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Smart Irrigation Based on Type of Crop Using IOT and Machine Learning Technologies

Sudheer Reddy[1*], Shyam Peraka[2], Vinodh Babu Pusuluri[3], Chakravarthi Jada[4]

[1,2,3,4]Department of Electronics and Communication Engineering, Rajiv Gandhi University of Knowledge Technologies - Nuzvid, India

[*]Corresponding Email: sudheerr5503@gmail.com

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ABSTRACT

Water is the main resource for the agriculture sector and a significant amount of water is getting wasted due to the usage of conventional and manual irrigation methods. Hence, it is essential to introduce an intelligent and automated management irrigation system for the optimum and effective utilization of water resources. In this publication work, we proposed a smart irrigation system that works /performs activities with the Internet of Things (IoT) and machine learning technologies to reduce water wastage. The main thought of the proposed methodology is to supply the required amount of water to the user-selected crop variety, depending on the fact that different crops need different quantities of water at various phases of the crop. The proposed system predicts the irrigation needs for selected crops depends on the seed category and phase of the crop. Also, the system uses several sensed ground metrics like soil moisture, crop water level, and humidity along with details about the next weather prediction. The proposed model uniquely determines the required crop water level (CWL) for supplying a minimum quantity of water to the opted crop if precipitation is predicted in the upcoming days. A mobile application (App) is also designed for monitoring as well as visualization of sensed and predicted values of crop water level and soil moisture. Our proposed smart irrigation system achieves better water management compared to the available methods. The entire system is implemented on a pilot scale and the results are fully encouraging.

Keywords: Crop Water Level (Cwl), Intelligent Irrigation System, Internet of Things, Precipitation, Evapotranspiration.

INTRODUCTION

The optimum utilization of water resources is essential due to the existing drought conditions and rapid intensification of the population around the world. According to estimates, the world and India's population is expected to exceed 9 billion [1] and 1.69 billion [2], respectively by 2050. Seawater makes up 97% of the earth's water resources, ice caps make up 2%, and the remaining 1% is available for irrigation and domestic purposes.

LITERATURE REVIEW

Water is the primary resource for agriculture and numerous research works have been organized by several research teams in precision agriculture around the world for optimal utilization of water resources. Agriculture and its related sectors are consuming 100 times the water required for domestic usage. Approximately 70% of the ground and river water is used for irrigation, making agriculture the main consumer of water resources [3]. Currently, about half of the total freshwater volume of 3600 KM3 is lost as a result of evaporation and transpiration from crops [4] and the remaining half is available in the form of groundwater.

In the agriculture sector, it is also required to meet the swiftly rising demands of food due to the rapid increase in population [5, 6, 7, 8, 9] trend. Hence, there is an immediate need to shift irrigation techniques from manual to automated, since crop yield depends on the usage of efficient irrigation methods [10]. There are several difficulties that exist in traditional irrigation techniques, as most of them are manually operated and costlier [11]. In the manual irrigation methods, the efficiency of water resource utilization rate is exceptionally low and hence crops are getting either less irrigated or over-irrigated. Another problem with manual irrigation methods is the reduced accuracy in determining the required amount of water [12, 13, 14, 15, 16, 17]. As technology is growing faster, the concept of automation has been included in various sectors such as industry, agriculture, etc [18]. As the groundwater level is getting reduced day by day due to excessive water usage in the agriculture sector, it is essential to introduce the concept of automation for irrigation in the agriculture sector [19]. Automation in the agriculture sector allows the saving of millions of quantities of water, irrespective of the availability of labor for operating the systems manually [20]. Various automation methods using IoT were used in agriculture to improve crop yield [21, 22].

Several smart solutions based on IoT are very helpful in the agriculture sector to minimize the usage/utilization of water resources [23]. IoT is a superior technology used for designing a smart agriculture management system and helps farmers by improving crop yield using low-cost solutions [24]. Many small-scale IoT-based irrigation systems were developed in agriculture to provide solutions related to irrigation for several varieties of plants [25]. Furthermore, irrigation systems using various field sensors and analysis of environmental conditions provide better solutions for water saving.

