AI-Based Yield Prediction and Smart Irrigation

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Abstract This chapter presents different techniques and applications of Artificial Intelligence for yield prediction and smart irrigation. Timely prediction of irrigation requirements and crop yields is necessary for farmer's welfare and satisfaction. The beforehand prediction significantly contributes to minimizing production cost and maximizing crop yields. The precise prediction of crops' yields is also useful for government, as it is effective in planning various schemes, transport needs, buying mechanisms, storage infrastructure, and liquid position of the economy before actual selling of crop by farmers to market. This chapter acknowledges the past breakthroughs and emerging Artificial Intelligence-based techniques in precision farming specifically for yield prediction and smart irrigation. Artificial Intelligence-based system provides sufficient information about crop yields at an early stage and its associated smart irrigation management system is effective in the judicious use of essential resources such as water and energy for agriculture.

Keywords Yield prediction · Smart farming · Precision agriculture · Smart irrigation · IoT · Temperature monitoring · Soil moisture · Crop · Artificial intelligence

1 Introduction

In recent years, an explosion in applications of Artificial Intelligence (AI) specifically in the domain of health care, weather forecasting, space programmes, automation, agriculture, etc. has been observed. Across the globe, more than half of the population is involved in agricultural practices. In the arena of agriculture, AI is adopted for the planning of farming activities, sales of agricultural products, weather forecasting,

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and yield prediction. Farmers are taking advantages of AI and getting higher production than traditional farming techniques. In traditional farming, cultivation was manual process irrigational needs of a crop and its yield was highly dependent on climate factors throughout the globe. The onset of inventions in industrial revolution and improvement in mechanisms involved in agricultural practices gave relief to miserable life of farmers. But still, it is a labor-intensive practice and dependent on mercy of monsoon.

Thus, there is a need of developing a system that automates the agricultural practices such as cultivation and irrigation, predicts yields, and help in better planning for systematizing the demand and supply of agricultural products throughout the globe. A blend of AI and IoT technologies intelligently gathers relevant information about different crops, their growth rate, and irrigation requirements. These technologies are effective in monitoring frequent climate change, weather forecasting, nutrition deficiency in plants, plants' health monitoring, pest control, weed management, etc. Researchers have covered a long way in developing subsidiary technology such as geo-positioning satellites (GPS), satellite imagery and sensors for monitoring of yield affecting parameters such as moisture, soil pH level, temperature, etc. Target experimentation at various stages of cultivation such as water resource management, weed elimination, diseases prediction, pest control, estimation of yield production and effective storage of agricultural products is still starving. These challenges can be addressed by applying the techniques of AI and data science.

A voluminous data about agriculture is collected using various sensors such as remote sensors, proximity sensors, temperature/humidity sensors, etc. Advanced Internet facilities disseminate this data to various channels such as the cloud. The introduction of online data storage at cloud, advancements in techniques of data processing, and increase in computation power become effective in dealing with challenges identified in agriculture. Use of advanced techniques makes agricultural predictions more precise, reliable, and useful.

1.1 Scope of AI in Agriculture

Traditional agricultural practices used by farmers are not adequate to fulfill the increasing demand. To serve this increasing demand, farmers need to adopt the latest advancements in agriculture such as use of state-of-the-art tools/machinery and AI-based techniques. It has been observed that most of the farmers are unaware of uses of pesticides specifically in what amount and when. Due to these practices, fertility of the soil, as well as yield production, degrades in an intensified way. A plethora of researchers has proved the increased gain in yield growth with the help of AI and automation. AI can contribute to agriculture in versatile ways. Authors explain the inclusion of AI in the following seven agricultural practices.

1.1.1 Weather Forecasting

One of the important advantages of AI in agriculture is weather forecasting. With the help of latest AI-based state-of-the-art weather forecasting techniques, it becomes easier for farmers to take appropriate decisions in planning respective crops. Nowadays, many weather forecasting devices are available for predicting the weather. Sehgal et al. [1] presented a visual tool (*ViSeed*) based on long short-term memory (LSTM) [2] which can be used for weather and soil predictions. With the help of such farmer-friendly tools, one can plan his/her crop activities, crop types in an efficient way.

1.1.2 Smart Irrigation

To cope with the shortage of water, there is a critical need for some smart irrigation systems that can irrigate more areas with low consumption of water. A comprehensive review of various techniques of smart irrigation has been presented in Jha et al. [3]. However, there is an availability of various low water consumption-based irrigation techniques, for example, sprinkler systems and drip irrigation systems; but these systems need human intervention up to a great extent. There is a scope to add features to existing systems to develop smart irrigation systems. The system continuously monitors the level of water in a crop, compares the water content available in soil and crop plant with standard need of water. It automatically starts sprinklers or drips as per water requirements of crop. Arif et al. [4] presented ANN-based models for predicting soil moistures.

A Neural Network-based irrigation system (Neuro-Drip) has been presented by Hinnell et al. [5]. On the other hand, an IoT-based smart irrigation management system has been presented by Goap et al. [6], Nawandar and Satpute [7]. AI in this field has contributed a lot in collaboration with the Internet of Things (IoT). For smart irrigation, there is a requirement of gathering of information about level of moisture present in the soil, water content in plants, humidity in atmosphere, temperature, etc. This information can be gathered using soil moisture sensors, temperature sensors, humidity monitoring sensors, etc. These sensors are connected to low price Arduino-based systems for storage of gathered information and executing analysis algorithms for predicting the water requirement of crop at a particular time.

1.1.3 Crop Disease Prediction and Health Monitoring

Traditional methods of monitoring crop health are time-consuming and inefficient especially for larger areas of thousands of acres. Many researchers have developed many AI-based architectures to overcome the challenges identified in the arena of traditional agriculture. Some architectures are surveyed in Kamilaris and Prenafeta-Boldú [8].

AI-based techniques with inclusion of image processing, deep learning, and data analysis provide an easy and effective way for disease prediction and health monitoring. The system captures crop images using high definition(HD) camera-enabled drones, unmanned aerial vehicles (UAVs), or satellite imagery. The captured images are used as dataset for training of Convolution Neural Networks (CNNs) [9], a class of Artificial Neural Network (ANN). CNNs extract useful features from fed images and make predictions about disease(s) in crops. The system is effective in continuous monitoring of health of plants and hence gives better solutions for calculating amount of pesticides to be used and time to use a pesticide.

1.1.4 Crop Readiness Identification

AI-based system captures images of a crop and analyzes them for determining the crop readiness in a particular area for harvesting. The crops can be categorized into different categories on the basis of readiness and other quality parameters before actually sending them to market. For categorization, use of various pattern clustering techniques viz. K-means, fuzzy C-means (FCM), expectation maximization (EM), and hierarchical clustering plays an important role.

1.1.5 Yield Prediction

Yield prediction is an area of interest for researchers for past many decades. Yield prediction requires yield mapping devices, which are still not easily available to farmers [10]. CNNs can solve the problem of yield prediction in an economic and easy way. Many researchers [10–12] have developed models to predict crop yields using AI-based methods which use RGB/normalized difference vegetation index (NDVI) images. Their experimental results on publically available dataset prove the usefulness of their models. A comparative analysis of CNN-based models with AI-based models clearly indicates that CNNs are more advantageous than traditional Machine Learning (ML) and AI-based techniques [13]. Authors will discuss the detailed process of predicting crop yields using CNN in Sect. 2.

