2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)

Smart Farming System using NPK Sensor

Bharadwaj Cheruvu
Computer Science Department
Gokaraju Rangaraju Institute of Engineering and Technology
Hyderabad, India
cheruvubob@gmail.com

Dr. S. Bhargavi Latha
Computer Science Department
Gokaraju Rangaraju Institute of Engineering and Technology
Hyderabad, India
s.bhargavilatha@gmail.com

Mada Nikhil
Computer Science Department
Gokaraju Rangaraju Institute of Engineering and Technology
Hyderabad, India
madanikhil143@gmail.com

Hitesh Mahajan
Computer Science Department
Gokaraju Rangaraju Institute of Engineering and Technology
Hyderabad, India
hiteshmahajan774@gmail.com

Kongari Prashanth
Computer Science Department
Gokaraju Rangaraju Institute of Engineering and Technology
Hyderabad, India
kongariprashanth23@gmail.com

***Abstract*—The human population is only growing, and certain steps are to be implemented to meet the future requirements with respect to food. This paper discusses the implementation of a smart farm using Internet of Thing. IoT has led to a faster form of gathering data and inferring from our surroundings. A farmer, with the help of this smart farm system, will be able to keep track of plant and soil vitals in real-time and use the recommendation system, based on a model trained from a dataset, to suggest the best suitable crop based on sensor values. IoT-enabled Smart Farming will enable growers and farmers to enhance productivity and reduce the wastage of resources. The proposed system is a more reliable concept and can be easily implemented as it consists of sensors that can collect vital information about the environment from soil nutrients, temperature, humidity, and soil moisture regularly which is displayed on an easy-to-understand interface to be interpreted by the growers and farmers to understand the best conditions to give their plants.**

Keywords—Internet of Things, smart farming, IoT sensors, NPK sensor, soil measurement, machine learning, python API, Thingspeak server

I. INTRODUCTION

The United Nations Food and Agriculture Organization estimates that an additional 75% of the production of agricultural produce is needed to sustain the world by 2050. With shrinking agricultural lands, slowing yield trends in major crops, water shortages, and depleting mineral reserves; we face a hunger-stricken world in the years to come.

In India, an estimated 60 percent of the land is used for agricultural purposes with majority of the population considering it their primary source of livelihood[1]. It's also believed that India will be the most populous state in 2023 and will continue to see an increase in its numbers and simultaneously parts of the existing agricultural land will be converted into amenities and residencies for the growing population. With other factors like increasing Global Warming, adverse climate change, excessive use of fertilizers and chemicals, Natural Calamities, etc. it is becoming crucial to address the prime agricultural concern: What will we do when the demand surpasses the supply? The advent of technological advances in the agricultural field has given some spite.

The term "Internet of Things" refers to a broad network of hardware and software, including sensors, microcontrollers, connections, user interfaces, and data processing capabilities, that enables communication between hardware and the cloud. IoT started off with modest beginning being part of Coca Cola machines and a toaster connected to the Internet. With technological advent in the 21st century, IoT has been at the forefront of major technological research in domains such as Smart Cities in [2], Smart Homes in [3], [4], Smart Energy in [5], Autonomous Vehicles in [6], [7], Healthcare in [8], Logistics in [9] and Smart Agriculture in [10] to name a few.

In the next section, we highlight the recent advances with respect to IoT applications in the sector of agriculture.

II. Literature Study

There have been several projects and research done using various technologies and Internet of Things has been one promising technology. IoT based solutions focused on reduces human involvement. IoT based agricultural solutions are classifies into Monitoring, Tracking and tracing, and Smart Precision Farming, Livestock Management and Greenhouse Production solutions as mentioned in [10], [11].

Some of the studies so far have dealt with Smart Farm mentioned in [12] provides the concept of traceability systems by collecting data from sensors and to monitor these in real-time, capabilities of Wireless Sensor Network (WSN) in [13], [14], a monitoring system for transmitting sensor data using the Wi-Fi technology to a database [15]. An android application to suggest crops based on a trained model was explained in [16].

Farmers tend to rely on their basic observations and conventional approaches when it comes to making decisions on what crop to plant without considering the nutrients or environment effect on the crop. A machine learning based recommendation system will help the farmer make an informed decision and the real-time monitoring system will help to keep a track of the crop conditions.

