

08

NC

CC

Journal of Agricultural Extension Vol. 27 (1) January 2023 ISSN(e): 24086851; ISSN(Print): 1119944X Website: http://journal.aesonnigeria.org; http://www.ajol.info/index.php/jae Email: editorinchief@aesonnigeria.org; agricultural.extension.nigeria@gmail.com

Creative Commons User License: CC BY-NC-ND

This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License

Automatic Irrigation Model Powered by Smart Rain Prediction Device in India https://dx.doi.org/10.4314/jae.v27i1.9

Geeta, Mahadeo Ambildhuke

Corresponding Author Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, deemed to be University, Hyderabad Email: geetu9181@gmail.com Phone:9948488044 https://orcid.org/0000-0001-9775-317X

Barnali, Gupta Banik

Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, deemed to be University, Hyderabad E-mail: <u>barnali.guptabanik@ieee.org</u> https://orcid.org/0000-0002-8107-9501

Submission: 7th Nov 2022 First request for Revision: 12th Dec 2022 Revisions: 21st December, 2nd January 2023 Published: 21st January 2023

Cite as: Geeta, M. A., Barnali, G. B. (2023). Automatic Irrigation Model Powered by Smart Rain Prediction Device in India. *Journal of Agricultural Extension 27* (1) 94-110 <u>https://dx.doi.org/10.4314/jae.v27i1.9</u> **Keywords:** Precision agriculture, automatic irrigation, rain prediction, machine learning

Conflict of interest: All authors declare no conflicts of interest in this paper. Acknowledgements The authors express their gratitude to the Editor-in-Chief and the anonymous reviewers for their comments and constructive suggestions. Funding: No funding was provided for this work. Author contribution

G M A. = 70% (Conceptualization, data collection and analysis, writing the original manuscript). BGB = 30% (Supervision and editing of the manuscript).

Abstract

This paper presents a simple rain prediction device-based automatic irrigation management algorithm using a combination of weather parameters and soil moisture measurements for the water balance required for a crop at each condition during its growing phase that will reduce farmer intervention for irrigation and avoid unnecessary irrigation by predicting the rainfall before starting the motor for irrigating the field. This device is powered by various technologies like deep learning to classify clouds responsible for rain, machine learning models to predict rainfall based on atmospheric parameters and the Internet of Things (IoT) using different sensors to collect data from the field. This algorithm is very appropriate for farmers who are in remote locations and are not able to use the internet and WIFI due to its unavailability. The device will be attached to the motor, will take the data from sensors and will do the rain prediction at device level only and will switch ON/OFF the motor based on the soil moisture value and rain prediction without any human intervention.

Introduction

Water is the most significant resource for each and every living thing and is used largely for the agriculture sector. Agriculture uses around 70% of the world's surface water in irrigating the land to produce_crops. Agriculture, which is the sole source of human food, is the world's main industry and major land use, accounting for 40% of all available land. Agriculture has a crucial role in a country's economic development Sah et al. (2018). Furthermore, crop-based food products provide for 78 percent of global average per capita energy demands, while other food sources such as eggs, milk, and meat account for the remaining 20% Brevik, Eric (2013). As a result, the

essential necessity is to meet the dietary demands of a growing population, which can only be met by increasing agricultural productivity. Agriculture and its related sectors provide 17 percent of India's gross domestic product, according to the Ministry of Statistics and Program Implementation (GDP, for the years 2009 and 2017). Furthermore, it employs almost two-thirds of India's workforce Deshpande (2017). In India, agriculture provides the prime source of income for more than 58 percent of rural households, Figure 1 depicts these agricultural dimensions. As a result, progress in the agriculture division is directly linked to the creation of jobs and the reduction of poverty in developing nations Srivastava et al. (2016). Monitoring agricultural activities is the most required necessity of today for minimizing human intervention in the field because of the scarcity of labour and urbanization. Demand for food is rising on daily basis and meeting it with traditional agricultural practices is becoming increasingly difficult. Agriculture monitoring is a top priority because it helps to reduce labour costs while increasing output which requires to adopt new technologies and modern practices.