Many IoT-based smart irrigation systems employing various sensors were proposed in agriculture. A smart system was designed to predict soil moisture using ZigBee technology without employing the control function of irrigation [26]. Using the information provided by the web applications environmental conditions were analyzed and [27] an effective agriculture system was developed, based on the weather forecast data for efficient usage of water resources, and with the appropriate analysis, it also improves the groundwater resources [28]. Several user-friendly environments are used for simulating the various irrigation parameters whenever there is a change in the environmental conditions [29]. An integrated autonomous system was developed using Bluetooth technology for assisting and monitoring the irrigation process [30]. In this system, the quality of the crop is verified based on the received sensor and controller information/data like temperature, soil moisture, humidity, etc. A system was designed to organize the irrigation schedule whenever it identifies the chance of rain and informs the user through a short message service (SMS) [31]. Depends on the changes in the environmental conditions and soil, an irrigation schedule was prepared on a weekly basis [32].

Two important factors that influence the crop water level and soil moisture are evaporation and precipitation. In geography and climatology, the wetness of soil is estimated with the monthly or annual proportion of the evaporation and precipitation [33]. Further, crop water level and moisture levels of the soil are estimated by the calculation of evaporation and precipitation ratio on daily basis.

Penman [34] proposed an empirical model for evaporation and it is given by,

$$Et \propto Eh + Em \text{ --------}\rightarrow (1)$$

This model states that total evaporation Et is proportional to the sum of the dynamic evaporation (Eh) and thermodynamic evaporation (Em). Dynamic evaporation depends on ultraviolet (UV) radiation, air temperature, air relative humidity, and land storm velocity. A framework for irrigation management was proposed [35] to achieve water saving based on several techniques such as stress index and thermal imaging. Compared to time-based irrigation scheduling, an irrigation framework-based evapotranspiration can save water up to 42% [36].

Several machine learning algorithms were implemented for obtaining precision agriculture and a better yield [37]. The authors in [6] designed a new irrigation method for saving water using automated techniques, WSN and GPRS. The authors in [38] proposed a methodology for estimating soil moisture with the help of SVM using various parameters of environment and soil. The authors [39] proposed various recommendations for effective irrigation using machine learning techniques. For irrigation planning prediction, the most effective model was found to be Gradient Boosted Regression Trees (GBRT), which had an accuracy rate of 93% and the introduced method is useful in irrigation management for agronomists. Roopaei [40] introduced an intelligent irrigation management system for optimum utilization of water resources using thermal imaging. An algorithm was developed for identifying the water requirements, non-uniform irrigation, and leaf water potential using image processing.

Most of the existing systems made decisions about irrigation planning without considering the weather forecast data (e.g. Precipitation). This leads to the wastage of freshwater resources and energy when rain is followed immediately after the irrigation process. Crop yield also reduces due to the excess amount of water in the crop. Hence, for handling such cases, IoT-based solutions along with the hybrid machine learning approaches are useful for predicting the precipitation information of upcoming days using online weather forecast data.

For effective and efficient utilization of freshwater resources, it is essential to design an irrigation system using dynamic prediction of crop water level patterns. This work represents a smart irrigation methodology, which predicts the crop water level of upcoming days using data collected by sensors and precipitation information. The designed system supplies water to the crop, based on its category, and phase and using the machine learning approaches. A novel-based smart irrigation algorithm is also updated with k-means clustering along with support vector regression (SVR) for predicting the crop water level of upcoming days using data collected by the sensors and weather data with the minimum mean square error. Using this algorithm, we can predict the precipitation information for upcoming days and if predicted rain in upcoming days, the proposed system supplies a nominal amount of water to the crop, which is measured by calculating the minimum threshold (TH_{min}) of water level to maintain crop growth. Furthermore, a mobile app is designed for monitoring the current and upcoming days' crop water levels.

A novice interaction of user-device is introduced in the proposed architecture and using the proposed system, farmers can reduce the burden of irrigating the crops manually and provide easy access for operating the system even from distant places. The proposed system uses an automated irrigation process that outperforms the following steps for optimum water resource utilization. It

Gets the soil statistics from the sensors and weather forecast information from the internet.

