Educational Administration: Theory and Practice
2022, 28(4), 481 - 489
ISSN: 2148-2403
https://kuey.net/
Research Article

Sustainable Agriculture: Leveraging Iot And Machine Learning For Data-Driven Agriculture

Arti Deshpande[1*]

[1*]Assistant Professor, Department of Computer Engineering, Thadomal Shahani Engineering College, Bandra West, Mumbai 400050

Citation: Arti Deshpande, (2022). Sustainable Agriculture: Leveraging Iot And Machine Learning For Data-Driven Agriculture, *Educational Administration: Theory and Practice*, 28(4)481 - 489
Doi: 10.53555/kuey.v28i4.9648

ARTICLE INFO

ABSTRACT

Agriculture is a crucial occupation in India, playing a key role in meeting the food demands of the nation. With the country's population increasing rapidly, farming has become a significant component of the economy. However, despite its importance, the adoption of advanced technologies like the Internet of Things (IoT) and Information and Communication Technology (ICT) in farming remains minimal, leading to numerous challenges in traditional agricultural practices. Emerging technologies such as IoT and machine learning hold the potential to address these limitations. The integration of these technologies into farming practices, often referred to as "smart farming," could substantially improve productivity, sustainability, and efficiency in agriculture. IoT devices can provide real-time insights into factors like soil moisture, weather conditions, and plant health. Machine learning models can analyze this data to guide farmers in making better decisions. Therefore, The aim of this paper is to propose a system that combines IoT and machine learning to overcome the current limitations faced in traditional farming. This integrated solution is designed to improve agricultural practices by increasing productivity, lowering costs, and helping farmers make informed decisions.

Keywords: Machine Learning, Internet of Things, Smart Agriculture.

1. Introduction

Agricultural is the most crucial industry for food welfare, nutritional values, sustainable growth, and poverty alleviation is agriculture. The Indian economy benefits greatly from this sector. Over 17% of the world's Gross Domestic Product (GDP) comes from it. However, there are other restrictions that are impeding advancement.. However, present farming practices are not producing enough due to restrictions. Lower productivity from manual farming, excessive yield production costs, difficulty forecasting the crop to be produced, water irrigation based on soil type, unpredictable weather, choosing the incorrect fertilizer that could affect the crop's overall yield, choosing a fertilizer for plant diseases, and more are the current challenges facing agriculture. Low productivity is a direct result of farmers' inability to work to their maximum potential due to a lack of technical developments.
Modern technologies like artificial intelligence, data science, big data, the internet of things, and nanoscience could be crucial to raising output overall. The conventional method mostly depends on human intuition, which occasionally fails. Therefore, an intelligent strategy that utilizes machine learning and the Internet of Things (IoT) is needed to increase crop output. One well-liked technology that has applications in the contemporary agriculture sector is machine learning. More nutrient-dense crops are produced when machine learning is used in agriculture. The study of computational algorithms that automatically learn and improve themselves as they acquire information and experience is known as machine learning (ML). Using sample data, sometimes known as "training data," machine learning algorithms create a model that allows them to make judgments or predictions without explicit qualification.

Machine learning algorithms are grouped into four categories: semi-supervised, supervised, reinforcement, and unsupervised. In supervised learning, a machine is trained through examples. The operator sends a known dataset of desired inputs and outputs to the machine learning algorithm, which must figure out how to get those inputs and outputs. Examples of supervised learning include random forest, regression, kNN, decision tree, and logistic regression. The Decision Tree method is a powerful learning technique that is frequently used to tackle classification problems. It can be used with both categorical and continuous dependent variables. Using this algorithm, we divide the population into two or more homogeneous groups. This is performed by defining as many separate classes as feasible depending on the most important attributes/independent variables. Linear regression is a supervised machine learning algorithm. It does a regression task. Regression models, which are based on independent variables, provide the required prediction value. Its primary goal is to determine the relationship between factors and predicting. The type of link evaluated between dependent and independent variables, as well as the number of independent variables used, varies amongst regression models. The Internet of Things (IoT) is a network of physical objects or individuals known as "things" that are equipped with software, electronics, a network, and sensors to collect and exchange data. The goal of IoT is to expand internet access beyond mainstream items like laptops, mobile phones, and tablets to more fundamental equipment like toasters. IoT makes practically everything "smart" by increasing various aspects of our life using data processing, AI algorithms, and networks. The Internet of Things and Cloud Computing complement one another, with both being marketed together when addressing technical resources and partnering to provide a stronger overall IoT service. Cloud computing serves a broader purpose in IoT by storing IoT data.