Figure 1: Importance of the agricultural sector for India

Various monitoring activities in the field of agriculture have been carried out using Artificial Intelligence, such as soil monitoring based on soil conditions to encourage multi-cropping by forming zones based on similar properties of soil and to help farmers in taking decisions on the usage of various resources like fertilizers, water, pesticides based on early disease prediction in the correct amount and at right time. Today, technology is spreading its wings in every sector, including agriculture so our farmers must be educated and should be motivated to integrate and make use of technology as much as possible to increase crop yield by reducing the adverse impact of traditional practices on the environment. Deep learning offers a vast range of applications, and its use in industry has advanced dramatically. Deep learning has a distinct benefit over machine learning in that it provides depth to the latter. Machine learning paradigm developments are breaking down barriers to required data analyses in many IoT-based applications. Deep learning models have demonstrated outstanding results in a variety of fields, including speech recognition, natural language processing, image recognition, information retrieval, indoor localization, physiological and psychological state detection, and so on, and these services serve as the foundation for IoT applications Mohammadi et al. (2018).

Wireless Sensor Networks (WSN) and Precision Agriculture (PA) applications bring together an exciting new area of research that will considerably increase agricultural production quality, precision irrigation, and cost savings. In addition, the ease of deployment, system maintenance, and monitoring paves the path for WSN systems to be accepted in PA. Implementation cost can be reduced and so make WSN a more appealing solution for all kinds of fields and cultivations using the optimized methodologies in selecting the appropriate sensor architecture. Internet of Things (IoT) has proven to be useful in real-time data monitoring and can benefit farmers through a variety of important approaches by selecting the crops according to the soil, amount, and time of fertilization at a particular location for a particular crop, weed detection etc. that can help them grow better crops and manage their fields more effectively. As food is the most basic need of any human being, this ultimately aids in the country's general growth.

Need for Precision Agriculture in India

Alarming obstacles to the global food system include global warming, resource depletion, surging food demand, and growing labour prices. However, the difficulties are greater and more numerous in India, including small and dispersed land holdings, declining productivity, depleting natural resources, seasonal production, climatic fluctuations, lack of an eco-regional approach and stagnant farm incomes. A time like these calls for the best possible use of scarce resources, which is where newly developed precision farming technologies can help enhance agricultural output and profitability.

With the massive challenges of biotic and abiotic pressures experienced by crops and the enormous need for food grain of 480 million tons (Mt) by the year 2050, the introduction and acceptance of contemporary technologies in Indian agriculture is unavoidable.

Drawbacks of Precision Agriculture

- **High cost:** Farmers may be discouraged from using this farming practice by high capital expenditures.
- Lack of technical expertise knowledge and technology: Before being used, precision agriculture techniques still need professional advice as they are in the initial stages of development.
- Not applicable or difficult/costly for small landholdings: Before the system has collected enough data to be completely implemented, it may take several years for small landholdings. It is a really challenging undertaking, especially the data collecting and analysis.
- Heterogeneity of cropping systems and market imperfections

Benefits of Precision Farming for Indian Agriculture

• In India, improving and expanding the use of precision agriculture technologies can aid in lowering production costs, raising productivity, and more effectively utilizing natural resources.

- By enhancing productivity, crop quality, sustainability, profitability, environmental protection, on-farm quality of life, food safety, and rural economic development, it has the potential to revolutionize modern farm management in India.
- Site-specific uses of irrigation, herbicides, and fertilizers in cotton fields, oil palm plantations in South India, and coffee and tea gardens in Eastern India can significantly lower production costs and chemical pollution in the environment.
- When there are not enough water resources, it can improve irrigation efficiency.
- Farmers can use forecasting to control issues like pests, illnesses, nutritional deficiencies, and plant diseases.
- Furthermore, it increases the sector's opportunities for skilled employment and introduces new techniques for assessing multifunctional factors such as non-market functions.
- It plays a crucial part in keeping track of greenhouse conditions in farming areas.

Policy Approach to Promote Precision Farming at Farm Level

- Determine the markets where crop-specific precision farming can be most effectively promoted.
- forming multidisciplinary teams of agricultural scientists from various fields, engineers, manufacturers, and economics to research the whole use of precision agriculture
- Give the farmers full technological support so they may create prototypes or models that can be copied on a wide scale.
- Farmers' fields should be the subject of a pilot study to demonstrate the effectiveness of precision agriculture.
- educating farmers on the effects of using unbalanced levels of agricultural inputs such as irrigation, fertilizer, insecticides, and pesticides

State of Precision Farming in India Compared to rest of the world

- Although precision farming is thought to have originated in the US, it has since spread throughout the world due to its advantages in terms of lower costs and increased productivity.
- European countries like the UK, Germany, France, and the Netherlands have adopted precision agriculture to maximize the use of fertilizer and pesticides and boost output.
- This trend has been further fuelled by environmental concerns. Countries like Canada, Australia, Argentina, and Brazil are putting precision farming principles into reality due to the necessity for a sustainable farming system.
- Asia, China, and India are among the nations experimenting with precision farming due to their growing populations, limited landholdings, and rising labour expenses