1.1.6 Weed/Pest Management

Traditionally, weed management was accomplished with a combination of many techniques viz. mechanical weed control, crop rotation, herbicides, etc. [14]. In addition to the above, various biochemical-based combined weed and pest control solutions are also available in the market, but they all results in reducing the yield productivity. The reduction in crop yield occurs due to the spraying of pesticides frequently and in a constant amount in a field. AI provides an intelligent solution for this challenge.

Recently, one AI-based autonomous robot called "*Agbots*" has been developed by McAllister et al. [14], which can do weed management in the field in an interesting manner. The idea behind AI-based weed management is to identify weeds automatically (by examining camera images obtained from autonomous robots) and perform corrective actions (mechanically weed removal or spraying herbicides) accordingly. Many other AI-based techniques are also available such as See and Spray (by Blue River Technologies [15]), which uses AI to identify and spray individual plants in milliseconds.

1.1.7 Precision Farming/Agriculture

The aim of precision agriculture (PA) is to increase yield production as well as quality by simultaneously reducing the overall cost and environmental pollution [16]. The quantity and quality of a crop depend on many parameters such as soil, weather, irrigation, etc. So, there is a requirement to monitor all these parameters at a regular interval of time. Traditional monitoring techniques are not adequate in accurate and efficient monitoring of these parameters.

So, there is vital demand for an automated system which can perform monitoring of parameters in an effective way. In modern era, proximity sensing and remote sensing dominate the field of agriculture and effectively monitor a plethora of parameters required for better prediction and planning of agricultural practices. Proximity sensing specifically deals with soil using high-resolution data. Remote sensing provides the geographical sensing of fields using various sensors. Thermal remote sensing provides some additional information such as temperature, water status, etc. It also helps us in getting many vegetation indices. Many researchers attempted to present several vegetation indices on the basis of various parameters. Xue and Su [17] presented a systematic reviewed of many vegetation indices. AI in collaboration with these techniques can provide cost-effective solutions for PA.

2 Yield Prediction

Manual record-keeping and monitoring trends in agricultural activities and yields are a tedious and time-consuming task. There are fair chances that farmers are not available all the time to keep track of all agricultural activities. Thus, it results in collection of incomplete and inconsistent data. AI-based solutions are effective to overcome such situations. In the era of technology, this is mandatory to motivate and train farmers for adoption of new tools and techniques. This is highly desirable to reduce the manual efforts, improve quality of crops, and to meet the increasing demand of food for increasing population.

Precision agriculture provides an intelligent solution to the challenges observed in the field of traditional agriculture. Increase in awareness and education make farmers to think about adoption of precision agriculture. Farmers are willing to adopt new strategies of precision agriculture but precise yield prediction is still a challenge due to shape irregularities, illumination conditions, etc.

Continuous monitoring of each activity involved for a crop from the stage of sowing seeds till harvesting contributes toward precision agriculture. The planning of timeline for agricultural activities on the basis of past experience and collected record is demonstrated in Nevavuori et al. [10].

Farmers are preparing timeline and maintaining record of following parameters for better prediction.

- Soil fertility and improving fertility by using manures, compost, organic and inorganic fertilizers, bio-fertilizers, etc.
- Growth rate of a crop.
- Irrigation requirements in terms of amount of water required and time and frequency of irrigation.
- Determining precise amount of pesticide and time of spraying pesticide.
- Identifying type(s) of weed growing with a particular crop, growth rate of weed and determining methods to destroy weed plants without harming the main crop.
- Season wise and crop-wise yield estimation.
- Summarizing timeline for future, based on accumulated knowledge and experience.

2.1 Machine Learning Techniques for Yield Prediction

Review of related literature reveals the existence of a significant research work in the field of Machine Learning (ML) techniques for agriculture. The categories of research work are specifically in yield prediction, disease prediction, crop quality prediction, yield estimation, price estimation and weed detection and eradication. In this section, authors give a brief summary of existing works in the domain of yield prediction using ML-based techniques.

Liakos et al. [18] demonstrate different ML models used for solving real-world problems. Most commonly used ML models are Artificial Neural Networks (ANNs) Deep Learning (DL), Support Vector Machine (SVM), Decision Trees (DT), Bayesian Models (BM), Ensemble Learning (EL), and Dimensionality Reduction (DR). There are numerous ML techniques available based on these ML models. These models are based on one or more ML techniques namely Convolution Neural Networks (CNNs), BackpPropagation Network (BPN), Feedforward Network (FFN), Hopfield Network (HN), Multilayer Perceptron (MLP), Radial Basis Function Network (RBF), Deep Boltzmann Machine (DBM), Deep Neural Networks (DNN), K-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA), Multiple Linear Regression (MLR), Generative Adversarial Networks (GAN), and Ensemble Neural Networks (ENN).

The process of yield prediction using Machine Learning starts with capturing images of crop. The image capturing process can be carried out by handheld devices

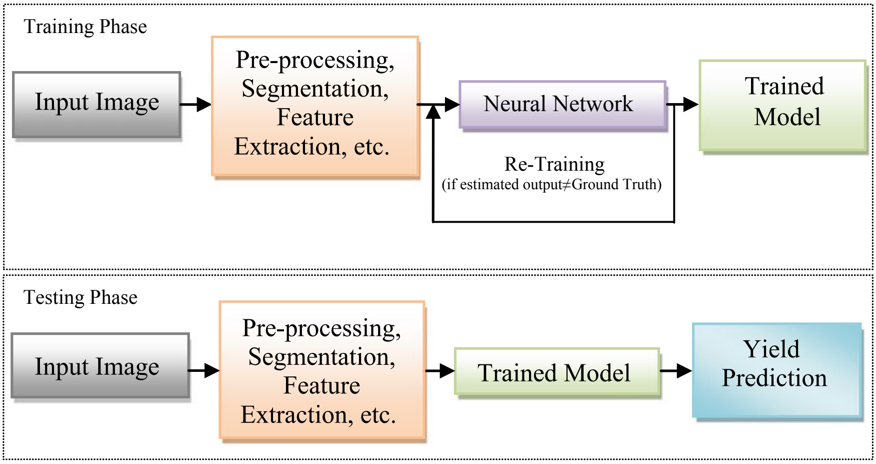

Fig. 1 Architecture of a general yield prediction system

such as mobile phone cameras, digital cameras, and satellite imagery, etc. After capturing, these images are used for providing training to suitable Neural Networks such as ANNs, MLP, and CNNs. The trained networks are used for making predictions in a desired domain. In case there is a mismatch in desired output and ground truth, then there is a need to retrain the model. The retraining continues until the model becomes capable of making precise predictions of yields. Figure 1 demonstrates the architecture of yield prediction using ML.

Let us look at some of the research works carried out by researchers in the field of crop yield prediction using ML techniques.