The Cloud is a centralized server that stores computer resources that are accessible at all times. Cloud computing is an efficient means for Internet of Things-generated huge data packages to transport. This study discusses how IoT solutions can help farmers overcome the supply-demand gap while maintaining high yields, sustainability, and environmental protection. Precision agriculture is the application of IoT technologies to optimize resource use and crop production while minimizing operating expenses. Advanced systems, wireless networking, software, and information technology services are all examples of IoT in agriculture development.

IoT and machine learning reveal previously hidden insights in outcomes, allowing for faster, more automated replies and better decision making. ML for IoT uses image, video, and audio data to predict future patterns, discover abnormalities, and improve intelligence. Machine Learning for Many other industries employ IoT to perform analytical functions across a wide range of applications, allowing the organization to produce unique insights and complex automated capabilities. There are various benefits to incorporating new technologies, including increased productivity, better crop distribution, crop pattern advice, and efficient resource utilization.

The purpose of this research paper is to present a solution that combines machine learning and IoT to address current farming practices' limitations while also creating various new opportunities. This research article elaborates on the suggested system's efficiency using a variety of test situations. The proposed model has several advantages, which are discussed in detail on the following pages.

2. Related Works

Several studies have explored IoT-based frameworks for smart agriculture. Some of the notable literature is as follows.

Abhiram et al. (2020) proposed an IoT-based smart farming system that enables efficient crop growth through real-time monitoring [1]. Similarly, Anusha et al. (2019) presented a model leveraging IoT for smart agriculture, emphasizing automation and data-driven decision-making [2]. Muthunoori and Munaswamy (2019) further advanced this concept by integrating sensor technology and cloud computing to enhance precision farming [3]. Sweksha et al. (2019) discussed an IoT-based smart agriculture model that provides real-time field monitoring [4], while Sriveni and Gonen (2020) combined IoT with cloud computing for enhanced data storage and analysis [6]. Varghese and Sharma (2018) explored an affordable IoT and machine learning framework for smart farming, demonstrating cost-effective solutions for resource-limited farmers [7]. Kumar et al. (2020) proposed a supervised machine learning approach for predicting crop yield in the agricultural sector. Their study focused on utilizing various environmental and soil-related parameters, such as temperature, humidity, and soil fertility, to enhance prediction accuracy [5]. Goap et al. (2018)] introduced an IoT-based smart irrigation management system that integrates machine learning and open-source technologies [8]. Balducci et al. (2018) explored various machine learning applications in agriculture by analyzing large agricultural datasets. Their research aimed at enhancing smart farming techniques through advanced data analytics [9]. Kamilaris and Prenafeta-Boldú (2018) conducted a survey on deep learning applications in agriculture, identifying key trends in image processing and automation [12]. Dholu and Ghodinde (2018) investigated IoT applications in precision agriculture, demonstrating how real-time data acquisition enhances decision-making [10]. Badage (2018) focused on machine learning-based crop disease detection, presenting an Indian agriculture-specific framework [13]. Treboux and Genoud (2018) proposed an improved machine learning methodology for high-precision agriculture, highlighting the importance of high-resolution data [14]. Doshi et al. (2018) introduced AgroConsultant, an intelligent crop recommendation system utilizing machine learning algorithms to assist farmers in selecting optimal crops [15]. This study aligned with broader research efforts to integrate data-driven decision-making in agriculture.

