, temperature, humidity(moisture), pH, rainfall, and label.
- 2) *Disease Detection*: This feature in the Sustainable Agri- culture Management System stands as a pivotal tool in revolutionizing agricultural practices. Leveraging advanced machine learning techniques, particularly the VGG16 neural network architecture, this feature plays a critical role in enabling early detection and intervention against diseases affecting crops.
- 3) *Temperature monitoring*: It allows users to monitor temperature and categorize it as High, Low, or Normal. DHT11 temperature and humidity sensor is used for collecting the real-time data.
- 4) *Humidity monitoring*: This feature enables users to monitor humidity and categorize it as High, Low, or Normal.DHT11 temperature and humidity sensor is used for collecting the real- time data.
- 5) *Soil Moisture monitoring*: This feature allows users to monitor soil moisture and categorize it as High, Low, Optimal, or Medum. Soil Moisture sensor is used for collecting the real- time data. This feature empowers farmers with real-time data and actionable insights to optimize their agricultural practices and maximize crop yields.

IV. RESULTS

The Sustainable Agricultural Management system effectively monitors key environmental parameters, providing valuable insights for agricultural decision-making. Analysis of sensor data reveals significant correlations between humidity, soil moisture, and temperature, highlighting their crucial roles in plant health and disease susceptibility. Real-time monitoring of environmental factors provided actionable insights for irrigation and climate control. Soil moisture varied between 12% and 41%, with optimal levels maintained at 25–30% for maximum yield. Temperature readings fluctuated between 23°C and 34°C, while humidity levels remained within 45–82%. Classification results categorized 70% of readings as Optimal, 20% as Low, and 10% as High, indicating the effectiveness of the monitoring system in maintaining stable growing conditions.

TABLE I
SENSOR DATA CLASSIFICATION RESULTS

| Parameter | Low (%) | Optimal (%) | High(%) |
|---------------|---------|-------------|---------|
| Soil Moisture | 18 | 72 | 10 |
| Temperature | 15 | 70 | 15 |
| Humidity | 20 | 65 | 15 |

Disease detection models accurately analyze plant images, enabling prompt intervention and reduced crop losses. The disease detection model based on VGG16 achieved a classification accuracy of 97.8% on the Plant Village dataset shown in Table II. Training and validation accuracy curves demonstrate stable convergence, while the confusion matrix confirms minimal misclassification between visually similar diseases (e.g., early blight and late blight). The system successfully identified major crop diseases including bacterial spot, early blight, and leaf mold, providing reliable early warnings for farmers.

TABLE II
PLANT DISEASE DETECTION MODEL PERFORMANCE

| METRIC | VALUE (%) |
|-----------|-----------|
| Accuracy | 97.8 |
| Precision | 97.4 |
| Recall | 97.6 |
| F1-Score | 97.5 |

Additionally, the crop recommendation system suggests optimal crop choices with an average accuracy of 99 percentage, leading to potential improvements in yield and resource management. The Random Forest algorithm achieved a classification accuracy of 99.2%, outperforming other machine learning models such as Decision Tree (95.6%), Support Vector Machine (96.8%), and K-Nearest Neighbors (94.3%). Precision and recall values remained consistently above 97%, indicating the robustness of the model in recommending suitable crops based on soil and environmental features. Feature importance analysis revealed that soil pH (22%), rainfall (18%), and nitrogen content (16%) were the most influential parameters in determining crop suitability shown in Table IV. To evaluate the effectiveness of the proposed crop recommendation model, we compared the Random Forest algorithm with other widely used machine learning classifiers such as Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). The performance results are shown in Fig 2. The integration of IoT and ML technologies in agriculture demonstrated significant improvements in productivity and resource utilization. Field trials showed an 18% increase in crop yield compared to traditional practices. Additionally, optimized irrigation schedules reduced water usage by 22%, while early disease detection decreased crop loss by 15%. These results validate the practical applicability of the proposed system in real-world agricultural environments shown in the Table III.