Wang et al. [19] developed a computer vision-based system which can automatically estimate the number of **apples** in an apple orchard. The system is accurate as well as faster in nature. This system contains a vehicle for moving in the field. The vehicle dismounted with high precision cameras on metal frames. Both vehicle and cameras are calibrated accurately according to coordinate frames. Apple regions are identified with the help of pixel properties. Their model used hue, saturation, and value for identification of specular reflections. Experimental results and analysis show that their model is able to calculate the number of apples accurately and rapidly.

Ramos et al. [20] proposed a method for counting the coffee fruits. Their machine vision system (MVS) is capable of counting and classifying **coffee** fruit. Harvestable and non-harvestable fruits were categorized in this work. They captured images via a mobile-based system and processed the images using linear estimation model to calculate the number of coffee fruits on a branch. MVS has five stages as: (i) acquisition, (ii) segmentation, (iii) fruit boundary/outline detection, (iv) adjustment of ellipses, and (v) detection, classification, and counting of fruits. Promising results were presented on the basis of experimental analysis and validation strategies.

Senthilnath et al. [21] presented a system based on Bayesian Information Criterion (BIC) for detection of **Tomatoes** in the image. They have used unmanned ariel vehicles (UAVs) for obtaining high-resolution RGB images. For categorizing pixels into two categories as "tomatoes" and "non-tomatoes," spectral clustering is used using K-means, self-organizing maps (SOM), and expectation maximization (EM). Morphological operations are used for segmentation. Their experimental results showed that the performance of EM was found better than K-means and SOM in the counting of tomatoes.

Pantazi et al. [12] presented performance comparison of three ML techniques (counter-propagation ANNs (CP-ANNs), supervised Kohonen networks (SKNs) and XY-fused networks (XY-Fs)) for **Wheat** yield prediction based on satellite imagery and online multilayer soil data. As we know that to predict the crop yield, there is a need for various parameters. In this system, researchers have used one such parameter called normalized difference vegetation index (NDVI), mentioned as follows:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R})/(\mathrm{NIR} + \mathrm{R}) \tag{1}$$

where NIR is near-infrared and R is red bands, which enables the accurate estimation of yield per area. On the other hand, to measure the soil properties, they have used vis-NIR spectrophotometers. Experimental results consisting of field maps show that the performance of SKNs was found best among three SOM-based models in predicting wheat yield crop.

Amatya et al. [22] developed a machine vision-based system for automatic harvesting of **Cherry** fruits because manual harvesting is very labor exhaustive which causes more than 50% of production cost. A Bayesian classifier is used to classify the detected branches, leaves, cherry, and background. After getting information about branches and cherry, we can harvest them accordingly. The system is capable of detecting branches with an accuracy of nearly 90%.

Sengupta and Lee [23] presented an SVM-based model for detection of immature green **Citrus** fruit in varying lighting conditions. The system is able to detect nearly 80% of citrus fruits in the tree canopy. In addition to the above, lots more work in the area of yield prediction is available. Liakos et al. [18] presented a systematic review of various Machine Learning techniques for agriculture. They have classified these techniques into different categories such as yield prediction, disease detection, weed monitoring, etc.

2.2 Remote Sensing-Based Yield Prediction

Remote sensing brings information about a field, crops, or an object without actually visiting the field. The information is captured with the help of different sensors and is made available in raw, processed, or analyzed form. It works on the principle of properties of objects. The properties may be chemical, physical, structural, energy

Fig. 2 The Remote Sensing process

Table 1 Various active and passive sensors for remote sensing [24]

Active sensors	Passive sensors
Laser altimeter	Accelerometer
Lidar	Hyperspectral radiometer
Radar	Imaging radiometer
Ranging instrument	Radiometer
Scatterometer	Sounder
Sounder	Spectrometer
	Spectroradiometer

emissions, etc. Sensors sense these properties and send to a storage system. In storage systems, the information is organized in a structured way. This information is analyzed to make decisions for deciding further actions required. Remote sensing techniques have numerous applications in agriculture viz. yield forecasting, damage identification, harvesting time prediction, irrigation estimation, and nutrient requirement prediction, etc. Figure 2 shows the process of remote sensing. It comprises of four basic steps viz. data capturing, data interpretation, information production, and decision making.

2.2.1 Data Capturing

The process of capturing data is done in either of two ways, i.e., active or passive. In the case of active remote sensing, sensors are focusing directly on objects and send the sensed information to the control station which is located on the ground. Active sensors make uses of their own energy sources for object illumination.

Passive remote sensing follows the concept of reflection. Objects are exposed to sunlight and then reflected wavelengths are sensed. The sensed information is further provided to control stations. The electromagnetic spectrum is being used for this purpose. List of some active and passive sensors obtained from [24] is given in Table 1

2.2.2 Data Interpretation

After capturing the required data, the process of processing that data needs to be done in order to obtain the required information. This processing may take a while depending upon the operations/statistical techniques being applied. This process is intended also for filtering of only relevant data which needs to be considered for the next phases. Various mathematical/statistical techniques are being applied in order to get the required information.

2.2.3 Information Production

The next step after interpreting data is the production of the required information. As we know that the processed data can be presented in the form of various visual representations such as graphs, charts, maps, GIS data, etc. We can get various types of information with the help of remote sensing data such as yield modeling/forecasting, nutrient deficiency graphs, area estimation, soil mapping, etc. These graphs/charts are the best way to represent the gathered information, by which we can take effective and timely decisions.

2.2.4 Decision Making

With the help of various visual representations, one can take effective decisions. The objective of these decisions is very clear: maximizing the net profit by increasing the quality as well as quantity of the crop. Also, there is a need to identify risk factors in achieving this objective. Nowadays, the process of decision making becomes easier with the help of various AI-based techniques. Once we have obtained the required information, we can present this information to the information scientists in order to save them in the knowledge base. On the basis of certain parameters AI/Machine Learning (ML) systems are able to predict/provide efficient decisions (such as the necessity of water treatment, moisture prediction, irrigation requirements, pesticide requirements, etc.) which makes farmers away from critical thinking process and obtaining maximum profits out of minimum/required efforts. Traditional ML techniques use feature extraction in the earlier stages, and on the basis of these features, different tasks (crop classification, yield prediction, etc.) were carried out [10]. But traditional ML techniques were not sufficient in producing the optimal decisions. Nowadays, it becomes possible to provide optimal decisions with the help of some advanced paradigms such as Deep Learning paradigm. Among various Deep Learning paradigms, Convolutional Neural Networks (CNNs) prove to be efficient in image analysis/classification. By combing Remote Sensing with Deep Learning techniques, we can have effective agricultural decisions that can maximize the farmer's profit.

2.3 Big Data-Based Yield Prediction

With the advancement of Information and Communication Technology (ICT), massive volumes of data are being generated. Big data techniques play important roles in analyzing these massive volumes for smart farming and yield prediction. The process of big data starts by implementing "data chain," which is the organized sequence of activities from capturing to decision making/marketing [25] mentioned as follows:

1. Capturing of data (Identifying sources of data, types, and purposes)
2. Storage requirements (Identifying storage location, permissions/authenticity, etc.)
3. Transfer from one location to another
4. The transformation from one form to another
5. Analysis (Identifying methods, purposes, and output)
6. Decision Making (Identifying strategies, risk assessment, etc.)