3. Proposed Solution

The proposed solution automates agricultural processes by integrating various IoT sensors and controllers. This study presents a system that utilizes sensors to measure soil moisture levels, as well as environmental temperature and humidity. These sensors, along with the NodeMCU, are connected to both a cloud platform and a smartphone, enabling real-time data retrieval [7]. The core components of the proposed system architecture include a temperature sensor, a soil moisture sensor, and a NodeMCU. The NodeMCU plays a crucial role in managing data transmission. The DHT11 temperature sensor and soil moisture sensor are deployed in the field and connected to the NodeMCU, which collects and processes data from these sensors. To estimate precise outcomes, a decision tree algorithm is applied to the collected data. The sensor data transmitted to the NodeMCU is stored in a database for future reference. Fig. 1 illustrates the Functional aspects of the proposed system [5].
The proposed solution integrates various hardware and software components to collect data through multiple sensors, which is then processed using software modules and machine learning algorithms to achieve the desired outcomes. This solution is structured into two primary modules: the IoT module and the Machine Learning module, detailed as follows:

3.1 IoT Module and Machine Learning Module
In this system, the IoT module is responsible for acquiring data using different hardware sensors, while the Machine Learning module applies various algorithms to process and analyze the collected information. The IoT module consists of the following hardware and software components:

a. NodeMCU
NodeMCU is an open-source firmware and a widely used name for the ESP8266 Development Board, a cost-effective platform designed for IoT applications. It enables seamless integration with sensors and cloud platforms for data processing.

b. Sensors
1. DHT-11: This is an affordable humidity and temperature sensor. It employs a capacitive humidity sensor and a thermistor to measure ambient air conditions, providing a digital signal as output without requiring analog input pins. Although simple to operate, it requires some time to collect data. This sensor monitors the temperature and humidity levels in the crop environment
2. Soil Moisture Sensor: This sensor measures the soil's moisture content by using two embedded electrodes. When inserted into the soil, it determines the volumetric water content, expressed as a percentage. This information is essential for monitoring and maintaining optimal soil moisture levels for plant growth.

c. 5V Relay Module
The 5V Relay Module is designed for high-voltage applications, capable of handling up to 220V AC while ensuring safety. When a signal is received at the IN pin, an indicator LED lights up, and the relay activates the output pins with an audible click. This module is crucial for controlling electrical components in automation systems.

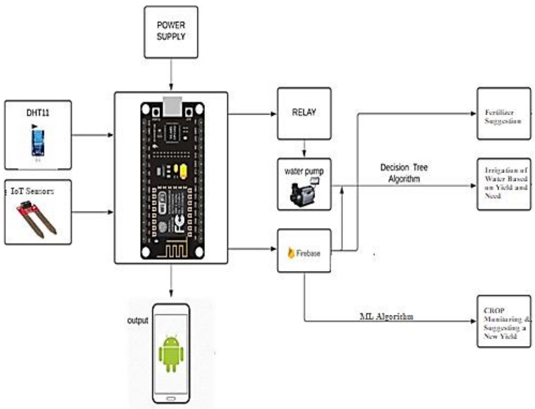

Fig. 1 Functional aspects of the proposed system

d. Software tools
a. Arduino IDE: The Arduino Integrated Development Environment (IDE) is a cross-platform software framework compatible with Windows, macOS, and Linux. It is primarily written in C and C++ and is designed for writing, compiling, and uploading programs to Arduino boards. Additionally, with third-party support, it can be used for programming other development boards.
b. Firebase: Firebase is a Google-powered platform that facilitates the development of mobile and web

applications by providing backend services such as real-time databases, authentication, cloud storage, and analytics.
The proposed approach collects data from multiple sensors and stores it for further analysis. It utilizes a supervised deep learning algorithm, where the system is pre-trained with known responses to recognize patterns effectively. By analyzing diverse datasets, the algorithm identifies trends and generates responses accordingly, a process known as data training. A larger dataset contributes to more precise and insightful observations. In the subsequent phase, the obtained results are validated. Since the system is already familiar with problem-solving patterns and potential solutions, it can determine the most appropriate solution at this stage. The accuracy of the output depends on several factors, including the volume of data, the algorithms applied, and additional considerations such as data noise and external influences in the training dataset.

