International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 8
***Article Received:** 25 June 2023 **Revised:** 12 July 2023 **Accepted:** 30 August 2023*

Intelligent Water Management in Precision Agriculture Using Machine Learning

Khadri S S, and Dr.Arpana Bharani

Department of Computer Science, Dr. A. P. J. Abdul Kalam University, Indore (M.P.)

Email ID:khadri885@gmail.com, arpanabharani@gmail.com

Abstract— India's economy heavily relies on agriculture, with a significant portion of the population engaged in agriculture-based businesses. Automation in agriculture holds the potential to enhance crop production quality and quantity while reducing resource consumption. However, the high investment costs associated with agricultural automation present a major challenge. To address this, a Machine Learning (ML) technique is proposed to optimize the costs associated with automating agricultural irrigation systems.The proposed ML model aims to reduce the implementation and operational costs of the remote sensor network used for irrigation. A dataset comprising soil moisture and temperature data was utilized, with the irrigation treatment type serving as the target variable. The dataset underwent preprocessing to ensure suitability for learning, followed by the application of k-means clustering for behavioral data analysis. This clustering technique grouped similar sensor readings, improving learning performance in terms of accuracy and training time.Two machine learning algorithms were then implemented to train the model and predict irrigation treatments, effectively minimizing the cost of deploying and maintaining sensors in the field. While the current system demonstrates significant cost efficiency, its overall performance remains reliant on the accuracy of the prediction model. Future work will focus on further enhancing the prediction accuracy to ensure optimal performance.This study highlights the potential of intelligent water management systems in precision agriculture, demonstrating how machine learning can contribute to sustainable and cost-effective agricultural practices.

Keywords—Machine learning, algorithm designs, support system, irrigation system, sensor network, prediction, automation.

1. INTRODUCTION

India is a predominantly agricultural country, with over 70% of its population relying on agriculture and related activities for their livelihood. However, a significant portion of farmers face challenges due to limited resources and expertise. These challenges include difficulties in monitoring, irrigation, fertilization, disease management, and achieving high crop yields. As a result, many farmers experience losses during every crop production cycle. Smart farming and precision farming have emerged as promising techniques to address these issues, but their implementation and maintenance are prohibitively expensive for most farmers. The costs of establishing sensor networks, communication channels, cloud servers, and employing monitoring technologies, along with their maintenance, require considerable investment and expertise.

To address these challenges, this paper proposes a Machine Learning (ML) model aimed at reducing the cost of sensor networks and automating irrigation systems. Automation in irrigation enhances crop productivity while conserving water and other resources. The proposed system consists of three key modules: data collection, data analysis and decision-making, and automated water supply. Unlike traditional irrigation methods, where farmers manually assess farmland and decide on water supply, this system relies on a machine learning-based decision-making process. This approach eliminates the need for costly ground sensors by leveraging affordable data collection methods and intelligent decision-making.

The paper begins with a review of recent advancements in irrigation system automation to identify essential datasets, machine learning techniques, and key features for consideration. The proposed model utilizes soil moisture and temperature data to train machine learning algorithms, which are then used to predict irrigation requirements. Experiments were conducted to evaluate the model's performance, with results documented in this study.

Furthermore, an extension plan is proposed to improve the accuracy and efficiency of the model. This work demonstrates the potential of machine learning to enable intelligent water management in precision agriculture, providing a cost-effective solution for farmers to improve productivity and sustainability.

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2. LITERATURE REVIEW

In order to understand and explore the techniques that opt for automating the irrigation system we have collected more than 25 articles and among 15 most relevant are reported in our related study. Table 1 provides the recent studies and development contributed by the different authors and researchers for improving the irrigation system. According to the studied literature, we observe that the automation of irrigation systems needs the implementation of wireless sensor networks or the Internet of Things. Additionally, we found that such kinds of systems also require a system that is capable to collect and analyze the data obtained from the farming land. This server is developed with the help of an efficient database and a machine-learning algorithm. Finally, a hardware module is also involved which obeys the server decisions or manually made decisions based on the collected and analyzed statistics of the moisture and temperature of the soil.

However, most of the available models are directly utilizing the statistics obtained from the sensors to transform into insights for decision-making tasks. Additionally, the techniques are providing notifications to the farm administrator to start the water supply. But there are fewer methods that utilize more parameters for providing insights such as weather conditions to approximate the final decision-making. In addition, there are some more techniques available that utilize the power of machine learning to predict the weather conditions and the soil moister and temperature. The involvement of prediction and machine learning methods will reduce the operational cost of the entire system. Therefore, in this presented work we are going to fully utilize the power of machine learning to remove the establishment of costly sensors and networks. Here, we are proposing a machine learning framework to utilize historical sensor-based collected data and predict the irrigation requirements.