Big data can play important roles in predicting the amount of yield prediction. Here, the emphasis is on analysis rather than big or small. An agricultural data without proper analysis is of no use until it is being analyzed properly. However, big data in agriculture is still in an early stage, and there is a need to do more work on big data with respect to agricultural applications. As mentioned above in the first step, we may require the capturing of data from multiple sources. If data is gathered from multiple sources, definitely it will not be in a uniform shape. It is the task of data analysts to prepare and arrange data in a uniform shape which in future can be transferred/transformed.

There are numerous data analysis techniques [26] available, but for analyzing agricultural data, we have to focus on some specific techniques such as scalable vector machines, K-means, NDVI, Wavelet/Fourier transformations, etc. In addition, to predict the crop yield, big data can do more with agricultural data such as weather forecasting, soil/land analysis, food availability, etc. In this regard, Kamilaris et al.[26] presented a systematic yet remarkable review of various big data techniques for agriculture.

3 Smart Irrigation Systems

Efficient utilization of water is a challenging task especially for places where availability of water is a major concern. For gaining high yields, one has to irrigate the field when needed or we can say that the exact amount and time of irrigation must be known. Nowadays with the help of new innovations in technology, we are living in the world of advanced irrigation systems called "smart irrigation." The word smart means, the sensors are able to sense the water requirements in plants. This ability is achieved by combining multiple technologies viz. automation, sensors, and knowledge (AI). Even though these systems are not costly in nature, due to lack of awareness, most of the farmers are adopting a traditional way of irrigation which results in inefficient utilization of water and low crop yield. Thanks to the researchers who have developed such low-cost smart irrigation systems. One such system is shown in Fig. 3.

Fig. 3 AI-based smart irrigation system [35]

The automation behind these smart irrigation systems is achieved using smart embedded systems. These smart embedded systems can be formed with the help of various technologies/devices such as Raspberry Pi, Arduino, power unit, temperature sensors, moisture sensors, Machine Learning, and Internet of Things (IoT) as shown in Fig. 4.

Jha et al. [3] presented a review of such irrigation systems in a systematic way. Smart irrigation systems are able to save a massive amount of water, which can be utilized for other important purposes of mankind.

Smart irrigation systems also ensure the reachability of water to each and every plant in an exact amount which results in maintaining the good health (by preventing them from dehydration and excessive/irregular irrigation) of the plant and makes away from diseases. It has been observed that some of the diseases in plants are due to improper irrigation which is mostly due to the adaptation of traditional irrigation systems. Continuous observations of sprinklers/drip modules are also necessary at regular intervals to prevent them from failures. Sometimes these systems need recalibrations due to degradation in performances or damages caused by animals/environment. In this situation, some part of the field is highly irrigated while some part remains unirrigated. The main challenge in designing a smart irrigation system is the nonuniformity of land and crop types. Some of the smart irrigation systems are discussed in the upcoming section.

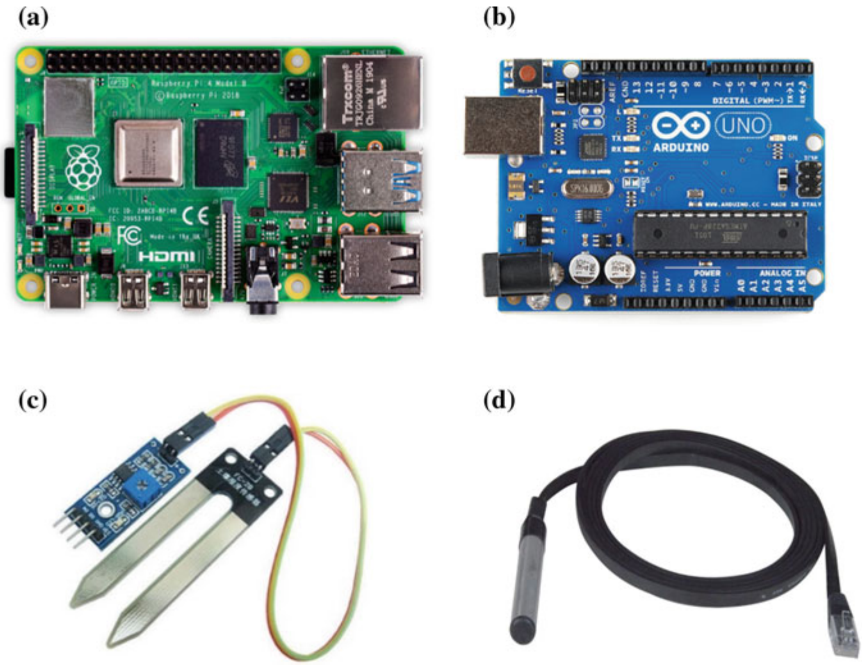

Fig. 4 Various devices for smart implementing smart irrigation systems: **a** Raspberry Pi, **b** Arduino, **c** soil moisture sensor, **d** temperature sensor

3.1 Existing Smart Irrigation Systems

Many researchers work in the area of smart irrigation systems so far. Let us discuss some of them as follows:

Suresh and Umasankar [27] developed a smart irrigation system which works on the solar power supply. The system is able to minimize electricity costs by utilizing solar power. It is composed of an automated water flow system which works by sensing the moisture level in the soil.

The intention behind the development of this system is to save both electricity as well as water in the Indian scenario. The block diagram of solar-powered smart irrigation is given in Fig. 5, which consists of solar panels, battery, converter module, and water pump. The system works on solar-powered supply, which is used to turn on the stepper motor to feed the water from well to storage tank on the basis of sensed moisture. The storage tank is mounted with a water outlet valve which is electronically controlled by moisture sensing circuitry. The moisture sensors are mounted inside the field of where cultivation of the crop is going on. Sensors are able to convert the moisture content to equivalent voltage which is compared with the

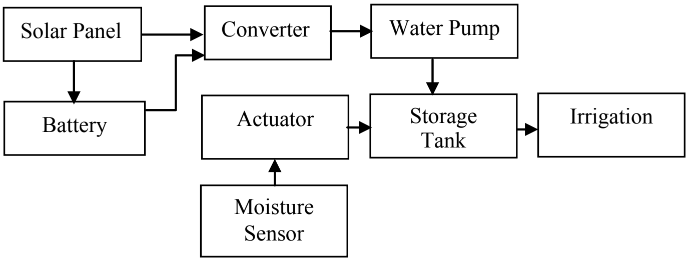

Fig. 5 Architecture of a solar-powered smart irrigation system [27]

reference voltage. The voltage difference level is used to find out the water requirements. Their experimental results showed that the system is capable of irrigating the field with the minimum usage of water and energy.

Kehui et al. [28] designed a system using wireless sensor network for monitoring of moisture and water height in the rice field. The system was tested on real time and proved to be feasible for irrigating rice fields. The working of the system is explained as follows:

1. Moisture data is calibrated to the data center.
2. The existing expert data available with the data center is being compared with real-time sensed data.
3. Irrigation instructions are being sent to the base station on the basis of irrigation requirements.
4. The base station sends these requirements to the irrigation control system (ICS).
5. ICS opens the electronic valve and closes after irrigation.
6. The process works in a cycle as per the irrigation requirements.