- Even though this technology has the potential to be successful, it is still in its infancy in India. To get this idea out to Indian farmers, organizations like Trimble, Tata Kisan Kendra (TKK), and Fasal, among many others, are working. TKK, a project started by Tata Chemicals Limited (TCL), aims to move rural India away from antiquated farming methods and toward the satellite and IT era. The TKKs deliver TCL's extension services to farmers, employing remote sensing to evaluate soil conditions, look at crop health, look for insect infestations, and predict crop yield. They help farmers quickly adjust to changing conditions, which increases crop yield and increases farmers' income.
- Precision farming is being aggressively implemented by the Tamil Nadu Precision Farming Project to cover a bigger geographic region.
- Despite initial hostility from the farmers, its programs for drip irrigation and crop production have received widespread acceptance (Mandal 2009)
- The Central Potato Research Station's (CPRS) investigation of the role of remote sensing in mapping the variability with regard to place and time (Shanwad 2004) will aid in the local farming of potatoes.
- The Dindigul area of Tamil Nadu has been chosen by the M S Swaminathan Research Foundation in cooperation with NABARD for the experimentation of Variable Rate Input Application (Shanwad 2004).
- Precision farming methods are being tested at the institution farm of the Indian Agriculture Research Institution.
- Variable Input Application in Different Cropping Systems has been started by Project Directorate for Cropping Systems Research (PDCSR), Modipuram and Meerut (UP), in Collaboration with Central Institute of Agriculture Engineering (CIAE), Bhopal.

Challenges in Adopting Precision Agriculture in India

- Due to its distinct pattern of land ownership,
- inadequate infrastructure,
- lack of farmers' willingness to take on the risk,
- social and economic circumstances, and demographic circumstances, the adoption of precision farming in India is still in its infancy.

Most of the Indian agriculture is carried out on small parcels of land, which restricts the economic benefits of precision farming equipment that is already in use and therefore, the farmers of developing nations like India, Brazil, and China rely on traditional farming rather than tech-driven farming practices.

For the Indian agricultural industry, the successful development and wide-scale application of precision agricultural technologies is still a long way off. Such smart farming concepts would enable the Indian agro-industry to undergo a transformation thanks to the nation's expanding IT sector and extensive research in the agriculture sector.

The need for automation in the agricultural sector is very essential, and there are numerous ways to put it into practice. Irrigation is the first area where automation is required for efficient water use. The soil moisture sensor monitors the moisture level of the soil and begins watering the farm when the value falls below the farmer's chosen threshold based on the type of crop and its age. The embedded system and the Internet of Things have aided in the development of a small system that monitors the farm's water level without the need for human intervention. The Internet of Things is mostly used in intelligent watering systems. As efficient use of existing fresh water is critical, and the water problem can be resolved with advancements in technology and the application of automation Ahmed et al. (2021).

Novelty: A rainfall prediction device prototype is introduced which is integrated with common and affordable sensors to sense atmospheric parameters and with a USB camera to capture sky images on a raspberry Pi where a rain prediction model based on a machine learning model that take input temperature, pressure and relative humidity as input and Deep learning model that works on cloud images to predict rainfall. Edge analytics is used to avoid the use of WIFI or the internet so the prediction of rainfall based on both models is given at the device level itself where the input parameters are sensed. The novelty of the device is that it can be used in many decision-making activities where rainfall plays a major role. It is used for nowcasting without the help of any internet or WiFi. 5V of power is required to switch on the device and is portable.

Precision irrigation is a critical step toward achieving food productivity and security while simultaneously implementing water-preserving techniques to overcome the unpredictable nature of rainfall and the impact of a water shortage caused by phenomena like drought in various regions of the world. The aim of Precision irrigation scheduling is to provide the proper amount of water to each plant at the right time to overcome the water loss caused by a process such as soil erosion, deep percolation, or evapotranspiration while avoiding excess- and insufficient irrigation, Benyezza et al. (2018), Devanand Kumar et al. (2020), Bigah et al. (2019), Gu et al. (2020). Irrigation Management is a key process in saving water consumption and other indirect expenditures occurred from other sources of energy like electricity or fossil fuel for operating pumps with good irrigation management through proper monitoring for optimal cost-effectiveness Togneri et al. (2019), Cáceres et al. (2021). The use of artificial neural networks for an estimate and modelling the non-linear characteristics of reference evapotranspiration has been proposed and explained by Sharma et al. (2016), Kelley et al. (2019), in addition to the importance of precise evapotranspiration estimation in aiding precision irrigation management. This approach uses parameters like temperature, humidity, wind speed, and solar radiation and was able to accurately estimate water requirements for the crop that may be used to take appropriate irrigation decisions. Penchalaiah et al. (2021) created an IoT-based data-driven irrigation system where soil moisture is predicted using this method, and the results are compared to predictions from other models. The new method is proven to be more effective, and the soil moisture content shown is promising. Bhoi et al. (2021) present an irrigation recommendation that incorporates machine learning methods like regression tree and Support Vector Machine, as well as agglomerative clustering. The system recommended performed admirably on both its own gathered data set and the accessible crop data collection. Risheh et al. (2020) using artificial neural networks and an IoT architecture, created a dependable system for greenhouse irrigation and demonstrate the superior