There is a need to build a user-friendly interface to communicate the model result based on the sensor values and to display the values in real-time for monitoring. The inclusion of a precision IoT component as the Nitrogen-Phosphorous-Potassium (NPK) sensor to measure the primary nutrients in the soil has been done as Nitrogen, Phosphorous and Potassium are the three primary components required for good crop growth. A fairly accurate model has to be trained to recommend the suitable crop depending on the dataset and its attributes.

In this research, we studied the major measurable factors deciding plant growth and how it can be monitored by the farmer in real-time to take an appropriate action. Our research involves a Plant recommender based on sensor values and a continuous monitoring system that can be accessible from the Python interface.

III. Proposed Approach

A. Components

In the IoT setup, we have used Nitrogen-Phosphorous-Potassium sensor, Digital Temperature and Humidity (DHT22) sensor, soil moisture sensor, ESP NodeMCU Wi-Fi module and MAX485 TTL to RS485 Module.

1) *NodeMCU, Figure 1, is an open-sourced software and hardware component built on the System-on-chip system called ESP8266. ESP8266, created by Espressif Systems, includes central processing unit (CPU), network capabilities, random access memory (RAM), an operating system (OS) and system development kit (SDK). It comes with 16 GPIOs and 1 analog input pin. However only 10 pins can be utilized for digital input and output. Its operating voltage is 3.3V with an input voltage ranging from 4.5V to 10V.*
2) *The NPK sensor, depicted in Figure 2 is a sensor used to measure the content of Nitrogen, Phosphorous and Potassium in milligram per liter. This has been an area of study in agricultural growth techniques recently as mentioned in* [17], [18]. *The measurements of such precision sensors will give an understanding on the fertility of the soil to the user. The sensor is resistant to long-term electrolysis, corrosion resistance and waterproof. It runs on a power supply of 5-30V DC. Its protection grade is 68 and has a resolution of 1mg/L. The measurement is done by detecting the conductivity transformation caused by different nitrogen, phosphorous and potassium concentrations. Since the output signal of NPK sensor is RS485 and this signal cannot be interpreted by ESP8266, we must make use of the MAX485 convertor module.*

Figure. 1. NodeMCU ESP8266 Wi-Fi Module

Figure. 2.NPK Sensors

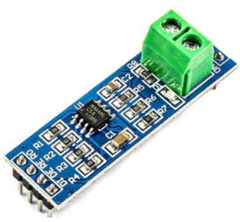

Figure. 3. MAX485 TTL to RS485 Convertor

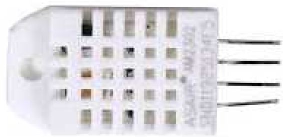

Figure. 4. DHT22 Sensor

3) *The MAX485 module, Figure 3, converts the TTL signals from NPK sensor to RS485 readings that can be interpreted by the ESP Module. It converts transistor-transistor logic (TTL) into RS485 to transmit high data rate prone differential communication as mentioned in* [19].
4) *The DHT22 Sensor is a low-cost sensor having a capacitive humidity sensor and a thermistor. DHT22, Figure 4, has a range 0-100% humidity with 2-5% accuracy and negative 40-80 ºC with an accuracy of ±0.5ºC*[20]. *It has 4 pins including ground, data, VCC and NC.*

B. Dataset

To train a ML model, we should have sufficient entries for each class and only those parameters that truly have a significant effect on the plants condition are taken into consideration before training. We have trained our model on the Crop_Recommendation dataset available on Kaggle which is based on the report from Indian Council of Agricultural Research. Most crops require 3 essential nutrients for growth, namely, Nitrogen, Phosphorous and Potassium. Hence, we have used a dataset having these parameters.

It has 2200 entries of 22 different plant species with parameters of Nitrogen content, Potassium content, Phosphorous content, temperature, humidity, pH of the soil and rainfall as depicted by Table 1. We ensure that the dataset does not have any null values or missing data that can hinder the training of the model. The dataset is split into a 75:25 split, where 75 percent of the data is part of training samples and the rest for testing.

TABLE I. DATASET STRUCTURE

Parameter	**Count**	***Data type***
Nitrogen content	2200	Int64
Phosphorous content	2200	Int64
Potassium content	2200	Int64
Temperature	2200	Float64
Humidity	2200	Float64
Label	2200	Object

C. Random Forest Classifier

Regression and classification problems are addressed by the supervised machine learning technique known as Random Forest Classifier. It uses multiple predictions from models and hence is an ensemble technique. The feature importance is a computed factor that signifies how well a certain selection of attributes affects the model.