Provides real-time information about current and upcoming days' crop water levels in the designed mobile app. Based on the predicted crop water level, the motor can automatically turned off/on to avoid wasting large amounts of water.
Gets the precipitation information of upcoming days using IoT and SVR + k-means clustering approaches.
If predicted rain in the upcoming days the system will supply a nominal amount of water to crop to save water and will be turned off automatically.
Estimates the schedule of irrigating crops for the complete season beforehand.
Completes the irrigation process based on precipitation information.

IRRIGATION FOR DIFFERENT CROPS

Based on the requirement of water for their growth, crops are generally divided into two categories (low and high-water-required crops). The Moisture sensor is very useful in case of lower water-required crops such as white legumes (green gram and black gram), Sunflower, and sesame crops, whereas the water level sensors are particularly useful in case of high water-required crops like Paddy, Sugar cane, etc. As we used both moisture and water level sensors, our system will work for all kinds of crops.
Generally, different crops require different water content. As per our research, paddy requires lower water content in the starting & ending stages. These stages can be irrigated using a moisture sensor and in the middle stages, it requires a high quantity of water. Hence, irrigation of the middle stages also be done with a water-level sensor. So, in this innovation, we divided the total duration of the crop into 5 different segments depending on the requirement of water. Table 1 depicts the required amount of water at various stages for different crops such as paddy, sugarcane, potato, corn, and wheat.

Table 1: Water Required for Different Crops.

S.No. (i)	Crop (Xi)	Stage1 (Si1)	Stage2 (Si2)	Stage3 (Si3)	Stage4 (Si4)	Stage5 (Si5)	Total Water Required (Liters/Acre) (TWi)	Total No. of Days (Ni)
1.	Paddy	5%	20%	40%	30%	5%	87,50,000	150
2.	Sugar Cane	20%	25%	40%	10%	5%	60,00,000	300
3.	Wheat	5%	30%	40%	20%	5%	26,37,000	90
4.	Potato	5%	20%	40%	20%	15%	45,00,000	120
5.	Corn	5%	20%	40%	20%	15%	27,30,000	90

METHODS AND TECHNIQUES

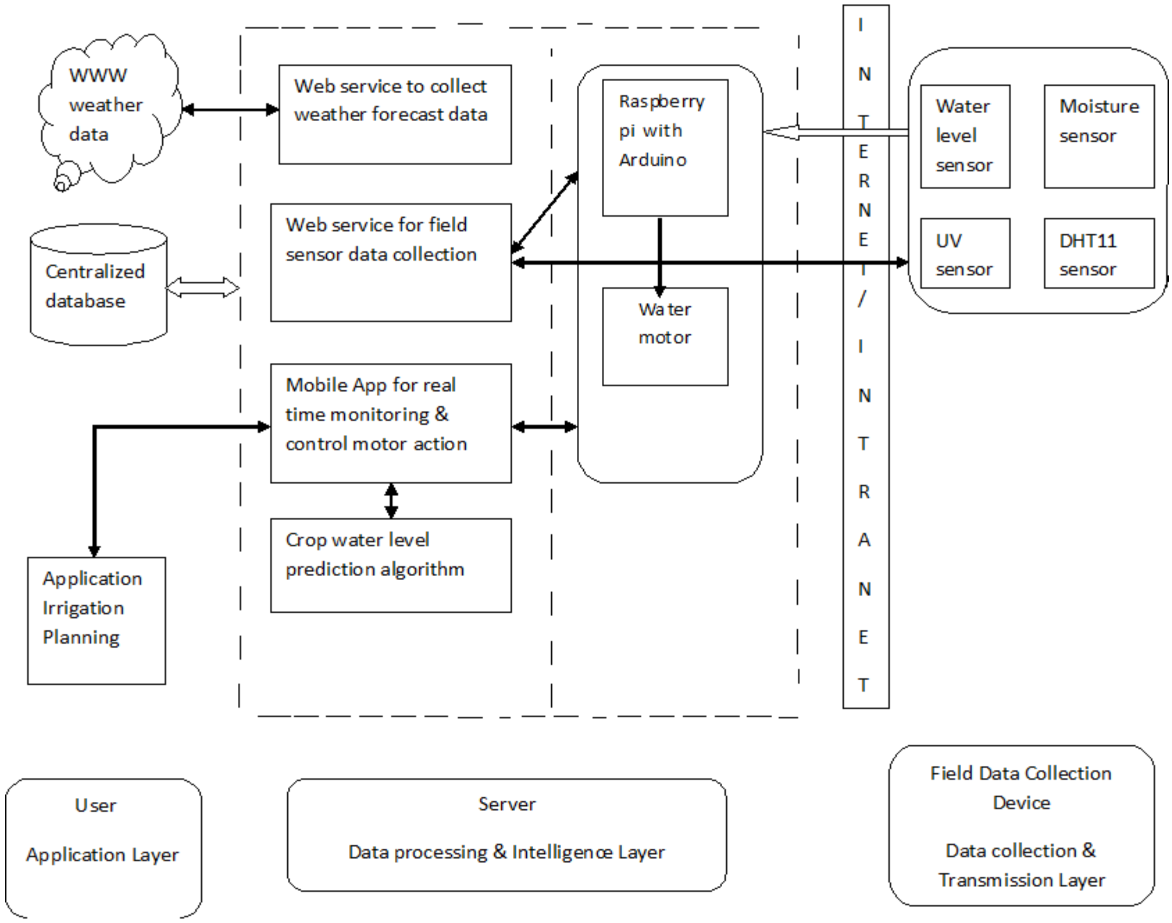
For effective and efficient irrigation management, the prediction of soil moisture, and crop water level are vital and their estimation depends on the evapotranspiration. Samani and Hargreaves [41] developed a method to estimate evapotranspiration ET0 based on maximum, and minimum temperatures (T_{max}, T_{min}) and extra-terrestrial radiation (Ra). It can be expressed mathematically as,