3. PROPOSED WORK

Based on studied literature, we planned to propose a Machine Learning (ML) model for predicting the water treatment based on sensor readings. In order to predict a water treatment an experimental model is presented. The model consists of five layers as demonstrated in figure 1. These layers are defined in this section.

3.1 Database

The machine learning models requires historical patterns for training. Therefore, we have considered a historical Soil Moisture and Temperature – Database from the KBS LTER core database [16]. The dataset consists of sensor readings and labelled with the appropriate water treatment. The dataset has seven attributes as demonstrated in figure 2(A).

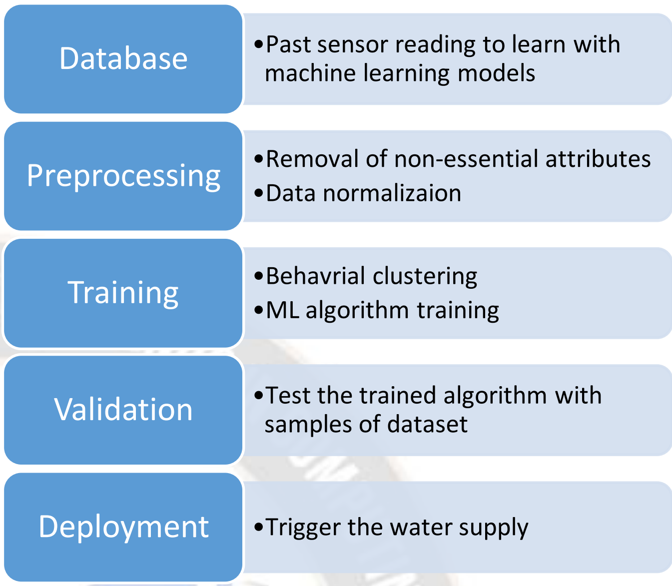

Figure 1 Layers of Proposed Irrigation Model

In this figure the attribute type and their description are given. The data is given for 10 years and have a total of 15706 instances. Here, we should need to predict "Treatment_Type", which consists of five labels (i.e. 1, 2, 4, 6, 7 and 8). The raw samples of dataset are given in figure 2(B).

Variate	Description
year	year in which sampling dat
sample date	sampling date
Trt	treatment
T0-2cm	temperature, 0 to 2 cm
T3-15cm	temperature, 3 to 15 cm
W0-2cm	water content, 0 to 2 cm
W3-15cm	water content, 3 to 15 cm

(A)

	Years	Date	Treatment_Typ
0	1998	01/01/1998	
1	1998	01/01/1998	
2	1998	01/01/1998	7 &
3	1997	31/12/1997	
4	1997	31/12/1997	

(B)

Figure 2 Dataset Details in terms of (A) Dataset Attributes (B) Raw Dataset Information

3.2 Data pre-processing

The data pre-processing is essential to make clean and suitable in format to utilize with the ML models. In order to enhance the data the following processes are involved:

1. Treatment type is considered here as the class variable thus for ease of utilization with the ML model, we convert these classes into five categories (i.e. 0, 1, 2, 3, 4).
2. The year attribute is additionally available with the date thus we removed year from the dataset.
3. Next the date attribute is converted into the index for sorting of the data.

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After data pre-processing the data is visualized in figure 3. After pre-processing four attributes and the class labels are given in figure 3. Next this data is normalized using min-max technique. The formula of min-max normalization is given as:

$$N = \frac{x - x_{min}}{x_{max} - x_{min}}$$

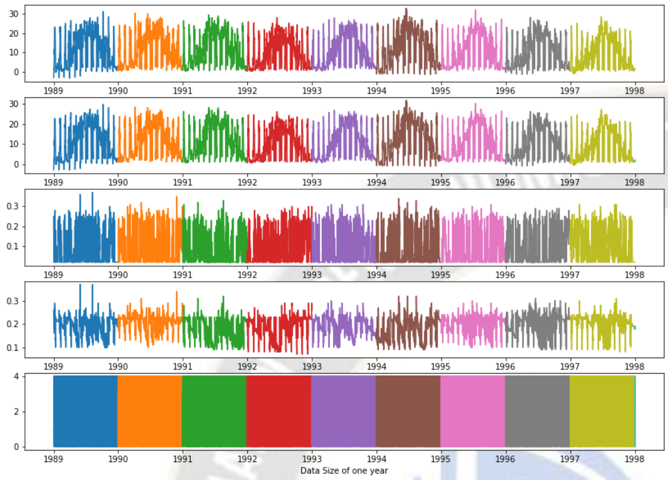

Figure 3 Dataset sensor reading plot for 10 years

The normalization process scales the sensors reading between 0-1. The normalization is not performed on classes. The normalization will help in enhancing the computational performance due to small set of calculation. After normalization we can also recover the original values.

3.3 Training

However, the sensor reading data has a time series prediction problem and but it can also considered as classification issue due to limited and fixed set of prediction variables. Therefore, according to the sensor reading, we need to predict the class of water treatment. Here we considered the water treatment prediction as classification problem. Therefore we also removed the date attribute from the dataset. Now we utilize the ML algorithms for taking training. In this context, an arrangement is presented to train the algorithm. The model is demonstrated in figure 4. In this diagram two components knowledge base and pre-processing is discussed previously. After data pre-processing we utilize k-means clustering. It is an unsupervised learning technique. This algorithm requires two input parameters first the number of clusters k and second the dataset D.

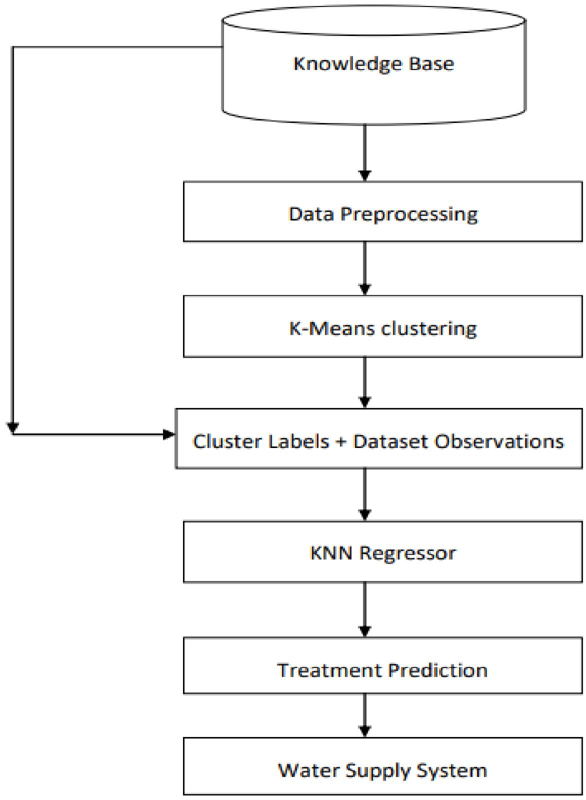

Figure 4 Flowchart of Proposed Model

The dataset D can be defined as:

$$D = \{I_1, I_2, \ldots, I_n\}$$

This dataset has five unique classes of water treatment therefore we have categorizing the data into five categories using the k-means. The k-means clustering first select the five random instances as centroid C. Here we are also utilizing the random centroid, because the entire dataset has continuous values therefore the traditional method of centroid selection and their optimization is appropriate. But a small modification is performed on distance measuring technique. Traditionally for distance measurement is defined by:

$$\Delta(C_i, I_i) = \sqrt{\sum_{i=1}^{N} (C_i - I_i)^2}$$

In place of normal distance measuring function we utilized here RBF kernel based distance, which can be defined as:

$$K(C_i, I_i) = \exp\left(-\frac{\|C_i - I_i\|^2}{2\sigma^2}\right)$$

This function will improve the learning performance due to non-linear relationship in data patterns. Using this modified

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clustering algorithm the data is mapped into class labels. Next, we need to train the ML algorithms for prediction task. In this context, for selection of appropriate ML model we compared five classical ML algorithms and two deep learning models. As classical ML algorithms, we considered the K-Nearest Neighbour (KNN) regressor, K-Nearest Neighbour (KNN) classifier, Support vector Machine (SVM), Support Vector Regression (SVR), and SVM grid search algorithm.