Vellidis et al. [29] developed a prototype for scheduling irrigation to cotton fields on the basis of soil moisture and soil temperature as shown in Fig. 6. This smart irrigation system works on the principle of smart nodes consisting of a combination of a sensor array, RFID tag for sending information to the central computer, and electronic circuitry. The tags used in these nodes have the capacity to transmit signals up to the range of 0.8 km. The smart nodes will send the sensed information at user-specified intervals. The information in each transmission is the unique node identification and 12 bytes of sensor values (two temperature values and three sensor values). The nodes are provided with a power backup of 9 V lithium batteries. The microcontrollers are programmed for efficient usage of power during information transmission and sensing moisture/temperature levels. The system was tested in a real environment which offered real-time monitoring of water in the soil. According to these values, users are able to schedule the irrigation requirements (which were not automated in this system).

Nasiakou et al. [30] presented a software system for reducing the irrigation cost by combining the smartness of renewable energy sources and irrigation as shown in Fig. 7. The system contains common information and common bus which is

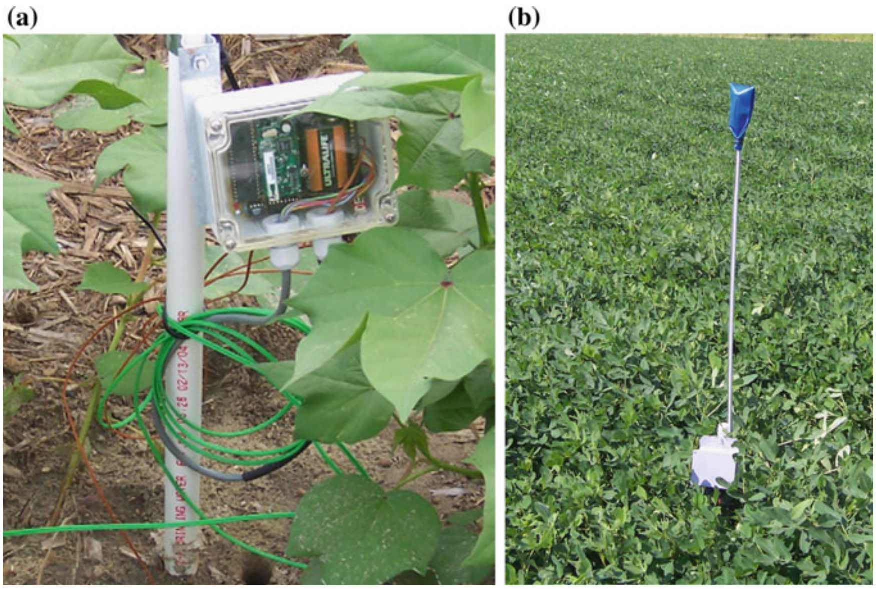

Fig. 6 Smart irrigation system [29], **a** smart sensor array for cotton field, **b** modified sensor array for peanut

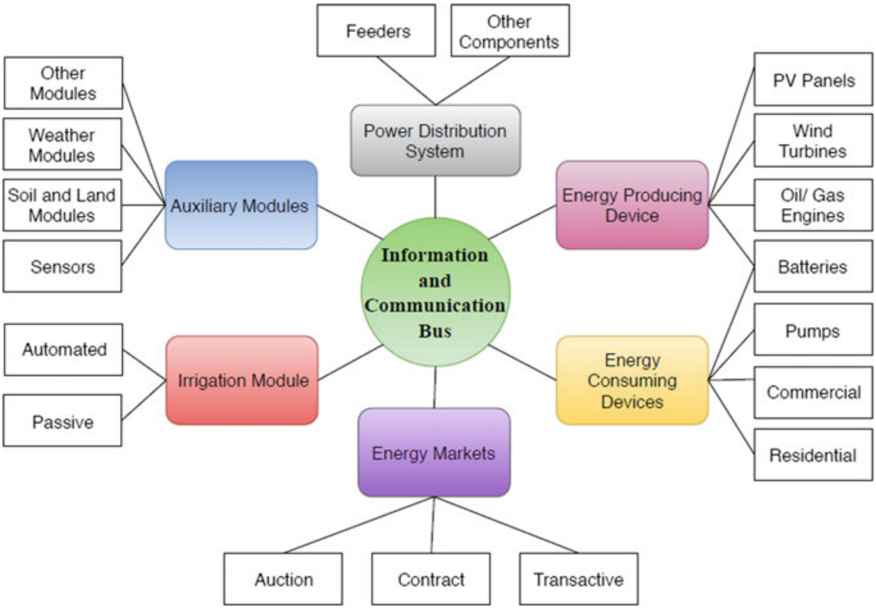

Fig. 7 Component view of energy-efficient irrigation system [30]

connected with six components as irrigation modules, energy-consuming/producing devices, power distribution system, energy markets, and auxiliary modules.

The main goal of designing this system is analyzing the capabilities of batteries and renewable energy sources to handle both residential as well as agricultural load. As shown in Fig. 7, the six basic components (irrigation module, power distribution module, energy consumption devices, energy-producing devices, energy markets, and auxiliary module) of their systems are connected to a common bus called information and communication bus. Every module has its designated purpose in contributing to the irrigation system. Power distribution module is responsible for distributing electricity flow to the whole system. It calculates the overall energy flow in terms of the voltage vector of different nodes. Electricity generating module is responsible for implanting various energy-producing devices, i.e., engines, turbines, PV panels, and batteries. Energy consumption module on the other hand provides possible energy-consuming devices which can be categorized into two categories, viz. residential/household devices and commercial devices. The energy market is responsible for organizing energy bids between producers and consumers. The main module of the system, i.e., irrigation module is capable of irrigating plants in two different ways, viz. automated and passive. All other components of the system such as temperature sensors, soil moisture sensors, humidity sensors are implemented in the auxiliary module of the system. Simulation of the system was achieved on R4 25:00 1 and IEEE-13 bus feeders equipped with 68 and 80 houses, respectively. The simulation gives promising results in terms of satisfying the irrigation requirements of both agricultural and residential design with low energy consumptions.

Navarro-Hellín et al. [31] presented a smart irrigation decision support system (SIDSS) for estimating the weekly irrigation requirements using sensors and Machine Learning techniques (PLSR and ANFIS). The system was tested on citrus plants located in the southeast of Spain. Performance of the system was tested with human expert values. A reduction of 22% irrigation requirements was observed using their system as compared with weather values of the previous year (i.e., irrigation requirements of the year 2015 are predicted on the basis of 2014).