performance of neural networks compared to the current alternative method of support vector regression using a dataset gathered by conducting tests on various soils also used transfer learning technique to reduce the processing power and speed up the training. Mehra et al. (2020) proposed an intelligent IoT-based hydroponic system using Deep Neural Networks. A prototype for Tomato plant growth as a case study was developed using Arduino, Raspberry Pi3 and Tensor Flow based on the numerous input parameters obtained, the system as created is sophisticated enough to provide the proper control action for the hydroponic environment. In order to achieve irrigation optimization with weather and soil conditions as key components, Difallah et al. (2017) created a linear programming model combined with a knapsack decisional form. The findings showed a reduction in water use of 28.5%. Better optimization would emerge from taking into account additional important extrinsic elements such as relative humidity, soil nutrients, wind speed, and sunshine length. In Alibabaei et al. (2021) the ANN controller is used to calculate the error by comparing the target soil moisture content to the actual soil moisture content, and based on that calculation, the valves were opened and closed. An Internet of Things (IoT)-based wireless sensor network (WSN) architecture was created by Kamaruddin et al. (2019) and it monitors and manages the irrigation system either manually or automatically. The communication network transceiver and CPU used in the suggested manner were NRF24L01 and will be used to transmit the soil moisture sensor data to the base station. The data from the sensor node will then be transmitted via the base station to the cloud server. For the purpose of connecting to an Android application and storing all the data in a database, this project used Thing speak as a cloud server., Kanmani et al. (2021), where Deep Learning models are frequently utilised for image and sound processing, deep learning models have greatly improved the state-of-the-art.

Proposed system

An automated irrigation system is proposed that works with sensors and sense atmospheric parameters, soil moisture and capture sky image to know the types of clouds present to predict the rainfall whether it will be no rain, low to medium rain or medium to high rain which will help in making decision on the time for which motor should kept on. As shown in Figure 2, the rain prediction model combines machine learning model using parameters from the atmosphere (temperature, relative humidity, atmospheric pressure) and deep learning technique (by giving input as sky/cloud image) to predict the intensity of rain.



Figure 2: Rain prediction device model

The working process is presented in the form of an algorithm as shown in Figure 3, where soil moisture is recorded continuously and once it reaches a nearby threshold it triggers a rain prediction model by sensing atmospheric parameters using sensors that are integrated with Raspberry Pi along with the integrated USB camera which gets activated and captures live images of the sky. Next, the atmospheric parameters temperature, relative humidity and atmospheric pressure are provided to the machine learning model as input, the Random Forest algorithm is trained on the dataset based on Hyderabad city which is collected from the NASA Power Data Viewer for Daily Data, that contains a variety of climate characteristics. The most important ones, however, are selected, and the data is taken for a 40-year period between May 1981 and 2021. Given that there are typically 64–65 rainy days per year, a large period is used to gather enough data and is used to predict the rainfall. The dataset is manually downloaded and created as per the requirements as well as experimented by Geeta Ambildhuke and Barnali Gupta Banik (2022). At the same time, the images of the sky/cloud are fetched as an input to the deep learning model trained on a ground-based cloud dataset to get the rainfall prediction based on the types of clouds present in the sky at that time is also demonstrated by Ambildhuke, Geeta Mahadeo, and Barnali Gupta (2021).