K-Nearest Neighbour (KNN) regressor is utilizing to predict continuous values as a regression algorithm. The algorithm is accepting the sensor reading for training samples and predicts a value between 0-4. Based on which the class labels are decided. This concept of training is also used with Support Vector Regression (SVR). On the other hand, during the training with KNN classifier, SVM, and SVM grid search algorithm based classification the algorithm trained with the class labels as water treatment. Similarly, we have trained two deep learning models CNN as classifier and Long Short Term Memory (LSTM) as predictive algorithm.

3.4 Validation and deployment

In order to validate the prediction model to apply appropriate algorithm for prediction, we conducted a set of experiment. The model performance is evaluated in two key parameters accuracy and training time. The accuracy A of model is evaluated using the following equation:

$$A = \frac{C_p}{T_p}$$

Where, C_p are total correctly predicted instances and T_p is the total samples given for prediction.

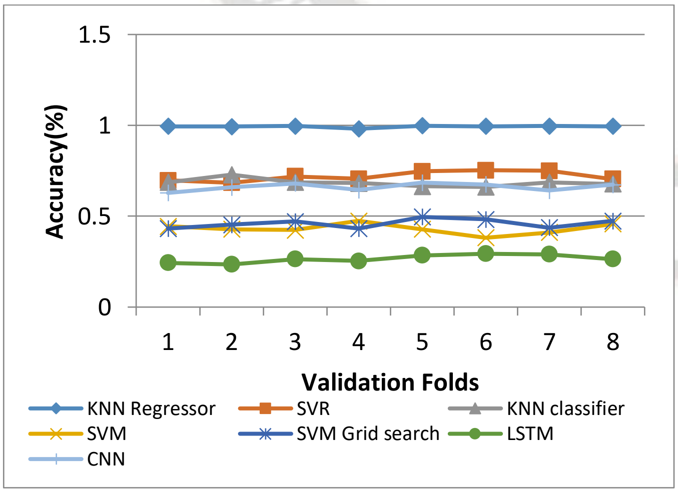

Figure 5 Accuracy comparisons of ML algorithms

The accuracy of the implemented ML algorithms is reported in table 2 and figure 5. The results obtained can be interpreted in two points of view:

1. **Case 1:** the comparison between deep learning models and classical ML algorithms. In this point of view the classical ML algorithms are performing better than deep learning techniques. We found both deep learning models are not providing acceptable accuracy.
2. **Case 2:** the comparison between classifiers and regressors. In this scenario the classification algorithms are less accurate as compared to regression based algorithms. Additionally, we found KNN regressor is providing more promising results as compared to other classification algorithms.

The comparative performance reported in figure 5 and table is demonstrated. In this diagram, X axis shows number of experiments conducted and accuracy is given in Y axis. According to this line graph the k-NN regressor is providing accurate results as compared to other implemented regression and classification based approaches.

For clearer representation the mean accuracy of the algorithms

Table 2 Comparison of Classical Classifiers

Observations	KNN Regressor	SVR	LSTM	KNN classifier	SVM	SVM Grid search	CNN
1	0.99550906	0.69754687	0.242899	0.68644068	0.44491525	0.43220339	0.628284
2	0.99391128	0.68385266	0.234414	0.72881356	0.4279661	0.45338983	0.659301
3	0.99644794	0.71825606	0.263819	0.68644068	0.42372881	0.47033898	0.680482
4	0.98139822	0.70533192	0.253482	0.68220339	0.47457627	0.43220339	0.643881
5	0.99745172	0.74750735	0.284891	0.66525424	0.4279661	0.49576271	0.684874
6	0.99450623	0.7532318	0.293384	0.66101695	0.38135593	0.48305085	0.674811
7	0.99601592	0.74909407	0.290012	0.68644068	0.41101695	0.43644068	0.641483
8	0.99443194	0.7046477	0.263804	0.6779661	0.45762712	0.47457627	0.672840

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are also measured. The figure 6 shows the mean accuracy of the implemented models. This shows the clear difference in accuracy of KNN Regressors to other algorithms. In addition, for testing the efficiency training time is also calculated. The training time is calculated using:

$$T_t = T_e - T_s$$

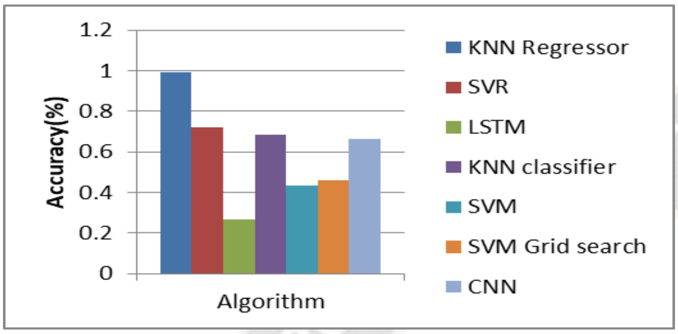

Figure 6 Comparison of ML models

Where, T_t is the training time, T_e is algorithm training end time, and T_s is training start time.