Figure 8 shows the prototype of the closed-loop irrigation system which is able to send feedback to a typical irrigation advisor system (shown in dashed box). Earlier,

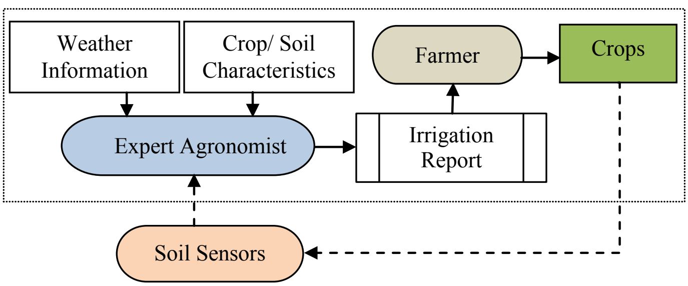

Fig. 8 Closed-loop irrigation advisor system [31]

the decisions were taken by expert agronomist on the basis of weather information and characteristics of soil/crop. The expert's knowledge is being used in their proposed system, which incorporates two Machine Learning algorithms along with expert knowledge to take irrigation decisions as shown in Fig. 9. They have developed their own wireless module (as shown in Fig. 10) for collecting information about soil/crop from a lemon field. The device is equipped with GPRS/GSM modem for accessing it from anywhere. The advantage of these modules is that they are powered with a solar power system and are capable of providing sufficient information for decision support systems. The collected information is being stored in the databases for making irrigation decisions along with previous knowledge of experts using Machine Learning algorithms.

Weather stations, on the other hand, are sending the following information:

Relative humidity (RH), temperature (T), rainfall (RF), wind speed (WS), vapor pressure deficit (VPD), dew point (DP), global radiation (GR). This information

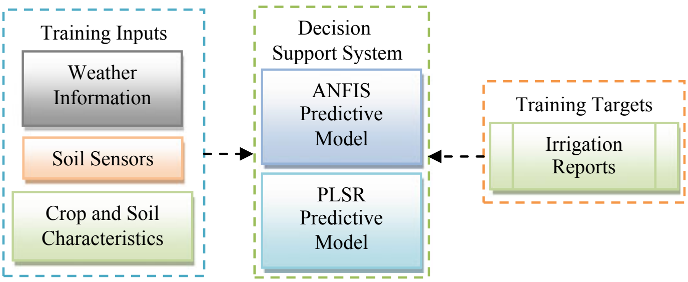

Fig. 9 SIDSS with training inputs and targets [31]

Fig. 10 Wireless information collection device with GPRS/GSM modem installed in the southeast of Spain for the lemon crop by Navarro-hellín et al. [31]

is made available to the public on the SIAM website [32]. The goal of SIDSS is to take final decisions on the basis of information collected from different sensors and expert's knowledge regarding water requirements or time requirements for constant water irrigation. They have incorporated two Machine Learning techniques, viz. partial least square regression (PLSR) and adaptive neuro-fuzzy inference system (ANFIS). PLSR is a statistical model which is needed for pursuing knowledge between predictor and response variables, whereas ANFIS is capable of generating fuzzy inference rules on the basis of given input/output dataset. The system was tested to three different locations and found to be suitable for scheduling irrigation requirements on the basis of continuous monitoring of soil/crop characteristics along with expert's knowledge.

Recently, Goap et al. [6] developed an IoT-based solution for smart irrigation using open-source technologies. The system is fully functional which takes advantages of its integration with the cloud using web-based services. The system works on the principle of sensed values (i.e., soil moisture, ultraviolet radiations (UV), soil/air temperature, and humidity) of from sensor nodes. The proposed system is intelligent enough in providing real-time irrigation decisions and web-based visualizations. The block diagram of their system is shown in Fig. 11.

Figure 11 shows the architecture of IoT-based smart irrigation system. The system is embedded with many components which are divided into three main units, viz. sensor network, server, and application layer. Sensor nodes are continuously sensing

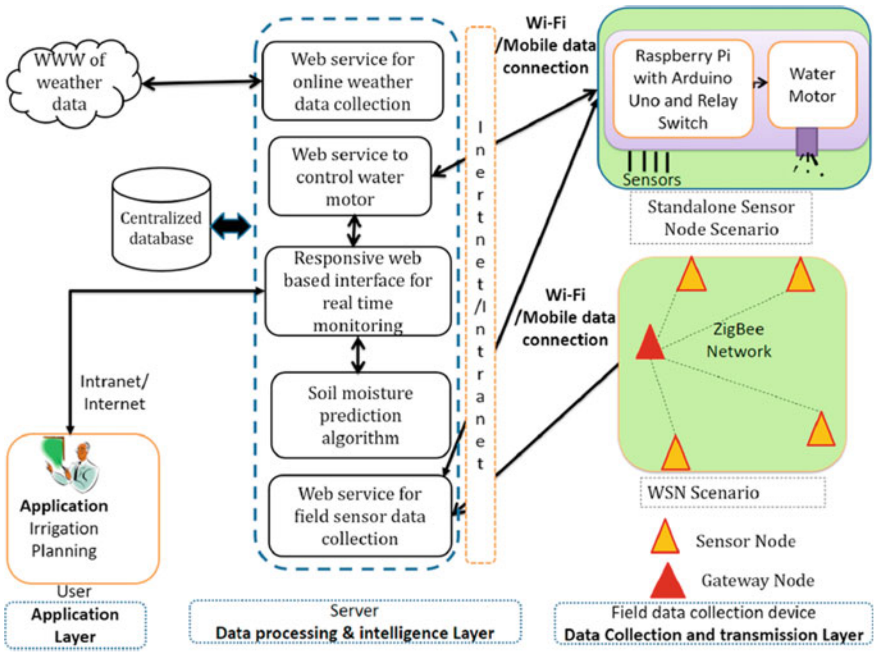

Fig. 11 The architecture of IoT-based smart irrigation system using open-source technologies [6]

the required values from the fields and sending them to the data processing server for storing them to a centralized database system. The centralized database along and other web-based data are collectively used for making irrigation decisions on the basis of an intelligent algorithm. The algorithm makes use of both supervised and unsupervised techniques which gives better accuracies while minimizing the mean squared error for predicting the soil moisture level of upcoming days. Values obtained from sensor units are being supplied to support vector regression (SVR) (modified SVM) model for providing training. After getting training, SVR is used to make predictions on soil moisture differences (SMD). For improving the accuracy of predictions, K-means clustering is used. The final predicted values are used for making irrigation decisions. The system gave promising results while tested on real environment.

Gu et al. [33] presented a software-based solution called Root Zone Water Quality Model (RZWQM) for scheduling irrigation requirements. The system is able to identify irrigation requirements on the basis of crop computed on the basis of agricultural models because it seems harder to calculate this stress in real time. Irrigation timings are suggested on the basis of water stress (WS) calculations by model, whereas irrigation depth is calculated on the basis of soil moisture threshold. The model captures weather inputs from databases of weather websites (historical and four days ahead of data) and on-site sensors. Water requirements for irrigations are calculated on the basis of Eq. (2).

$$\mathrm{IR}_{(t0)} = K\left\{\sum_{(i=1)}^{N}\left(\theta_{(fci)} - \theta_{(t(0)i)}\right)\cdot D_{(i)}\right\} - P_{(t0+4d)} \tag{2}$$

where

$IR_{(t0)}$ is the required water supply for irrigation

i represents layers of soil

N represents the deepest rooting depth derived from crop biomass

$\theta_{(fci)}$ represents volumetric θ at the field capacity of ith layer of root

$(t_{(0)i})$ represents volumetric θ on the irrigation day at ith layer of root

K represents the proportion of irrigation losses which needs to be done again

$P_{(t0+4d)}$ represents expected accumulative rain and data of the next four days.