Step 1: Soil Moisture sensor placed in soil will continuously sense the data and once the data goes below the threshold value , It will activate the rain Prediction Device
Step 2: Initialize sensor data (Sdata ={T, H, P}) from the sensors connected
Step 3: Pass these values to a trained machine learning model
Step 4: $p1=$ Output of the machine learning model based on current parameters $\{T, H, P\}$
Step 5: Capture Sky cloud image using an USB camera attached to the device
Step 6: Feed captured cloud/sky image as input to the deep learning model
Step 7: p2=output from deep learning model
Step 8: If p1==p2=" No Rain to Low rain"
Step 9: Switch ON the motor and irrigate the land for 30 minutes
Step 10: If p1==p2=" Low to Medium Rain"
Step 11: Switch ON the motor and irrigate the field for 20 minutes
Step 11: If p1==p2=" Medium Rain to High Rain"
Step 12 Do not switch ON the Motor and repeat the rain prediction every hour
Step 13: If p1!= p2 (Output from both approach did not match) Repeat the Rain prediction every hour (3 times) Finally
If (P1=" No Rain to Low rain" && P2 =" Low to Medium Rain")
Switch ON the motor and irrigate the field for 30 minutes
ElseIf(P1=" No Rain to Low rain" && P2 =" Medium Rain to High Rain")
Switch ON the motor and irrigate the field for 20 minutes
ElseIf(P1 =" Low to Medium Rain" && P2 =" Medium Rain to High Rain")
Switch ON the motor and irrigate the field for 10 minutes
Step 14: STOP

Figure 3: Algorithm for automatic water balance irrigation model powered by rain prediction

Once the inputs are given to the machine learning model and deep learning model the output is given as the intensity (as probability) of rain, whether it will be No rain to Low Rain, Low to Medium Rain or Medium to High rain and then depending on the rainfall prediction the motor will be ON and irrigate the field for particular time as shown in Figure 4.



Figure 4: Workflow of the automatic Irrigation model

Methodology

The state of the soil water for an irrigated crop must be monitored on a regular basis to assist the irrigation manager in making irrigation decisions. Irrigation scheduling is typically accomplished in one of two ways. One method is to use soil moisture sensors to monitor soil water directly. On the other hand, the soil-water balance strategy, uses weather data to account for soil-water in the rooting depth. Weatherbased or evapotranspiration (ET) based irrigation scheduling or water balancing method are common terms for this method.

Evapotranspiration

In a farm environment, ET offers an objective and reliable estimate of the water requirements of actively growing crops. Irrigators can better schedule irrigations using evapotranspiration data resulting in higher yields and higher water productivity.

ET is described as the cumulative process of evaporation from soil and plant surfaces, as well as transpiration from plant canopies to the atmosphere via the stomates (tiny holes on the leaf surface). Water is released in the form of water vapor from the plant surfaces and soil into the atmosphere as part of the ET process. Advanced approaches can be used to directly measure crop ET. However, the most typical approach of predicting the ET rate for a specific crop involves first computing reference ET_0 and then using the appropriate crop factors to determine real crop ET explained in Antonopoulos et al. (2017).

The formula for determining the water need is discussed in Eq. (1) based on agricultural literature.

ET₀ * K_c= W_{required} or (ET_c)

(1),

Where, W_{required} denotes the amount of water required.

Where ET_0 is the reference evapotranspiration - which is the evapotranspiration from a reference crop and is calculated using standardized Penman-Monteith equation and K_c is the crop factor. Kc varies by crop development stage as elaborated in Djaman et al.(2018).

Technology Used

Deep Learning Model is implemented to get the prediction from the cloud images captured that uses a transfer learning approach to train the pretrained model on new dataset of cloud images. Machine learning models are trained on three atmospheric temperatures, humidity and pressure to get rain prediction and Random Forest Model is selected due to its good accuracy and predictions. The main feature of this device is the use of Edge analytics where the collection of data, processing of data and predicting output and automation is all done at the device level that does not require any cloud infrastructure and internet connectivity so can be used at any remote location without internet and requires only a power of 5V to start the device as demonstrated by Geeta Ambildhuke and Barnali Gupta Banik (2022).

Software Use

Python code is used to build the DL Model and also to get the sensor data collected from the sensors connected to the Raspberry Pi device. Because the Deep Learning model and machine learning models were trained on Python 3, all

supporting libraries with the required versions Keras 2.4.3, Tensor Flow-2.4.0-rc2, Scikitlearn-0.20.2, and OpenCV -4.5.3 were installed.

Device Setup

The device consists of Raspberry Pi which is the controller that has a trained machine learning model (pickle file) and deep learning model (.h5 file). To collect the real data, sensors like DHT11, BMP 180, USB Camera, are connected for the prediction of rainfall along with motor and soil moisture sensor. This is used to automate the irrigation process without any intervention of the farmer and this device does not require any cloud platform and WIFI as the input collection, running models and giving prediction is all done at the device level itself. The specification of DHT11 and BMP180 sensors are shown in Table 1 and Table 2. As BMP180, OLED Display are I2C devices, they are connected to Raspberry through I2C interface available on board. I2C devices have their unique address and can access the modules through these unique address for sending and receiving the data.