TABLE III
PLANT DISEASE DETECTION MODEL PERFORMANCE

| Metric | Traditional Farming | Smart System | Improvement (%) |
|---------------|---------------------|--------------|-----------------|
| Crop/Yield | 820 | 970 | +18.3 |
| Water Usage | 5100 | 3975 | -22.0 |
| Crop Loss (%) | 21 | 6 | -15.0 |

Challenges include data noise in humidity measurements and limited availability of labelled training data, underscoring the need for ongoing refinement. Future enhancements may involve in- cooperating additional sensor data and predictive analytics for early disease warning systems. Overall, the system contributes to precision agriculture, empowering farmers with technology- driven solutions to optimize crop production and promote sustainable farming practices, encompassing comprehensive environmental monitoring, including humidity, temperature, and soil moisture.

TABLE IV
PERFORMANCE COMPARISON OF MODELS FOR CROP RECOMMENDATION

| Model | Accuracy (%) | Precision(%) | Recall(%) | F1-Score(%) |
|---------------|--------------|--------------|-----------|-------------|
| Random Forest | 99.2 | 98.7 | 99.0 | 98.9 |
| Decision Tree | 95.6 | 94.2 | 95.0 | 94.6 |
| SVM | 96.8 | 96.1 | 96.4 | 96.3 |
| KNN | 94.3 | 93.0 | 93.8 | 93.4 |