$ET_0 = 0.0023\ T_{Max} + T_{Min} + 17.8\ R$ ------------→ (2)

The authors [42] developed an estimation method based on evapotranspiration. The main reason for reduced food production is the usage of traditional farming methods. Cobanar [43] developed a new model for estimating evapotranspiration using the inference of the Neuro-Fuzzy (NF) network. This NF model depends on air temperature, solar radiation, and relative humidity.

An easy-to-use unsupervised learning approach is k-means clustering [44]. It uses an effective methodology for dividing a given set of data into a predefined number of clusters fixed apriori. The key factor is defining k-centers, one for every cluster. It assigns each data point to the closest k-center after determining the ideal value for k-center points through an iterative procedure. A cluster is formed by data points that are closer to a specific k-center.

Fig-1: Proposed smart irrigation system architecture.



A smart architecture shown in Fig-1 is developed for collecting, intelligent processing, and transmission of physical parameters of soil and weather forecast data. An algorithm is designed using machine learning techniques of SVR + k-means clustering for estimating the crop water level of upcoming days and it is based on forecasted weather data, and field data collected by sensors. The proposed SVR and k-means algorithm provides better accuracy and gives the minimum mean square error (MSE) [45] for predicting the crop water level. The proposed SVR model is trained by the data (relative humidity of the air, air temperature, UV radiation, soil moisture, and crop water level) using various sensors inserted in the field as shown in Fig. 5. Using a trained SVR model, the crop water level for the upcoming days is forecasted, and the anticipated value is fed into a k-means clustering algorithm to obtain the crop water level values (k-means centroid value) with improved accuracy and minimum MSE. The predicted crop water level (Table-3) is utilized in the proposed irrigation algorithm discussed in section

4.1 for using natural rain efficiently to design an effective algorithm.
The modified version of SVM [46] is SVR [47], where in lieu of categorical, the numerical value is the dependent variable. SVR is characterized by the usage of kernels and sparse solutions and it is an effective tool for estimating the real value functions.

PROPOSED SYSTEM

This work proposes an automated irrigation system which is capable of identifying the crop water requirements. The terminology used in the paper is representated in Table 2.

Crop Water Level Prediction Algorithm:

- Initialization of weather forecast data.
- Initialization of sensor data. Train the SVR model using sensor data.
- Develop an SVR model using weather forecast data and sensor data.
- Train the SVR model for predicting crop water levels of upcoming days.
- Predicted Crop water level for upcoming days. k-means clustering for predicting more accurate crop water levels.
- New predicted crop water level (NPCWL0, NPCWL1,……..,NPCWLn).