All existing irrigation calibrations are being removed and RZWQM is then recalibrated on the basis of calculated WS. GUI of RZWQM irrigation scheduling software is shown in Fig. 12. The system is able to save the water requirement with a trivial reduction (0.03–3.81%) in crop yield. Experimental results showed that the system is able to save water and maintain the crop yields.

Nawandar and Satpute [7] proposed an IoT and Neural Network-based low-cost smart irrigation system. IoT is used for connecting various devices, whereas Neural Networks are used for irrigation decision-making purposes.

The system is user-friendly in the nature that it provides various crop-related details like estimated irrigation requirements, soil statistics, zone-wise irrigation alert, and remote data monitoring through message queue telemetry transport

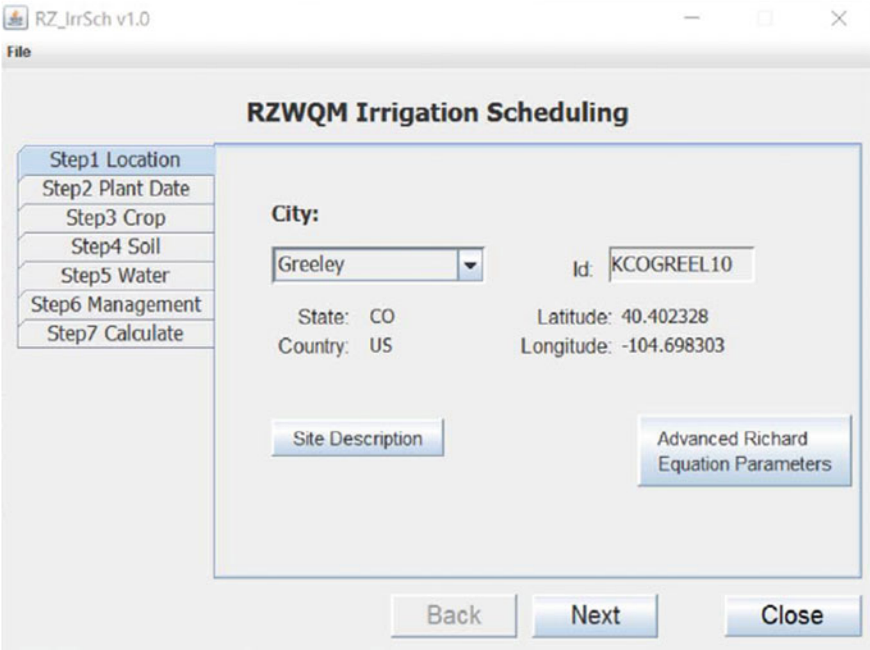

Fig. 12 The interface of RZWQM scheduling software [33]

(MQTT) protocol. The architecture of the proposed low-cost smart irrigation system is shown in Fig. 13.

The system consists of a unified sensor pole (USP) which is called as brain of this system. The purpose of including USP is to take intelligent decisions about irrigation process. USP senses real-time data (i.e., temperature, humidity, and soil moisture) from smart nodes and sends them to both irrigation unit (IU) and sensor information unit (SIU). SIU is capable of logging sensor data to website through 802.11x. A

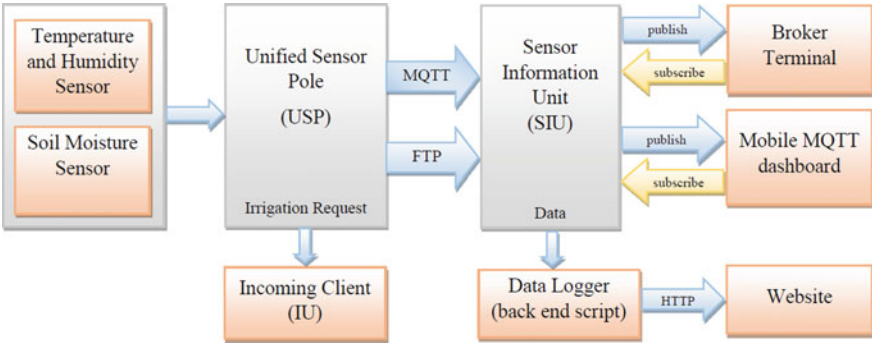

Fig. 13 Architecture of IoT and Neural Network-based low-cost smart irrigation system [7]

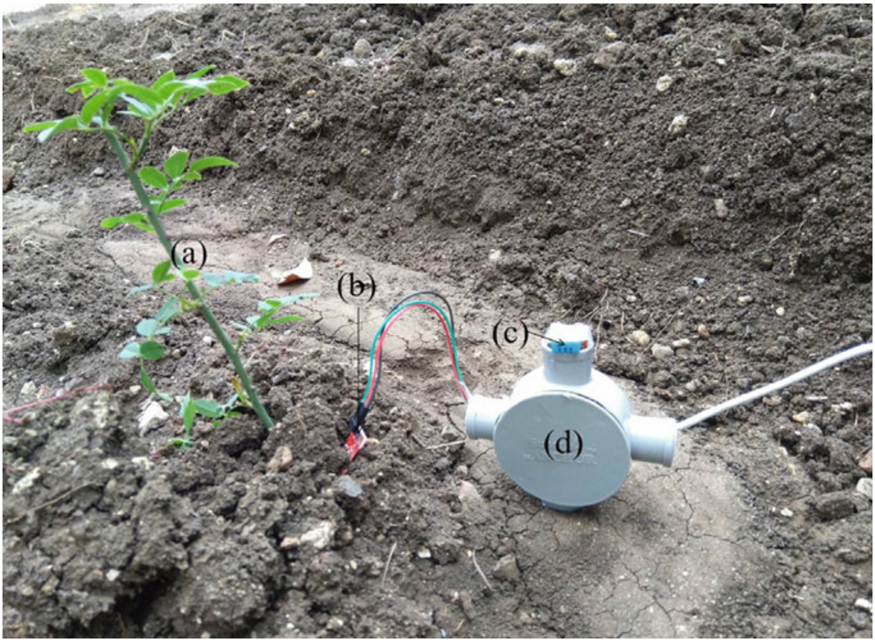

Fig. 14 Installation of IoT-based smart irrigation system [7]: **a** plant, **b** moisture sensor, **c** humidity and temperature sensor, **d** USP

HTTP server hosts these data to a webpage for remote monitoring. Installed module is shown in Fig. 14, which costs ≈$13. USP is responsible for providing sensed values at various regular intervals. The position of smart node is decided on the basis of water availability. Low water availability spaces cause massive logging of same data at regular intervals. So, the area which is having average availability of water is chosen for the installation of these sensors, because it is able to sense the water requirements of nearby areas. IU on the other hand is responsible for making intelligent decisions about irrigation requirements. USP has the capability to work in either admin or user mode. It works in admin mode until it times out. USP is connected with irrigation unit which instructs stepper motor via relay to start or stop.