Consider the importance of node *j* as explained in (1).

$$im_k = wt_k I_k - wt_{lt(k)} I_{lt(k)} - wt_{rt(k)} I_{rt(k)} \quad (1)$$

im_k = importance of node k.

wt_k = weighted samples number that reach node k.

I_k = impurity value for k node.

lt(k) = child node on left split of node k.

rt(k) = child node on right split of node k.

Whereas the importance for an individual feature is calculated from (2).

$$fi_k = \frac{\sum_{n:\text{node j splits on feature k}} im_j}{\sum_{m \in \text{all nodes}} im_m} \quad (2)$$

fi_k = importance of the feature k.

im_j = importance of the node j.

After which the data is scaled between 0 and 1 using (3).

$$Nfi_k = \frac{fi_k}{\sum_{j\,\in\,\text{all features}} fi_j} \quad (3)$$

The final feature importance is the average over all the trees represented by (4).

$$F_k = \frac{\sum_{j\,\in \text{all trees}} Nfi_j}{T} \quad (4)$$

F_k = importance of feature k computed from all trees.

Nfi_j = normalized feature importance for k in tree j.

T = number of trees generated.

The reason for using Random Forest i.e., the accuracy comparison is expressed in Table 2. It is also advantageous due to its diversity in each model and stability due to majority voting.

TABLE II. COMPARISON BETWEEN CLASSIFIERS

Classifier	**Accuracy (%)**
Logistic Regression	88.000
K Neighbours	91.090
Decision tree	94.090
Gradient Bossting	94.545
Random Forest	95.090

D. Hardware Organization

The sensors that are implemented are NPK sensor for measuring nutrient content, DHT22 for temperature and humidity and a soil moisture sensor.

The sensors will connect to the NodeMCU ESP8266 microcontroller Wi-Fi module. The block and schematic diagram are given in Figure 5 and Figure 6 respectively. Block Diagram shows the general arrangement of principal parts or functions to show the relationship between them. The system will require MAX485 module to integrate the NPK with NodeMCU whereas the other sensors can be directly connected.

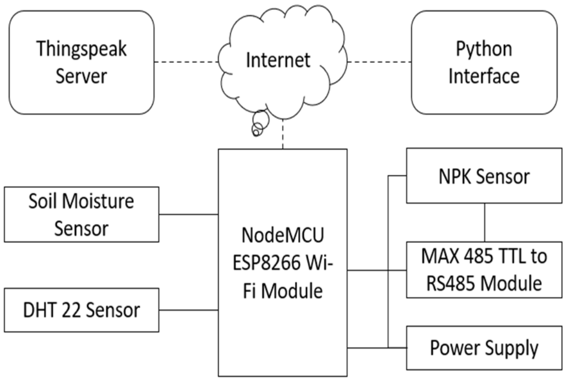

Figure. 5. Block diagram for system.

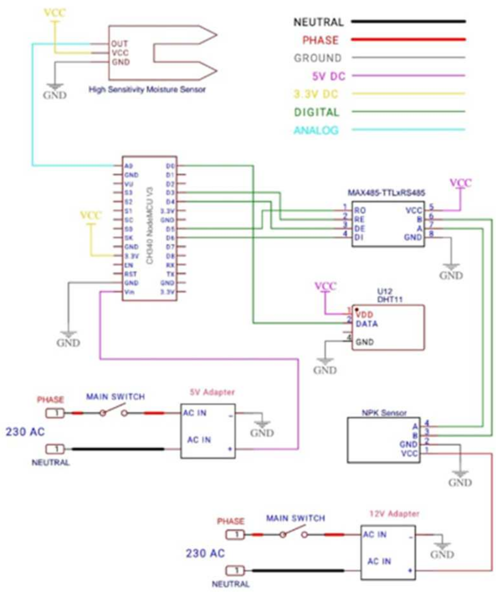

Figure. 6. Block diagram showcasing connectivity and functionality of components.

E. Data Analytical Tool and User Interface

Initially the data is transmitted to IoT analytical platform called Thingspeak. MQ Telemetry Transport (MQTT), a publish/subscribe communication method that utilizes TCP/IP sockets or WebSockets, is used to update sensor values. explained in [21]–[23].