The classification process comprises two key phases: learning and evaluation. In the learning phase, the model is trained using input data to enhance its predictive capabilities. The decision tree algorithm is frequently utilized for classification, as its robust nature improves dataset analysis and validation accuracy [8]. Among the most fundamental and efficient algorithms in smart agriculture, the decision tree algorithm belongs to the supervised learning category. Unlike other supervised learning techniques, it is widely applied to both regression and classification tasks. The primary objective is to train a model that can predict the value or category of a target variable based on prior training data. To determine the classification of a record, the root node of the decision tree serves as the starting point. Each attribute value of the root node is compared to the attributes within the dataset. Based on these comparisons, the decision tree follows a specific branching path leading to subsequent nodes until classification is complete. The proposed solution also integrates an Android application for monitoring and remotely analyzing soil sensor data. This data is transmitted to the app via a Wi-Fi module embedded in the NodeMCU. The application, developed using Android Studio and Firebase, provides real-time insights into field irrigation conditions, allowing users to make informed decisions regarding crop management. Delta: The Delta is the total amount of water needed by any crop during its base cycle for full-fledged nourishment expressed in depth of water (i.e. in 'cm' or 'inches'). Each crop has unique growth requirements. A certain amount of water is needed for every crop to mature. Crop Delta varies depending on the type of crop. The following are the formulas for different equations [9].

Total amount of water required for a crop (T) = (Delta * Yield Area)/1000 litres

No. of days required for the growth of the crop = n days' Irrigation Interval = K days
Total no. of irrigation (Ni) = n days/K times
The quantity of water needed per time interval = T/Ni litres

To assess the moisture content of the soil, a moisture sensor is used. It is fed to the NodeMCU, which determines whether or not the moisture level is less than the threshold. If it is less than the threshold, it triggers the solenoid valve to open, and the relay module unlocks the submersible water pump, allowing water to escape. A water flow monitor will now measure the running water, and an estimated volume of water will be supplied to the farm. The proposed system prototype functions in real time using a soil moisture sensor. This sensor continuously monitors the moisture levels in the soil. The system operates based on predefined thresholds set according to the specific soil and plant type. When the soil moisture level drops below the designated threshold, the system automatically activates the water pump to irrigate the fields. Conversely, when the moisture level exceeds the threshold, the system halts the water supply, ensuring optimal irrigation without human intervention. This automation allows the pump to regulate water distribution efficiently based on real-time soil conditions. Additionally, a mobile application provides detailed insights into the entire operation, enabling users to monitor and manage the irrigation process remotely.

3.1 Machine Learning Module
The proposed solution has following output modules:

3.1.1 Detection of Crop Diseases
The diagnosis of leaf spot diseases involves several key steps, including capturing images using a camera, enhancing the images, grading and segmenting them, extracting shapes and color features, and classifying diseases based on factors such as lesion percentage, lesion shape, color border, spot characteristics, and leaf color. The first phase of this process is image acquisition, where photographs of various leaves are captured for classification. In the second phase, pre-processing is performed to enhance image quality. The third phase involves segmentation and grading, where the significant portions of the image are identified and classified. Next, feature extraction is carried out on the infected regions of the leaf, based on fundamental pixel characteristics. Analytical techniques are then applied to select the most relevant features, reducing redundancy and improving accuracy. Finally, the classification process is completed using a Support Vector Machine (SVM) classifier to determine the disease grade. Fig. 2 illustrates the block diagram for crop disease detection.