DHT11 Sensor	Specifications		
Temperature range	0°C to 50°C		
Humidity range	20% to 90%		
Operating power	3.5V to 5.5V		
Accuracy	±1°C and ±1%		
Price	\$4 to \$ 5		

Table 1: DHT11 sensor specifications

Table 2: BMP180 sensor specifications

BMP180 Sensor	Specifications
Pressure range	300 hPa to 1100 hPa
Operating power	3.5V to 5.5V
Accuracy	± 0.2 hPa
Price	\$3 to \$ 4

As Raspberry PI does not have analog data pins, to read the soil moisture data, an analog-to-digital converter module ADS1115 is used for converting the soil moisture values received from the soil moisture voltage values to analog values. Analog to Digital Converter (ADC) used here is an I2C device and the module is connected to I2C pins on the Raspberry Pi board. Through I2C communication the data is read and processed as per the requirement of the application. Once the soil moisture sensor values cross a threshold value, then the prediction is taken and switch the 5V water pump ON/OFF accordingly which is controlled by a motor driver shield.

The sensors are chosen based on their simplicity and affordability and are working very well with the device and captures input data from the atmosphere as the requirements. Different temperature sensors are available some of which are compared based on some properties as shown in Table 3.

Sensor	DHT11	DHT22	SHT71
Parameters	Temperature,	Temperature,	Temperature,
Measured	Humidity	Humidity	Humidity
Voltage required	3.5 to 5.5 V	3.5 to 6 V	2.4 to 5.5 V
Temperature range	0°C to 50°C	-40 °C to 80°C	-40 °C to
			123.8°C
Humidity range	20% to 90%	0% to 100%	0% to 100%
Accuracy	±2°C and ±2%	±0.5°C and ±1%	±0.4°C and ±3%
response speed	Slow	Fast	Fastest
power	High	Low	Lowest
Consumption			
Price	\$4 to \$5	\$4.99 to \$ 9.99	\$30 to \$40

Table 3: Comparison between similar temperature/humidity sensors

Many researchers used different controllers and successfully implemented automatic irrigation models with different sensors and weather data from nearby weather stations. For the data collected and analysed as shown in Figure 5 the Arduino UNO is the most popular node for irrigation automation and monitoring, Veerachamy et al. (2022). For the requirement of the proposed device deep learning and machine learning models need to be run on the device level only Raspberry Pi is chosen for the experiment.





Results and Discussion

The device prototype is made with the IoT components to sense atmospheric parameters using sensors like DHT11, BMP 180, USB Camera, and Soil Moisture Sensor.

Arduino-based Soil moisture Sensor is used to monitor the amount of moisture in the soil. Soil moisture level can be determined by the output voltage produced based on resistance. If water is more conductivity will be more and resistance will be less and vice versa. For easy understanding, the output voltage is scaled between 0-100 values. When the value of Soil moisture is 100, it means the soil is completely dry García, L.et al. (2020).

- 1. Based on the soil nature various threshold values are devised to know the wetness using a soil moisture sensor and the motor is allowed to work only on need.
- 2. Once the soil moisture value goes near the threshold the rain prediction model gets started and the USB camera gets activated to capture the current sky images and are passed as input to the deep learning model to get the prediction of rainfall based on types of clouds present in that location at the current time.
- 3. Equally, the atmospheric parameters sensed are passed as input to the machine learning model to predict the rainfall probability based on the sensed parameters at the current location at the current time.
- 4. Based on the prediction the motor will be ON for the time to fulfil the need of crops by keeping track of rain.

The device is used for rain prediction before taking the decision on irrigating the crop when soil moisture goes below the threshold. The motor pump and controller are connected by the relay. The relay performs the function of a digital switch, turning the motor pump ON or OFF in response to commands from the controller. A 5v Dc motor is used to pump water for the demonstration purpose. The deployment cost at initial stage, particularly for small-scale farmers, is one of the key hurdles in adopting digital technologies, machine learning and software applications in terms of enhancing sustainable precision irrigation.



Figure 6: Automatic irrigation using real time parameters

As depicted in Figure 6. The soil moisture shows little change and remains almost constant after evening hours as there is no significant loss in moisture from the plant due to reduced evapotranspiration rate.