Using the Thingspeak Application Programming Interface (API) keys, we can transfer readings from the sensors to their respective fields on the Thingspeak platform[24], [25] as depicted in figures 7-12. Data on the Thingspeak Server is represented in the form of graphs with suitable limits and units. The data is updated as and when a new value is read by the sensor. Each field indicates a specific sensor value that it visualizes, and the field numbers are set in the Arduino Sketch.

The Python based user interface allows the farmer to continuously monitor and recommend the suitable crop based on the conditions at any time. The interface was created using FLASK, that was used for similar cause in [26], Thingspeak API keys to transfer the data and the trained classifier on the dataset. FLASK is a community-maintained micro web framework. The user interface is depicted in Figure 13.

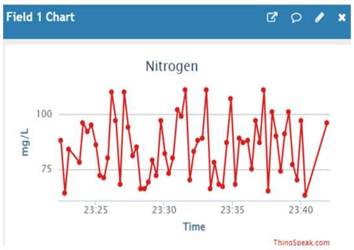

Figure. 7. Thingspeak - Nitrogen content graph

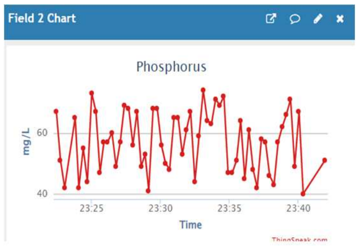

Figure. 8. Thingspeak - Phosphorous content graph.

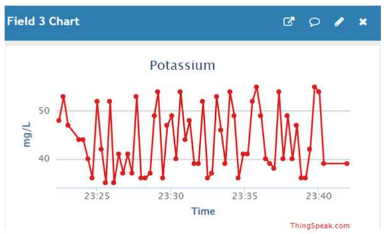

Figure. 9. Thingspeak - Potassium content graph.

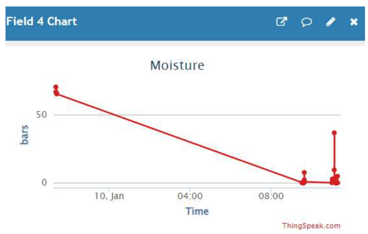

Figure. 10. Thingspeak - Moisture content graph.

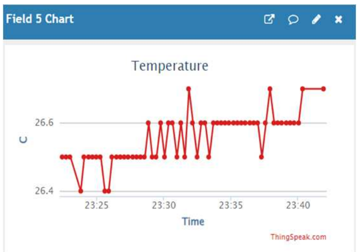

Figure. 11. Thingspeak - Temperature graph.

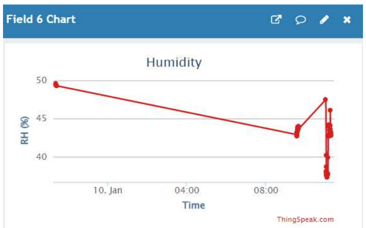

Figure. 10. Thingspeak - Humidity graph.

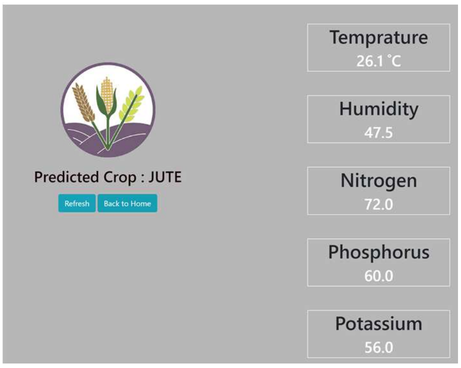

Figure. 13. User Interface for the monitoring and recommendation system created by Python and Flask.

IV. RESULTS

The distribution of data samples is made evenly to train the model better. 25 percent of each labels data sample is used in validation of the model and the results for each label along with its precision, recall, and f1-score are given in the classification report expressed in table 3. The overall classification report is given in table 4 using weighted parameter. The metrics used to evaluate the model are explained below based on the confusion matrix in Figure 14. A confusion matrix will result in 4 terms.

True Positives (TP) is the number of positive cases correctly predicted. True Negatives (TN) is the number of negative cases correctly predicted. False Positives (FP) is the number of negative cases that are misclassified. False Negatives (FN) is the number of positive cases that are misclassified. The mentioned equations are explained in [27].