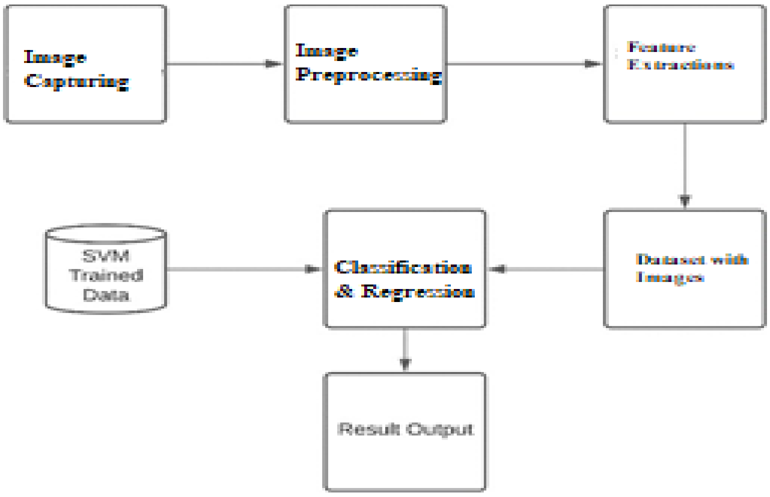

Fig. 2 Block diagram for Detection of Crop Disease

In the proposed solution, the machine learning algorithm utilized for detecting crop diseases is the Support Vector Machine (SVM). SVM is based on mathematical principles and achieves enhanced performance through the Structural Risk Minimization (SRM) theorem. SRM is designed to maximize the margin of class separation, improving the classification process. Initially developed for binary classification problems, SVM aims to find the optimal hyperplane that maximizes the margin between the closest data points, known as support vectors. Today, SVM is widely used for pattern recognition and classification tasks. Support Vector Machines (SVM) belong to a category of supervised learning methods that can be applied to both classification and regression problems. The SVM classifier undergoes training to categorize test data into two or more classes. Various studies have demonstrated that SVM effectively classifies small datasets, nonlinear patterns, and high-dimensional data. The foundation of SVM lies in the concept of a decision plane, which establishes the decision boundaries separating different classes. This classifier categorizes objects by dividing them with a boundary line. However, real-world classification problems are often more complex, requiring advanced structures to enhance differentiation. The primary objective of SVM is to correctly classify new data points (test cases) based on existing training examples. The multiclass SVM model incorporates knowledge from the classification process to improve accuracy. In the context of crop disease detection, multiclass SVM is applied to identify and categorize leaf spot diseases. The classification process relies on analyzing leaf color, which are segmented based on vector weights. Additionally, pixel segmentation data, containing both diseased and healthy pixel information, is used to train the SVM model for effective disease detection in leaves.

3.1.2 Water Irrigation

The advanced machine learning techniques has newly classified data with known results is provided to the computer to help it recognize patterns. The system analyzes different types of data along with solutions to various challenges and identifies trends. This process is known as data training. The greater the amount of available information, the more accurate the conclusions will be. Classification typically involves two key phases: learning and estimation [11]. During the learning phase, a model is developed using input training datasets. A robust algorithm is then applied to interpret and analyze the decision tree algorithm, which is considered one of the most fundamental and reliable techniques.

The following steps outline the process:
[1] Begin with the root node, which represents the complete dataset.
[2] Use an Attribute Selection Measure to determine the most significant feature in the dataset.
[3] Divide the dataset into smaller subsets based on potential values of the selected feature.
[4] Construct a decision tree node using the best attribute.
[5] Repeat this process until no further nodes can be identified, marking the final node as a leaf node.

Unlike many other algorithms, the decision tree algorithm is widely used to solve both regression and classification problems. Its primary objective is to develop a model capable of predicting a function or class of input variables by formulating simple and clear decision rules derived from past data. To determine the classification of a data point, the process begins at the root node, which serves as the starting point of the decision tree. Based on the given conditions, a specific path is followed through the branches, leading to the next node. Fig. 3 illustrates the block diagram for water irrigation.

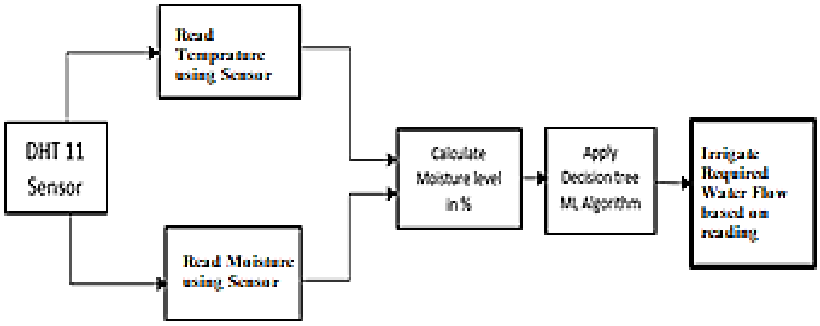

Fig. 3 Functioning of Water Irrigation Module

The formula for calculating soil moisture will be given as follows
Moisture in the Soil = 21+ (1.3*temp-0.21*humidity)/100