This necessitates the digitization of the farm process, as well as the usage of sensors, actuators, and networking of precision agriculture devices. Water use efficiency can be enhanced by better predicting irrigation needs, better matching timing and volume to plant water needs, and adaptively compensating for water loss owing to evapotranspiration. This automatic irrigation results in a higher yield while utilizing less irrigation and wasting less irrigation water. The system becomes smart and can have certain autonomous features for irrigation decision-making as a result of the model's training and ultimate implementation. As a result, most of the irrigation stress experienced by farmers and users can be reduced.

Conclusion and Recommendations

National and international institutes have recognized the notion of climate-smart agriculture, and various programmes have been launched to create climate-smart technologies. However, the adoption and distribution of climate-smart technology, tools, and behaviours is still primarily a continuous and complicated process. The farming community can only optimise water usage through the use of smart irrigation systems. It is a smart system because of the auto mode, and it may be further adjusted for application-specific conditions. The integration of smart technology like deep learning, machine learning and IoT is majorly driving agriculture to sustainability and productivity by achieving sustainable precision irrigation by controlling the usage of water. To fill the technology gap, adopting best practices is crucial, and digital communication is required. Technology diffusion heavily relies on agricultural extension, an area where the private sector is becoming more involved.

For the Indian agricultural industry, the successful development and wide-scale application of precision agricultural technologies are still a long way off. Such smart farming concepts would enable the Indian agro-industry to undergo a transformation thanks to the nation's expanding IT sector and extensive Agri-IT research. Rapid socioeconomic developments including urbanization, energy consumption, and economic expansion are opening new possibilities for the use of precision farming in India. India should employ technology depending on the demands of the nation's socioeconomic situation rather than blindly embracing the sophisticated precision agriculture technologies used by Western nations.

References

- Ahmed, A. A., Al Omari, S., Awal, R., Fares, A., & Chouikha, M. (2021). A distributed system for supporting smart irrigation using Internet of Things technology. *Engineering Reports*, 3(7). <u>https://doi.org/10.1002/eng2.12352</u>
- Alibabaei, K., Gaspar, P. D., & Lima, T. M. (2021). Crop yield estimation using deep learning based on climate big data and irrigation scheduling. *Energies*, *14*(11), 3004. <u>https://doi.org/10.3390/en14113004</u>
- Ambildhuke, G. M., & Banik, B. G. (2021). Transfer Learning Approach-An Efficient Method to Predict Rainfall Based on Ground-Based Cloud Images. *Ingénierie des Systèmes d'Information*, 26(4).<u>https://doi.org/10.18280/isi.260402</u>
- Ambildhuke, G., & Banik, B. G. (2022). IoT based Portable Weather Station for Irrigation Management using Real-Time Parameters. *International Journal of Advanced Computer Science and Applications*, *13*(5). <u>https://doi.org/10.14569/ijacsa.2022.0130533</u>
- Benyezza, H., Bouhedda, M., Djellout, K., & Saidi, A. (2018), November). Smart irrigation system based ThingSpeak and Arduino. In 2018 International conference on applied smart systems (ICASS) (pp. 1-4). IEEE. https://doi.org/10.1109/icass.2018.8651993
- Bhoi, A., Nayak, R. P., Bhoi, S. K., & Sethi, S. (2021). Automated Precision Irrigation System Using Machine Learning and IoT. In *Intelligent Systems* (pp. 275-282). Springer, Singapore. <u>https://doi.org/10.1007/978-981-33-6081-5_24</u>
- Bigah, Y., Rousseau, A. N., & Gumiere, S. J. (2019). Development of a steady-state model to predict daily water table depth and root zone soil matric potential of a cranberry field with a subirrigation system. *Agricultural Water Management*, 213, 1016-1027. <u>https://doi.org/10.1016/j.agwat.2018.12.024</u>
- Brevik, E. C. (2013, April). Climate change, soils, and human health. In *EGU General* Assembly Conference Abstracts (pp. EGU2013-7).
- Cáceres, G., Millán, P., Pereira, M., & Lozano, D. (2021). Smart farm irrigation: Model predictive control for economic optimal irrigation in agriculture. *Agronomy*, *11*(9), 1810. <u>https://doi.org/10.3390/agronomy11091810</u>
- Deshpande, T. (2017). State of agriculture in India. *PRS Legislative Research*, *53*(8), 6-7.
- Devanand Kumar, G., Vidheya Raju, B., & Nandan, D. (2020). A review on the smart irrigation system. *Journal of Computational and Theoretical Nanoscience*, *17*(9-10), 4239-4243. <u>https://doi.org/10.1166/jctn.2020.9053</u>