Table-2: Nomenclature used in the work

Variable	Input/ Output Type	Variable Details
Pg Pd C	Input Input Input	Plant Growth Stage Date of Plantation Crop Type
Sm CWLn	Input Output	Soil Moisture Crop Water Level of nth stage
PCWLn	Output	Predicted Crop Water level of nth stage
Temp	Input	Average air temperature on a day
H	Input	Average air humidity on a day
UV	Input	Average Recorded Ultra Violet Radiation on a day
Sd SVR	Input Input	Soil Data (Temp, H, UV) Support Vector Regression
SVM	Input	Support Vector Machine
THn	Input	nth stage threshold of Crop water level
Wd NOC	Input Input	Array of weather forecast data Number of Clusters

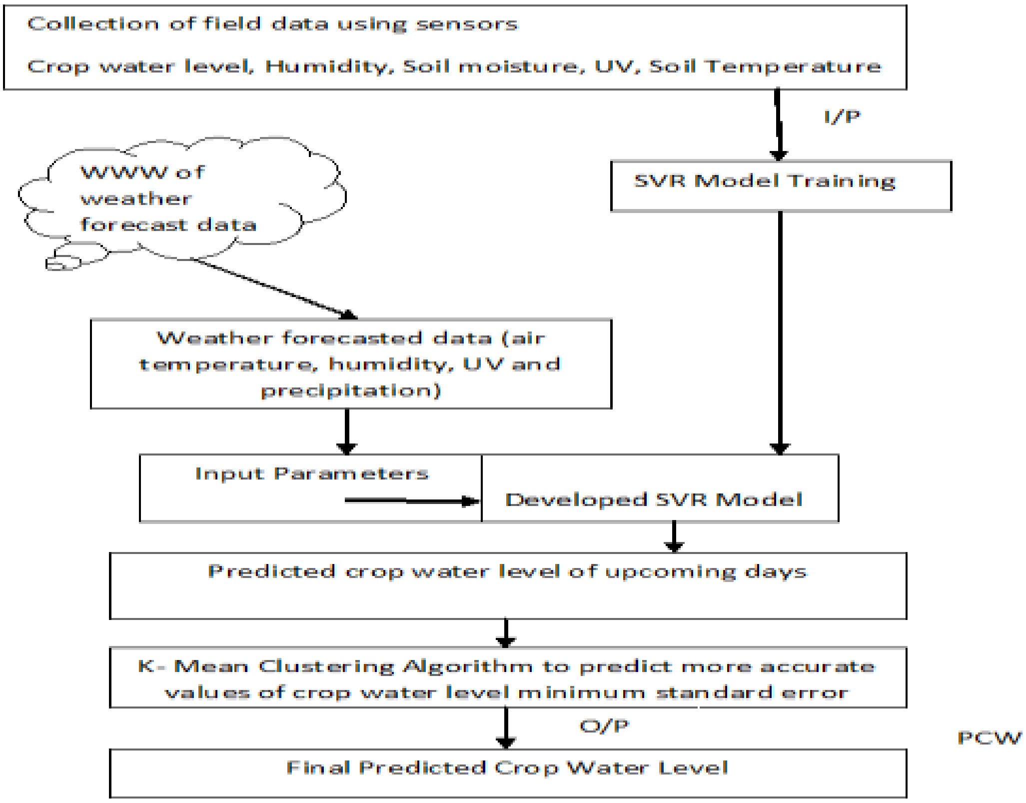


Fig-2: Crop water level prediction algorithm.

Irrigation Scheduling Algorithm:

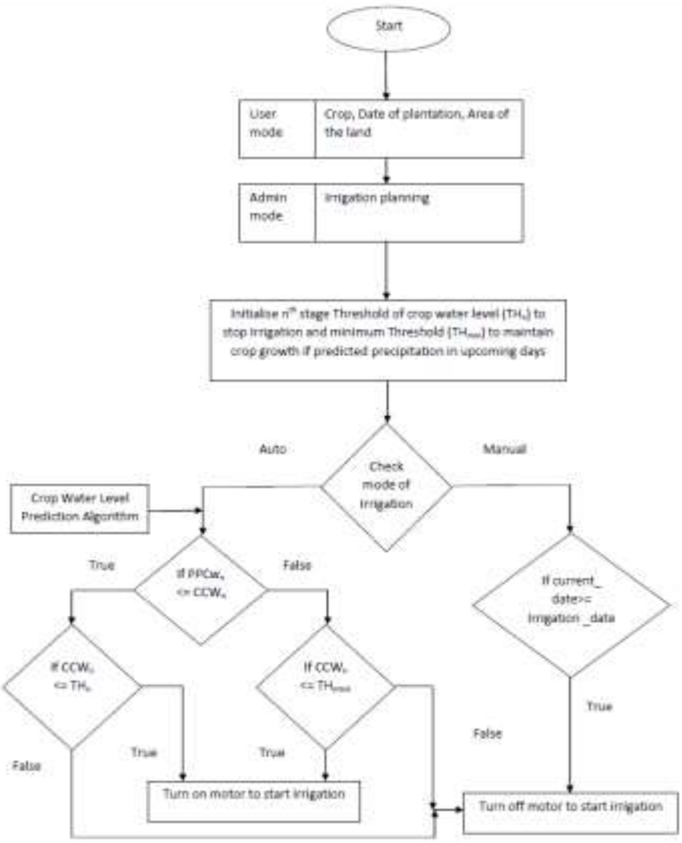


Fig-4: Prototype of the proposed irrigation system.

- Initialize the threshold for crop water level based on the phase and category of crop.
- Minimum threshold to maintain crop growth if precipitation is predicted in upcoming days.
- Set auto or manual mode.

If (mode = auto) // Condition for checking mode of operation

{

If (PCW_n <= CCW_n) // Condition for checking current crop water 12 levels of the n^{th} stage with predicted crop water level of the n^{th} stage.

{

while (CCW_n <= TH_n) // Condition for irrigating the crop till the crop water level reaches the pre-defined threshold value.

{

Turn on the motor to start the irrigation

}

Turn off the motor to stop the irrigation

}

Else

{

while (PCW_n <= TH_{nmin}// Condition to maintain minimum threshold

as Predicted Precipitation in upcoming days.

{

Turn on the motor to start the irrigation

}

Turn off the motor to stop the irrigation process

}

}

Else

{

Enter the date for starting the irrigation process

{

If (Currentdate >= IrrigationDate)

{

While (TH_n >= CCW_n)

{

Turn on the motor to start the irrigation

}

Turn off the motor to stop the irrigation

}

Else

{

Turn off the motor to stop the irrigation

}

}

Experimental Setup:

The prototype of the proposed irrigation system is shown in Fig-4. For performing the experiment, we created an artificial field with the dimensions of 32*21*12 with red clay (Fig-5). Weather forecast data is collected from the internet and field data is collected using sensors. We used the prototype's UV, water level, moisture, humidity, and temperature sensors to collect the parameters from the field. The collected sensor data is given as input to Arduino-Uno, which is integrated with the Raspberry Pi. A Python language program is dumped into the Raspberry Pi board for fetching of hourly data from sensors. A mobile app interface (Figs 6 and 7) is developed for visualization, monitoring the real-time sensor data, decision support system, and irrigation scheduling. The responsive mobile app interface is developed using Flutter software and PHP programming language for real-time monitoring of the crop soil moisture and the water level. In the mobile application, the user enters the basic details about the crop such as the date of the plantation, the type of the crop, and the area of the land. Based on these details, the system determines the complete irrigation schedule. The Python script that is executing on the Raspberry Pi sends the signal to Arduino-Uno to stop or start the motor. In the proposed system the Wi-Fi module is used as the communication medium between the server and field sensors. The proposed system has the provision of scheduling irrigation at any stage. The user-entered details are uploaded to the cloud and these values are compared with the predefined thresholds of crop water level. Based on these threshold values the system makes decisions. The internet enabled raspberry pi controls the motor action for proper irrigation to the crops.

Fig-4: Prototype of the proposed irrigation system

The proposed irrigation system operates in two modes and those are manual, and auto. In the manually operated mode, the user controls the irrigation and takes the decision based on the predicted crop water level for upcoming days. In auto mode, the system sets several thresholds of crop water level based on the type of crop and stage of the crop. In auto mode, the system independently schedules the complete irrigation process without manual interference and makes the decisions using weather forecast data and precipitation information. In case of rainy conditions in the irrigation date, then the system will maintain the minimum threshold required for maintaining the crop growth until the arrival of rain. If there are no rainy conditions in the upcoming days, then it will maintain the required threshold.