3.1.3 Crop Suggestion

The system described assists farmers in identifying the most suitable crops based on various environmental factors. Users enter location-specific parameters through a graphical user interface (GUI), and the input data is stored in a vector. This vector is then used to query a crop dataset. The input data is matched with the dataset, and the K-Nearest Neighbors (KNN) machine learning algorithm classifies the crop based on its similarity to the provided parameters.
The KNN method is a popular data mining technique where each feature in the training dataset is treated as a separate dimension. The value for each feature becomes the coordinate of the data point in that dimension, creating a multi-dimensional space. The distance between two data points in this space is a measure of their similarity, calculated using an appropriate distance metric.
The algorithm works by identifying the 'k' nearest data points to the new observation and assigning the most common class among these points. This allows the system to determine which crops are most suitable for the given conditions.

The steps involved in the process are as follows:
1. Input Data: The user provides information about the location and environmental parameters.
2. Set K Value: The number of neighbors, ‘k’, is chosen.
3. Distance Calculation: For each entry in the dataset, the system computes the distance between the input and each data point and stores these in a sequence with the corresponding indices.
4. Sorting: The distances and indices are sorted in ascending order of distance.
5. Select Top K: The first 'K' closest data points are selected.
6. Label Collection: The labels for these K points are collected.
7. Regression: If regression is used, the mean of the K labels is returned.
8. Classification: If classification is used, the mode (most frequent label) of the K labels is returned.

As a result, the system suggests the best crop based on the user's input, which is then displayed to the user via the GUI. The KNN algorithm helps to create, train, and evaluate the system using variables X and Y, which refine the recommendations. The input is matched with the crop dataset, and the system outputs a list of crops best suited for the given conditions.

4. Results and Discussion

This section elaborates the different results obtained in implementing the proposed system. The results of different modules are explained as follows:

4.1 Crop Disease detection

The proposed system employs the Support Vector Machine (SVM) machine learning algorithm for crop disease detection. The findings are calculated using the SVM method. This module defines leaf spot illnesses using the SVM multiclass technique. The weight of the vectors is utilized to distinguish the color of the leaf. Both infected and non-diseased pixel information are used to train the supporting vector machine for leaf disease segmentation. The findings of Crop Disease detection are displayed in Fig 4.