The percentage of accurate results among all predictions is known as accuracy.

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

The number of correctly predicted positive outcomes is called precision.

$$\text{Precision}=\frac{TP}{TP+FP} \tag{4}$$

Recall or sensitivity is the proportion of correctly predicted positive cases among all the positive examples in the data that the classifier produced.

$$\text{Recall}=\frac{TP}{TP+FN} \tag{5}$$

The F1-Score is measured as the harmonic mean of the two. The following shows its calculation.

$$\text{F1 Score}=2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{6}$$

TABLE III. CLASSIFICATION REPORT

Label	**Precision**	***Recall***	***F1-Score***
Apple	1.00	1.00	1.00
Banana	1.00	1.00	1.00
Black gram	0.81	0.85	0.83
Chickpea	1.00	1.00	1.00
Cocunut	1.00	1.00	1.00
Coffee	1.00	1.00	1.00
Cotton	1.00	1.00	1.00
Grapes	1.00	1.00	1.00
Jute	0.81	0.89	0.85
Kidney beans	1.00	1.00	1.00
Lentils	0.72	0.76	0.74
Maize	1.00	1.00	1.00
Mango	1.00	1.00	1.00
Moth bean	0.93	0.90	0.91
Mung bean	1.00	1.00	1.00
Muskmelon	0.96	1.00	0.98
Orange	1.00	1.00	1.00
Papaya	1.00	1.00	1.00
Pigeon peas	0.88	0.85	0.87
Pomegranate	1.00	1.00	1.00
Rice	0.88	0.79	0.84
Watermelon	1.00	0.96	0.98

TABLE IV. MODEL CLASSIFICATION REPORT

Parameter	Percentage (%)
Accuray	95.090
Precision	95.593
Recall	95.454

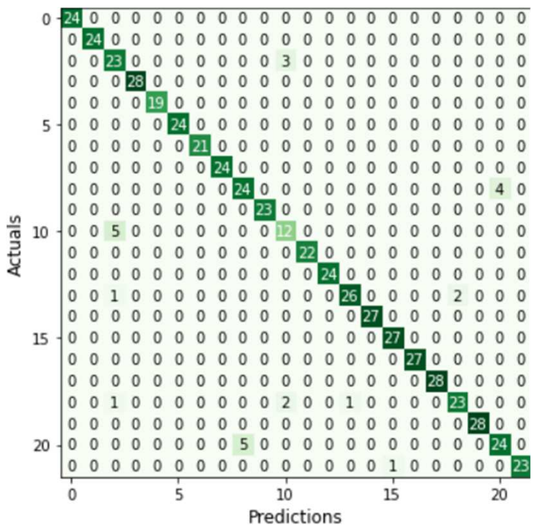

Figure. 14. Confusion matrix of model.

V. DISCUSSION

Random Forest classifier worked well with the dataset giving us a highly accurate model for over 22 different plant species. Random forest Classifier decides from a set of decision trees making it efficient. The web interface can be easily accessed and rather simple to use. It offers a custom recommender and continuous monitoring option with recommendation of plant species to grow based on last available data point that is obtained from the sensors. As it is connected to the Internet, the transfer of data to the analytical tool, Thingspeak and user interface happens within a fraction of a second. The recommendation system is not only accurate but quickly responsive too.

The IoT-enabled smart farm will help the farmer and grower to make decisions based on soil conditions quickly and accurately as compared to that of a soil testing. The continuous monitoring will keep the farmer aware of the crop's condition and can aid in timely response.

In the future, more data samples can be included to the dataset which currently has 2200 data sample points for 22 plant species. Similarly other plant species can be included to widen the scope of the system.

With time, next generation sensors can replace existing sensors to make the system more accurate and sensitive to the parameters. Additional parameters can be considered that have an impact on the growth of plant. Microcontrollers allow easy addition of sensors and simple codes can implement them.

One can even implement a Global system for mobile communication (GSM) module to improve connectivity better. Additional improvements will make the system more versatile and improve efficiency.

VI. CONCLUSION

This paper has presented an IoT-based recommendation and continuous monitoring system. The different hardware components, the integration between the components, dataset used for training, model training, model accuracy and implementation of a API using Thingspeak and Flask were discussed. The Wi-Fi module results in lesser delay and easier connectivity. Advancements like these will help farmers by recommending, monitoring, and thereby helping them grow better and lead to sustainable agriculture.