Fig-5: Water supply to the field

RESULTS

The effectiveness of the proposed irrigation system depends on the estimation accuracy of crop water level (Tables 3 and 4). For verifying the accuracy of the proposed crop water level prediction algorithm (Fig-3), the hourly data of various parameters of the field such as soil moisture, temperature, air humidity, air temperature, crop water level, and UV are collected for three weeks. 70% of the collected data is utilized for the training purposes and 30% is used for testing purposes. Using the SVR + k-means algorithm we have estimated the crop water level of upcoming days (Figs 2 and 3) and summarized results are shown in Table 3 and 4. The homepage of the mobile app is shown Fig-6, current and predicted crop water levels, and current soil moisture are shown using the application interface in Fig-7. The predicted crop water level using the proposed algorithm is nearer to the actual crop water level as compared with the existing SVR algorithm and is shown in the graph (Fig-8). From tables 3 and 4 it can be observed that prediction of crop water level using SVR + k-means achieves better accuracy with minimum MSE in comparison with the SVR approach.

CONCLUSION

The crop water level is an essential parameter for developing an efficient irrigation model. The crop water level is affected by several parameters.

Date	PCWL recorded using sensor	PCWL by SVR	PCWL using SVR+k-means Algorithm
01-09-2020	22.40	22.21	22.34
02-09-2020	23.43	24.56	23.45
03-09-2020	23.26	23.96	23.28
04-09-2020	22.89	23.12	23.34
05-09-2020	23.12	24.31	23.34

Table-3: Crop Water Level based on the sensors' info. And the SVR + k-means Algorithm

Variable	PCWL SVR	PCWL using proposed SVR+k-means Algorithm
Correlation Coefficient(R)	0.96	0.96
R Squared(Accuracy)	0.94	0.94
MSE	0.14	0.10

Table-4: Comparison of Accuracy, MSE, and Correlation Coefficient.

Fig-6: Mobile App Homepage

Crop Water Level using the Proposed SVR + k-means Algorithm and Sensor Data. PCWL captured via sensor PCWL by SVR using SVR+k-means Algorithm Comparison of accuracy, MSE, and correlation coefficient. Variable PCWL SVR PCWL using suggested SVR+k-means Algorithm Correlation Coefficient(R) Squared (Accuracy) of the environment like air temperature, air humidity, UV, soil moisture, and temperature etc. With the usage of advanced technologies, the accuracy in predicting the weather forecast data has improved, and the crop water level is predicted using the expected weather forecast data for the upcoming 295 days. This research work introduces a smart irrigation methodology using the Internet of Things and hybrid machine learning approaches. The developed irrigation system utilizes the recent past of the sensors and weather forecast data for predicting the crop water level of upcoming days. The prototype of the proposed system is cost-effective and it uses efficient machine learning techniques. The results of the implementation demonstrate that the suggested irrigation scheme achieves water conservation. The proposed irrigation system provides the solutions to various problems in the existing irrigation process and it saves a significant amount of water. In the proposed system we fixed the water level based on the various crop parameters instead of going with the quantity of water. Hence, the irrigation process is independent of the area of land. As we used water level sensors for irrigating the crops and using the crop water level concept water reaches every corner of the land.