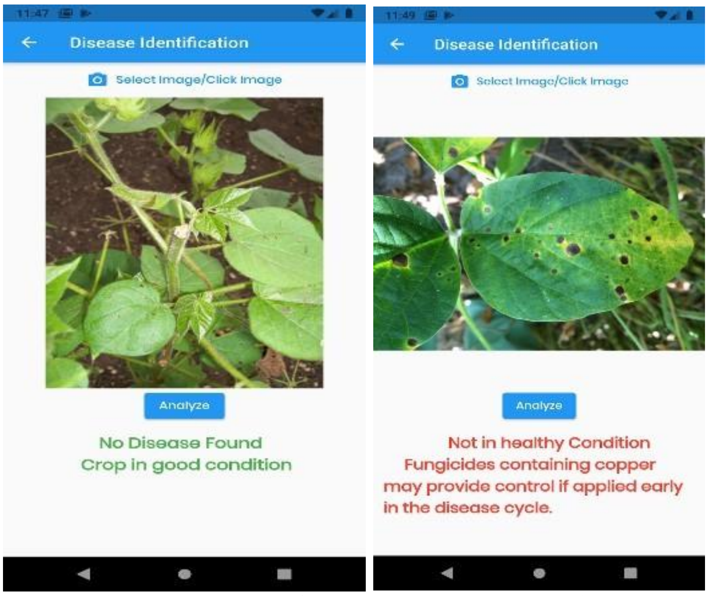

Fig. 4 Results of Crop Disease detection

4.2 System of Irrigation of Water

The suggested system automates the agricultural process through the use of several IoT and machine learning modules. The many sensors in the IoT module collect the data required for the machine learning module to perform the analysis and produce the desired insights and outcomes. The suggested system employs a DHT11 sensor to assess soil temperature and humidity, which are then used to determine moisture levels. Fig. 5 shows the results of soil moisture based on temperature and humidity levels. Temperature and humidity are measured, and the resultant soil moisture is expressed as a percentage. The key components are the Node MCU, DHT11, and soil moisture sensor. The Node MCU plays an important role in the process by storing data and running a database server. The DHT11 and soil moisture sensor are put in the field and connected to the Node MCU. The data acquired by these sensors is forwarded to the Node MCU for processing and access. The decision tree method is applied to data to predict right outcomes. The results are delivered to farmers via an application. The sensor readings provided to Node MCU are preserved in Firebase (cloud) for further use.

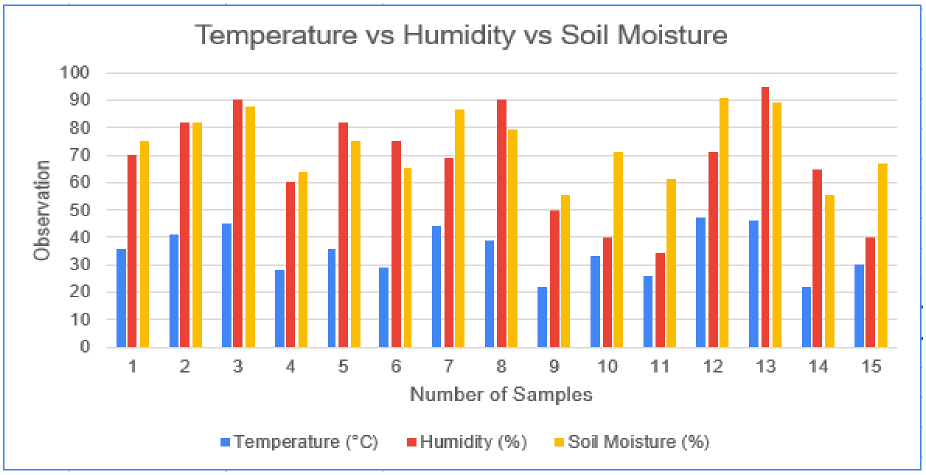

Fig. 5. Results of Soil moisture based on amount of temperature and humidity

In the proposed solution, the real-time retrieval of temperature, humidity, and moisture Irrigation parameters are shown in Fig. 6.