- Difallah, W., Benahmed, K., Draoui, B., & Bounaama, F. (2017). Linear optimization model for efficient use of irrigation water. *International Journal of Agronomy*, 2017.
- Djaman, K., O'Neill, M., Owen, C. K., Smeal, D., Koudahe, K., West, M., ... & Irmak, S. (2018). Crop evapotranspiration, irrigation water requirement and water productivity of maize from meteorological data under semiarid climate. *Water*, *10*(4), 405. https://doi.org/10.3390/w10040405
- García, L., Parra, L., Jimenez, J. M., Lloret, J., & Lorenz, P. (2020). IoT-based smart irrigation systems: An overview on the recent trends on sensors and IoT systems for irrigation in precision agriculture. *Sensors*, *20*(4), 1042. https://doi.org/10.3390/s20041042
- Gu, Z., Qi, Z., Burghate, R., Yuan, S., Jiao, X., & Xu, J. (2020). Irrigation scheduling approaches and applications: A review. *Journal of Irrigation and Drainage Engineering*, *146*(6), 04020007. <u>https://doi.org/10.1061/(asce)ir.1943-4774.0001464</u>
- Kamaruddin, F., Abd Malik, N. N. N., Murad, N. A., Latiff, N. M. A. A., Yusof, S. K. S., & Hamzah, S. A. (2019). IoT-based intelligent irrigation management and monitoring system using arduino. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 17(5), 2378-2388. <u>http://doi.org/10.12928/telkomnika.v17i5.12818</u>
- Kanmani, R., Muthulakshmi, S., Subitcha, K. S., Sriranjani, M., Radhapoorani, R., & Suagnya, N. (2021). March). Modern irrigation system using convolutional neural network. In 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 592-597). IEEE. https://doi.org/10.1109/icaccs51430.2021.9441917
- Kelley, J., & Pardyjak, E. R. (2019). Using neural networks to estimate site-specific crop evapotranspiration with low-cost sensors. *Agronomy*, *9*(2), 108. https://doi.org/10.3390/agronomy9020108
- Mehra, M., Saxena, S., Sankaranarayanan, S., Tom, R. J., & Veeramanikandan, M. (2018). IoT based hydroponics system using Deep Neural Networks. *Computers and electronics in agriculture*, 155, 473-486. https://doi.org/10.1016/j.compag.2018.10.015
- Mohammadi, M., Al-Fuqaha, A., Sorour, S., & Guizani, M. (2018). Deep learning for IoT big data and streaming analytics: A survey. *IEEE Communications Surveys & Tutorials*, *20*(4), 2923-2960. <u>https://doi.org/10.1109/comst.2018.2844341</u>
- Penchalaiah, N., Nelson Emmanuel, J., Suraj Kamal, S., & Lakshmi Narayana, C. V. (2021). IoT Based Smart Farming Using Thingspeak and MATLAB. In *ICCCE* 2020 (pp. 1273-1295). Springer, Singapore. <u>https://doi.org/10.1007/978-981-15-</u> 7961-5_117
- Risheh, A., Jalili, A., & Nazerfard, E. (2020)). Smart Irrigation IoT solution using transfer learning for neural networks. In *2020 10th International Conference on Computer and Knowledge Engineering (ICCKE)* (pp. 342-349). IEEE. https://doi.org/10.1109/iccke50421.2020.9303612
- Sah, D., & Devakumar, A. S. (2018). The carbon footprint of agricultural crop cultivation in India. *Carbon Management*, *9*(3), 213-225. <u>https://doi.org/10.1080/17583004.2018.1457908</u>
- Shanwad, U. K., Patil, V. C., & Gowda, H. H. (2004). Precision farming: dreams and realities for Indian agriculture. *Map India*.
- Singh, R., Singh, H., & Raghubanshi, A. S. (2019). Challenges and opportunities for agricultural sustainability in changing climate scenarios: a perspective on

Indian agriculture. Tropical Ecology, 60(2), 167-185. <u>https://doi.org/10.1007/s42965-019-00029-w</u>

Togneri, R., Kamienski, C., Dantas, R., Prati, R., Toscano, A., Soininen, J. P., & Cinotti, T. S. (2019). Advancing IoT-based smart irrigation. *IEEE Internet of Things Magazine*, 2(4), 20-25. https://doi.org/10.1109/jotm.0001.1900046

Things Magazine, *2*(4), 20-25. <u>https://doi.org/10.1109/iotm.0001.1900046</u> Veerachamy, R., Ramar, R., Balaji, S., & Sharmila, L. (2022). Autonomous Application Controls on Smart Irrigation. *Computers and Electrical Engineering*, *100*, 107855. <u>https://doi.org/10.1016/j.compeleceng.2022.107855</u>