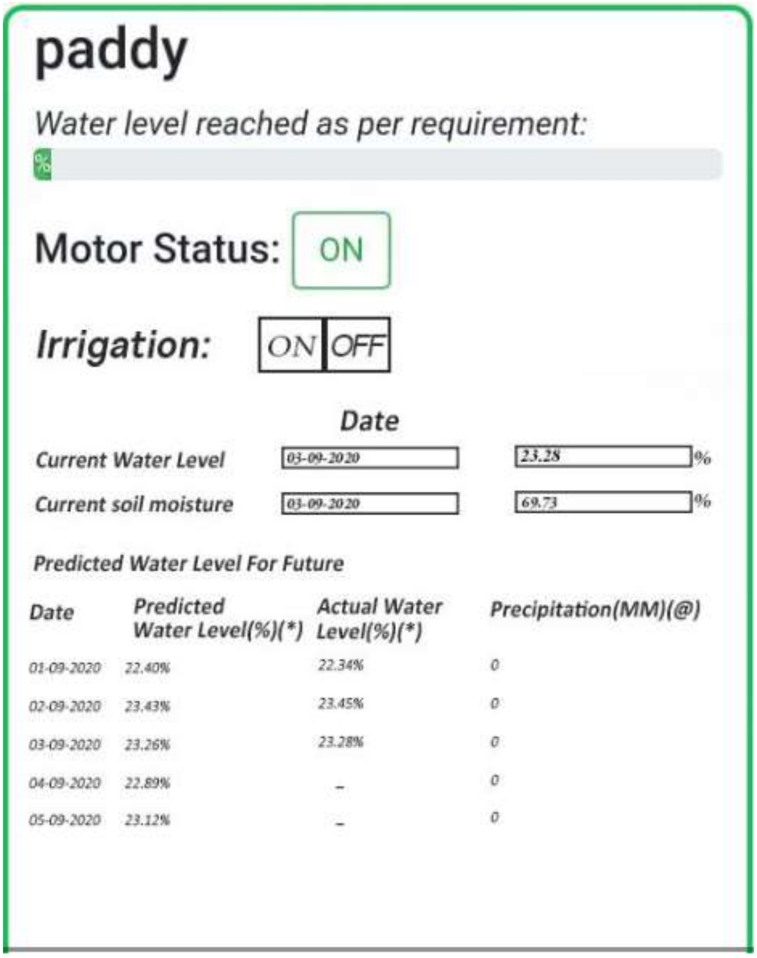


Fig-7: App interface for real-time monitoring

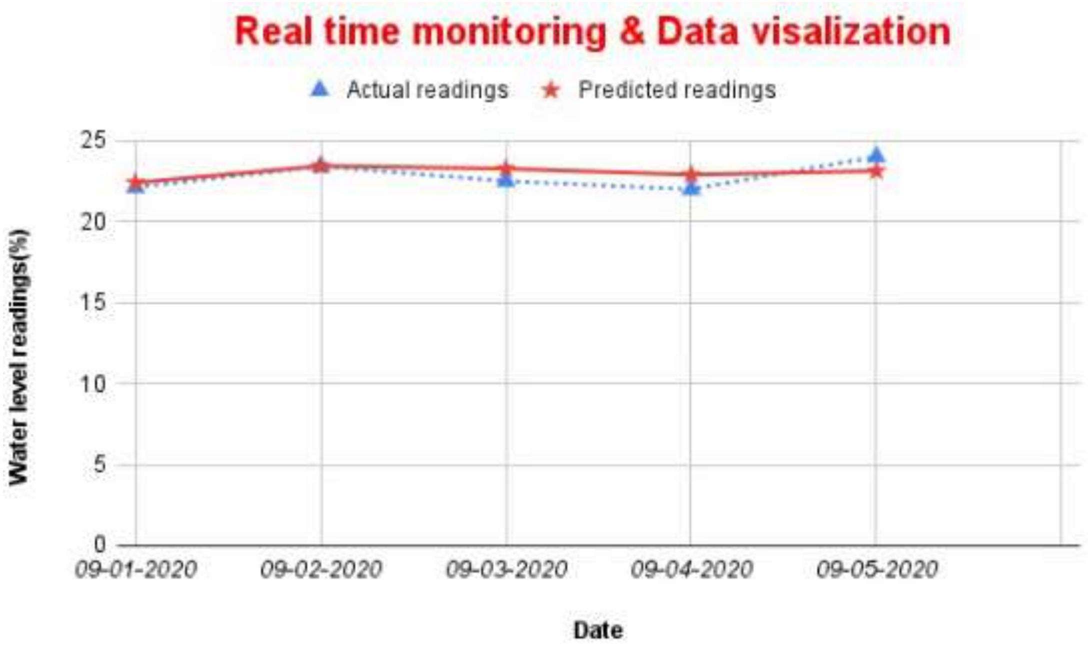


Fig-8: Graphical representation of results

Ethical Declaration

Conflict of interest: No declaration required. **Financing:** No reporting required. **Peer review:** Double anonymous peer review.

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