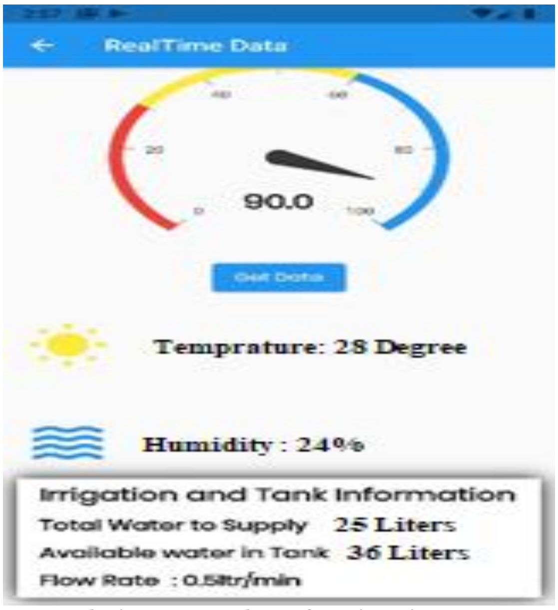

Fig. 6. Real-time Results of Irrigation Parameters

5. Conclusion

Agriculture is a key industry in our country's economic development. However, this industry falls behind in the adoption of emerging technologies such as IoT and machine learning. As a result, manual farming faces numerous challenges, including lower productivity, high yield production costs, difficulty predicting the crop to be grown, water irrigation issues, volatile weather conditions, incorrect fertiliser selection, difficulty selecting a fertiliser for plant disease, and so on. The suggested method helps to overcome these issues by utilizing IoT and machine learning technology. The application of the proposed approach may result in numerous previously unknown benefits, such as fixing the water irrigation problem, recommending crops and fertilizers for plants, detecting crop diseases, saving on human labor costs, and so on. It allows farmers the opportunity to choose the best crop for their specific land area and season. It supports farmers in observing and studying crops to ensure that no crops are diseased. It also continuously monitors the temperature and humidity, which are then used to determine moisture. The moisture level determines how much water will be irrigated to the farm. Machine learning techniques in the proposed solution will be utilized to select a suitable crop for cultivation. As a result, the system will be robust, scalable, and user-friendly. The strategies outlined in the suggested solution can assist farmers in overcoming agricultural challenges while minimizing physical labor and increasing agricultural yield. This will help the country's economic development while also increasing the GDP.

REFERENCES

[1] Abhiram MSD, Jyothsnavi Kuppili, N.Alivelu Manga. “Smart Farming System using IoT for Efficient Crop Growth”, 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science.

[2] A.Anusha, A.Guptha, G.Sivanageswar Rao, Ravi Kumar Tenali. “A Model for Smart Agriculture Using IOT”, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-6, April 2019.

[3] Muthunoori Naresh, P Munaswamy. “Smart Agriculture System using IoT Technology”, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7 Issue-5, January 2019.

[4] Sweksha Goyal, Unnathi Mundra, Prof. Sahana Shetty. “SMART AGRICULTURE USING IOT”, International Journal of Computer Science and
Mobile Computing, Vol.8 Issue.5, May- 2019.

[5] Dr. Y. Jeevan Nagendra Kumar, V. Spandana, V.S. Vaishnavi, K. Neha, V.G.R.R. Devi. “Supervised Machine learning Approach for Crop Yield Prediction in Agriculture Sector”, Proceedings of the Fifth International Conference on Communication and Electronics Systems (ICCES 2020).

[6] Sriveni Namani, Bilal Gonen. “Smart Agriculture Based on IoT and Cloud Computing”, 2020 3rd International Conference on Information and Computer Technologies (ICICT).

[7] R. Varghese and S. Sharma, "Affordable Smart Farming Using IoT and Machine Learning," 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2018, pp. 645-650, doi: 10.1109/ICCONS.2018.8663044.

[8] A. Goap, D. Sharma, A.K. Shukla, C. Rama Krishna, "An IoT based smart irrigation management system

using Machine learning and open source technologies," Computers and Electronics in Agriculture, vol. 155, 2018, pp. 41-49, ISSN 0168-1699.
[9] F. Balducci, D. Impedovo, G. Pirlo, "Machine Learning Applications on Agricultural Datasets for Smart Farm Enhancement," Machines, vol. 6, no. 3, 2018, p. 38, doi: 10.3390/machines6030038.
[10] K.G. Liakos, P. Busato, D. Moshou, S. Pearson, D. Bochtis, "Machine Learning in Agriculture: A Review," Sensors, vol. 18, no. 8, 2018, p. 2674, doi: 10.3390/s18082674.
[11] M. Dholu and K. A. Ghodinde, "Internet of Things (IoT) for Precision Agriculture Application," 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), Tirunelveli, India, 2018, pp. 339-342, doi: 10.1109/ICOEI.2018.8553720.
[12] A. Kamilaris and F.X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, 2018, pp. 70-90, ISSN 0168-1699.
[13] A. Badage, "Crop Disease Detection using Machine Learning: Indian Agriculture," International Research Journal of Engineering and Technology (IRJET), vol. 5, no. 9, Sep. 2018, pp. 866, e-ISSN: 2395-0056, p-ISSN: 2395-0072.
[14] J. Treboux and D. Genoud, "Improved Machine Learning Methodology for High Precision Agriculture," 2018 Global Internet of Things Summit (GIoTS), Bilbao, Spain, 2018, pp. 1-6, doi: 10.1109/GIOTS.2018.8534558.
[15] Z. Doshi, S. Nadkarni, R. Agrawal, and N. Shah, "AgroConsultant: Intelligent Crop Recommendation System Using Machine Learning Algorithms," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, 2018, pp. 1-6, doi: 10.1109/ICCUBEA.2018.8697349.