Acknowledgment

This research has been conducted in the supervision of faculty and aid from staff of Gokaraju Rangaraju Institute of Engineering and Technology.

References

[1] M. Pyingkodi et al., "Sensor Based Smart Agriculture with IoT Technologies: A Review," in 2022 International Conference on Computer Communication and Informatics (ICCCI), Jan. 2022, pp. 1–7. doi: 10.1109/ICCCI54379.2022.9741001.

[2] N. Mishra, P. Singhal, and S. Kundu, "Application of IoT products in smart cities of India," in Proceedings of the 2020 9th International Conference on System Modeling and Advancement in Research Trends, SMART 2020, Dec. 2020, pp. 155–157. doi: 10.1109/SMART50582.2020.9337150.

[3] D. Shin, K. Yun, J. Kim, P. V. Astillo, J. N. Kim, and I. You, "A Security Protocol for Route Optimization in DMM-Based Smart Home IoT Networks," IEEE Access, vol. 7, pp. 142531–142550, 2019, doi: 10.1109/ACCESS.2019.2943929.

[4] Institute of Electrical and Electronics Engineers, 2019 4th International Conference on Internet of Things: Smart Innovation and Usages (IoT-SIU).

[5] Universiti Tunku Abdul Rahman and Institute of Electrical and Electronics Engineers, ICSGCE 2018 : 2018 International Conference on Smart Grid and Clean Energy Technologies : 29 May - 1 June, 2018, Tunku Abdul Rahman, Sungai Long Campus, Kajang, Malaysia.

[6] S. Kuutti, S. Fallah, K. Katsaros, M. Dianati, F. Mccullough, and A. Mouzakitis, "A Survey of the State-of-the-Art Localization Techniques and Their Potentials for Autonomous Vehicle Applications," IEEE Internet of Things Journal, vol. 5, no. 2. Institute of Electrical and Electronics Engineers Inc., pp. 829–846, Apr. 01, 2018. doi: 10.1109/JIOT.2018.2812300.

[7] Amity University, Institute of Electrical and Electronics Engineers. Uttar Pradesh Section, Institute of Electrical and Electronics Engineers, and Amity University. School of Engineering and Technology, 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN) : 7-8

March 2019, Amity School of Engineering and Technology, Noida, India.

[8] M. N. Bhuiyan, M. M. Rahman, M. M. Billah, and D. Saha, "Internet of Things (IoT): A Review of Its Enabling Technologies in Healthcare Applications, Standards Protocols, Security, and Market Opportunities," IEEE Internet of Things Journal, vol. 8, no. 13. Institute of Electrical and Electronics Engineers Inc., pp. 10474–10498, Jul. 01, 2021. doi: 10.1109/JIOT.2021.3062630.

[9] Y. Song, F. R. Yu, L. Zhou, X. Yang, and Z. He, "Applications of the Internet of Things (IoT) in Smart Logistics: A Comprehensive Survey," IEEE Internet of Things Journal, vol. 8, no. 6. Institute of Electrical and Electronics Engineers Inc., pp. 4250–4274, Mar. 15, 2021. doi: 10.1109/JIOT.2020.3034385.

[10] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming," IEEE Access, vol. 7. Institute of Electrical and Electronics Engineers Inc., pp. 156237–156271, 2019. doi: 10.1109/ACCESS.2019.2949703.

[11] V. K. Quy et al., "IoT-Enabled Smart Agriculture: Architecture, Applications, and Challenges," Applied Sciences (Switzerland), vol. 12, no. 7. MDPI, Apr. 01, 2022. doi: 10.3390/app12073396.

[12] K. Wongpatikaseree, P. Kanka, and A. Ratikan, "Developing Smart Farm and Traceability System for Agricultural Products using IoT Technology," in 2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS), Jun. 2018, pp. 180–184. doi: 10.1109/ICIS.2018.8466479.

[13] N. Ahmed, D. De, and I. Hussain, "Internet of Things (IoT) for Smart Precision Agriculture and Farming in Rural Areas," IEEE Internet Things J, vol. 5, no. 6, pp. 4890–4899, Dec. 2018, doi: 10.1109/JIOT.2018.2879579.