MQTT broker sends sensor values through messages in an energy-efficient way. Examples of some famous MQTT brokers are Mosca, RabbitMQ, HiveMQ, Cloud-MOTT, etc. The principle of sending message is publish–subscribing mechanism, in which sensor nodes are publishing data to MQTT on topics. Subscribes on the other hand are end users, which use the published topics. For taking intelligent irrigation decisions, a Neural Network is provided training of real-time data as well as crop database inputs. The system showed promising results after installation. Figure 15 shows the crop growth after installation.

Fig. 15 Crop growth after installation of IoT-based low-cost smart irrigation system [7]

3.2 Architecture of Proposed Smart Irrigation Systems/Automated Irrigation Infrastructure

As discussed in the previous section, various smart irrigation systems have been proposed by many researchers which are overcoming the drawbacks of traditional irrigation systems (drip irrigation, direct pump/canal irrigation, sprinkler irrigation, tube well irrigation) that need continuous monitoring of field. Most of these smart irrigation systems are capable of automated irrigation of crop field on the basis of sensor values. Sensor nodes are the most essential part of these systems. Other important components include but not limited to: controller unit, wireless medium, GSM module, Arduino, display unit, relay, Raspberry Pi, water pump, sprinklers/drip modules, etc. The difference in these systems arises due to two things, viz. variety/capability of sensor nodes and their organization with other components. Temperature sensors are responsible for observing the amount of temperature adequate for a particular crop, whereas moisture sensors are capable of sensing level of moisture in soil. It is the responsibility of system designer to obtain the values from these sensors continuously or at some specified intervals. Some systems were found to be energy efficient in the sense that wireless nodes must not sense and send the information continuously; rather, they were calibrated to do these tasks at user-specified interval thresholds. A controlled unit is continuously observing these sensed values and enables water pump operations (On and Off). The positioning of sprinklers/drip modules should be mounted specifically according to the plant/crop and land structure. There is no general irrigation system available which can satisfy the irrigation requirement of all types of crops/fields, because the structure and irrigation needs are not same for all crops. Considering these versatilities in the field/crop, intelligent irrigation systems should be capable of making decisions on real-time sensed values as well as

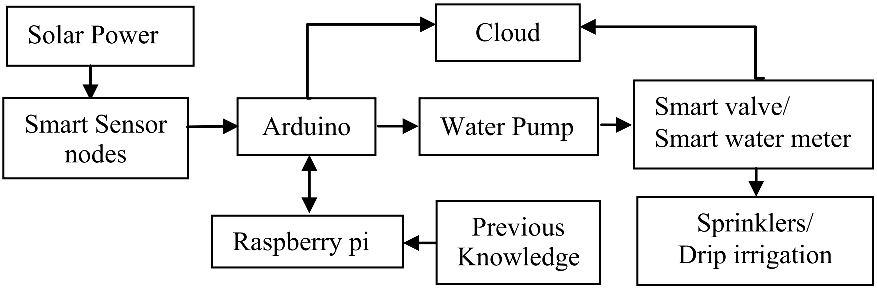

Fig. 16 The architecture of the proposed smart irrigation system CS-HYSIS

analyzing the previous knowledge. After observing various irrigation systems in the previous section, an architecture of a smart irrigation system named cloud and solar power enabled hybrid smart irrigation system (CS-HYSIS) has been proposed as shown in Fig. 16.

3.2.1 Working Principle

As shown in Fig. 16, the system contains smart sensor nodes which are provided power supply from solar panels. The choice of solar panels may vary according to the weather conditions (if the system is being installed in a cloudy/rainy environment, definitely advanced controllers for solar panels need to be installed). The sensor nodes contain three sensor units mentioned as follows:

- Temperature sensor
- Soil moisture sensor
- Humidity sensor

These smart sensor nodes are directly connected to the Arduino controller. The controller enables water pump to turn on or off on the basis of real-time sensor values and existing knowledge (trained inside a Neural Network) from Raspberry Pi. The concept of existing knowledge has been incorporated in this system to irrigate the plants during unavailability/failure of sensor nodes. Because sensor nodes may stop working due to various reasons, i.e., power failure, fault in a part of sensor, physically damaged by any animal(s), etc. This feature prevents plants from dehydration in case of failure of smart sensor nodes. Existing knowledge can be obtained from previous data or from agricultural expert. Pretrained network plays an important role in providing overall predictions about irrigation requirements. The controller is able to make decisions either on the basis of real-time values (obtained from smart sensor units)/pretrained network or from both. It analyzes both existing pieces of knowledge and real-time values in order to make appropriate decisions (turning on or off the water pump) on the basis of user-specified thresholds (i.e., moisture level, humidity level, and temperature).

The most important part of this system is that it is able to send all irrigation-related data to the cloud, for making analysis and future purposes. User can see the current and past irrigation usages anytime on a smart web-based or app-based portal. The interface may provide several additional features, i.e., start/stop irrigation, total water consumptions in a particular amount of time/area, real-time sensor values, etc. Smart valve/smart meter will count the units of water consumptions and send these details to the cloud. With the help of this methodology, we can make sense about total water consumption/requirements for a particular crop and monthly/weekly consumption of water. These values can be used for making future plans/decisions about water requirements.

The position of sprinklers and drip modules is calibrated manually according to the situations of different crops/fields. Nowadays, the sprinklers are so smart in the nature that they can itself irrigate the field smartly. Traditional sprinklers are not able to irrigate the fields properly. Wi-Fi enabled sprinklers provide the facility for controlling the sprinkler nozzles using smartphones. The direction of the nozzles and speed of water spraying can be controlled through smartphones. Even some smart sprinklers are able to make their own irrigation schedules as well. For more information on smart sprinklers, please refer to the review of latest sprinklers which is provided in Top 8 Best Smart Sprinkler Review [34]. The choice of sprinkler systems is also challenging for implementing smart irrigation systems in order to do optimized irrigation.

The proposed system is able to achieve precision agriculture by doing optimized irrigation and can provide several advantages as follows:

- Cost minimization:
  - Optimum utilization of energy (obtained through solar power systems
  - Optimum utilization of water (sprayed through smart sprinklers as per requirements).
- Increase in crop growth:
  - Achieving good health of plants by providing them optimized irrigation in order to prevent them from dehydration and excessive/irregular irrigation.
- Reduction in manpower requirements for irrigation.
- Providing complete irrigation data through cloud computing.
- Efficient utilization of existing knowledge through Artificial Intelligence.

4 Conclusion

Yield prediction and smart irrigation systems using AI-based techniques are demanding in precision agriculture. This chapter examines the critical parameters for predicting both crop yields and irrigation requirements in a systematic way. After carefully examining many existing systems, we have provided effective prototypes and solutions to meet the expectations of the current scenario. It has been observed that AI-based techniques play a major role along with other hardware components such as Raspberry Pi, soil moisture sensors, temperature sensors, humidity sensors, etc. in predicting the crop yields and irrigation requirements. If both yield prediction and smart irrigation systems are well equipped with AI-based technologies, then these can prove the effectiveness in minimizing the overall agricultural cost, increasing growth in the economy and minimizing wastage of essential resources such as water, energy. These techniques are effective in reducing human efforts and fasten the planning of agricultural practices. But minimizing the cost of system deployment and training of uneducated and non-techno-savvy farmers is still challenging.

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