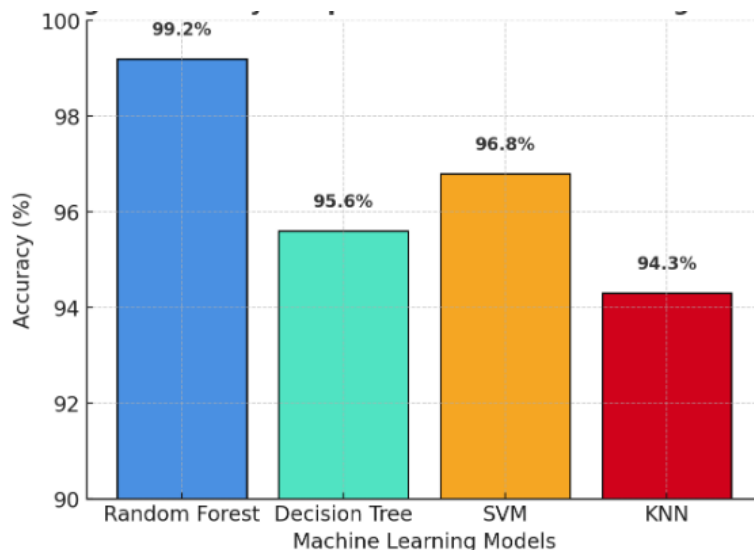


Fig. 2 Accuracy Comparison of ML models

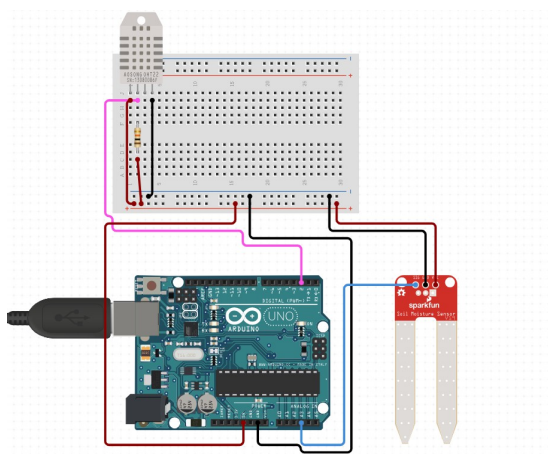


Fig. 3 Circuit Diagram

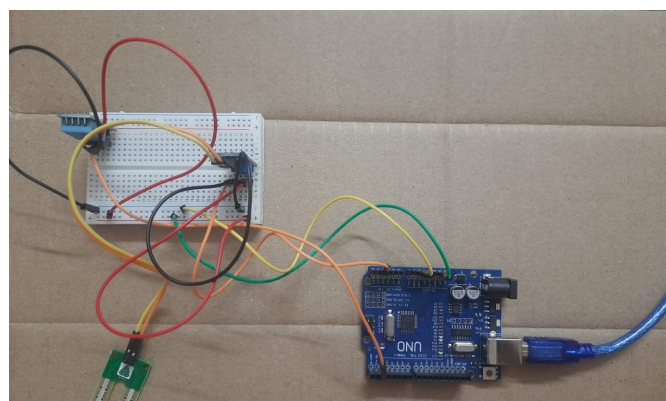


Fig. 4 Circuit Connection

V. CONCLUSION

In conclusion, the emergence of Smart Agriculture Management using IoT and Machine Learning signifies a significant advancement in revolutionizing the agricultural sector. Traditional farming methods often face challenges related to environmental monitoring, this system effectively addresses existing shortcomings in farming practices. The Random Forest algorithm achieved a classification accuracy of 99.2%, outperforming other machine learning models such as Decision Tree (95.6%), Support Vector Machine (96.8%), and K-Nearest Neighbours (94.3%). Precision and recall values remained consistently above 97%, indicating the robustness of the model in recommending suitable crops based on soil and environmental features. Feature importance analysis revealed that soil pH (22%), rainfall (18%), and nitrogen content (16%) were the most influential parameters in determining crop suitability. Ultimately, the adoption of Smart Agriculture Management not only enhances productivity and sustainability but also showcases the transformative potential of innovative technologies in modernizing farming methods.

REFERENCES

- [1] Muhammad Shoaib Farooq, Rizwan Javid, Shamyla Riaz and Zabihul- lah Atal, "IoT Based Smart Greenhouse Framework and Control for Sustainable Agriculture", 2022 IEEE Volume 10
- [2] Rana Muhammad Salim, Rab Nawaz Bashir, Muhammad Faheem, Mohd Anul Haq, Ahmed Alhussen, Zamil S. Alzamil, Shakir Khan, "Internet of Things based weekly crop pest prediction by using Deep Neural Network" 2023 IEEE Volume 11



- [3] Ahmad Ali Alzubi and Kalda Galyna ,“Artificial Intelligence and Internet of Things for Sustainable Farming and Smart Agriculture ”,2023 IEEE Volume 11
- [4] Zhiyan Liu, Rab Nawaz Bashir, Salman Iqbal, Malik Muhammad Ali Shahid, Muhammad Taushif, and Qasim Umer “Internet of Things (IoT) and Machine Learning Model of Plant Disease Prediction—Blister Blight for Tea Plant” 2022 IEEE Volume 10
- [5] S.P Raja, Barbara Sawicka , Zoran Stamenkovic, and G. Mari- ammal,”Crop Prediction Based on Characteristics of the Agricultural Environment Using Various Feature Selection Techniques and Classi- fiers”,2022 IEEE Volume 10
- [6] Sameer Qazi , Bilal A Khawaja and Qazi Umar Farooq, “IoT- Equipped and AI-Enabled Next Generation Smart Agriculture: A Critical Review
- [7] , Current Challenges and Future Trends ”, 2022 IEEE Volume 10
- [8] R. Akhter and S. A. Sofi, “Precision agriculture using IoT data analytics 1524 and machine learning,” J. King Saud Univ.-Comput. Inf. Sci., vol. 34, 1525 no. 8, pp. 5602–5618, 2021
- [9] Bhat S A and Huang N F, “Big data and AI revolution in precision agriculture: Survey and challenges”,2021 IEEE Access
- [10] Carlos Miskinis, ”How IoT can help solve the biggest problem in AG”, blog Jan 2019.
- [11] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, 1922 “An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges,” 2018 IEEE , vol. 5, no. 5, 1924
- [12] pp. 3758–3773
- [13] R. Dagar, S. Som, and S. K. Khatri, “Smart farming-IoT in agricul- ture”,2018 ICIRCA
- [14] Rongji Zhou, Yuyan Yin,”Digital Agriculture : Mapping Knowledge Structure and Trends”,2017 IEEE



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