[14] T. M. Bandara, W. Mudiyanselage, and M. Raza, "Smart farm and monitoring system for measuring the Environmental condition using wireless sensor network - IOT Technology in farming," in 2020 5th International Conference on Innovative Technologies in Intelligent Systems and Industrial Applications (CITISIA), Nov. 2020, pp. 1–7. doi: 10.1109/CITISIA50690.2020.9371830.

[15] W.-L. Chen et al., "AgriTalk: IoT for Precision Soil Farming of Turmeric Cultivation," IEEE Internet Things J, vol. 6, no. 3, pp. 5209–5223, Jun. 2019, doi: 10.1109/JIOT.2019.2899128.

[16] A. Sharma, M. Bhargava, and A. V. Khanna, "AI-Farm: A crop recommendation system," in 2021 International Conference on Advances in Computing and Communications (ICACC), Oct. 2021, pp. 1–7. doi: 10.1109/ICACC-202152719.2021.9708104.

[17] W. Fan, K. A. Kam, H. Zhao, P. J. Culligan, and I. Kymissis, "An Optical Soil Sensor for NPK Nutrient Detection in Smart Cities," in 2022 18th International Conference on Intelligent Environments (IE), Jun. 2022, pp. 1–4. doi: 10.1109/IE54923.2022.9826759.

[18] M. Masrie, A. Z. M. Rosli, R. Sam, Z. Janin, and M. K. Nordin, "Integrated optical sensor for NPK Nutrient of Soil detection," in 2018 IEEE 5th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA), Nov. 2018, pp. 1–4. doi: 10.1109/ICSIMA.2018.8688794.

[19] Z. Xing, D. Li, Y. Shan, Y. Jin, and J. Shao, "The Design and Implementation of a C8051F-Based Embedded Image Acquisition System," in 2010 2nd International Workshop on Intelligent Systems and Applications, May 2010, pp. 1–3. doi: 10.1109/IWISA.2010.5473493.

[20] Y. A. Ahmad, T. Surya Gunawan, H. Mansor, B. A. Hamida, A. Fikri Hishamudin, and F. Arifin, "On the Evaluation of DHT22 Temperature Sensor for IoT Application," in 2021 8th International Conference on Computer and Communication Engineering (ICCCE), Jun. 2021, pp. 131–134. doi: 10.1109/ICCCE50029.2021.9467147.

[21] D. Parida, A. Behera, J. K. Naik, S. Pattanaik, and R. S. Nanda, "Real-time Environment Monitoring System using ESP8266 and ThingSpeak on Internet of Things Platform," 2019 International Conference on Intelligent Computing and Control Systems (ICCS), pp. 225–229, May 2019, doi: 10.1109/ICCS45141.2019.9065451.

[22] H. Benyezza, M. Bouhedda, K. Djellout, and A. Saidi, "Smart Irrigation System Based Thingspeak and Arduino," in 2018 International Conference on Applied Smart Systems (ICASS), Nov. 2018, pp. 1–4. doi: 10.1109/ICASS.2018.8651993.

[23] L. Mhatre and N. Rai, "Integration between wireless sensor and cloud," in 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Feb. 2017, pp. 779–782. doi: 10.1109/I-SMAC.2017.8058285.

[24] A. Akhtar, T. Ahmad, N. Sabahat, and S. Minhas, "IoT Based Home Automation System Using ThingSpeak," in 2019 International Conference on Computing, Electronics & Communications Engineering (iCCECE), Aug. 2019, pp. 163–168. doi: 10.1109/iCCECE46942.2019.8941737.

[25] L. Mhatre and N. Rai, "Integration between wireless sensor and cloud," in 2017 International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Feb. 2017, pp. 779–782. doi: 10.1109/I-SMAC.2017.8058285.

[26] A. Singh, R. Akash, and G. R. V, "Flower Classifier Web App Using Ml & Flask Web Framework," in 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Apr. 2022, pp. 974–977. doi: 10.1109/ICACITE53722.2022.9823577.

[27] J. Almulla and T. Alam, "Machine Learning Models Reveal Key Performance Metrics of Football Players to Win Matches in Qatar Stars League," IEEE Access, vol. 8, pp. 213695–213705, 2020, doi: 10.1109/ACCESS.2020.3038601.