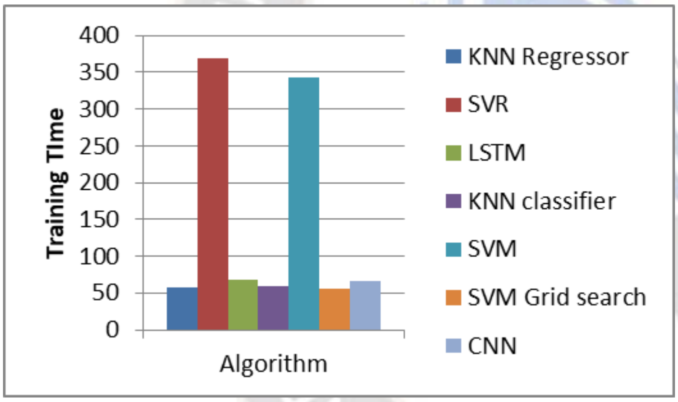

Figure 7 Training time

The mean training time of the ML algorithms are demonstrated in figure 7. The X axis of this diagram shows the algorithm names and Y axis shows the training time. The training time is measured here in terms of seconds (Sec). According to the obtained results we can see the SVM and SVR are the time consuming algorithms and requires a significant amount of time to produce results. Based on both the parameters the KNN regressor is providing accurate and efficient results. Therefore the KNN regressor is applied on the proposed model.

3.5 Deployment

The prediction model is intended to employ on an irrigation system. Therefore, the water supply system can be triggered based on the prediction of the given model. The flow chart of the proposed model is given in figure 4. This model can help to manage the farm irrigation system without physical sensor network implementation or Internet of Things (IoT) installation. The model can work stand alone and provide prediction of water treatment type to switch on or off the water supply. The model consists of a knowledge base of 10 years sensor reading, a data pre-processing module, k-means clustering algorithm for behavioural similarity. The predicted class labels of the k-means clustering is included with the data and then KNN regressor will be used for final model training and prediction of water treatment type.

4. KEY HIGHLIGHT

The proposed work is mainly considers the study and design a predictive ML model to accurately predict the required water treatment types. The well denoted dataset is used for exploring the data variations. Then the model is implemented. In order to achieve high accurate results the ML algorithm selection is performed based on the comparison of new and classical ML approaches. The implementation has been successfully performed using python technology, and results are evaluated. Based on the results we have selected KNN regressor. However, the system is able to predict more than 99% accurate treatment predictions but the system is not suitable in practice.

The main reason behind that, the model provides predictions based on sensor readings, but weather conditions are change or influence the water treatment scenarios. In this context, it is required to perform more refinement of the contributed model by incorporating the weather predictions. Additionally, only prediction has not been verified with the actual land and soil conditions. Thus accurate weather conditions also need to be incorporated for practical implementation and deployment of the model.

5. CONCLUSIONS

Machine learning techniques are useful in various real-world applications. Now, these days its presence is also available in various agricultural activities for automation, monitoring, and security. By using machine learning we also preserve the expensive resources and waste of resources. In this context, we have presented an ML model for irrigation system automation. This system aims to reduce the implementation cost of irrigation systems and control the wastage of water and monitoring. The system is working automatically and currently not requires any kind of sensor. Thus the model is low-cost for implementation. But the model needs correction and enhancement thus in near future we are incorporating the following components:

1. Implementation of limited sensor nodes for verifying the actual soil conditions
2. Implementation weather condition forecasting module for improving the irrigation model.

Table 1 Literature Summary

Ref	Work explained	Technology	Features
[1]	Predicting soil moisture and managing the water usage in accordance with rain	Raspberry Pi, Heroku, and edge nodes as Pi with actuators and sensors	MongoDB
[2]	Yield prediction and smart irrigation	-	planning schemes, transport, buying mechanisms, storage, and liquidity
[3]	Detail of a smart irrigation system to cover large urban areas	soil temperature/ moisture and air temperature	-
[4]	IoT-based platform for smart irrigation	Use of ML	-
[5]	Intelligent irrigation system	soil and weather	parameters are selected through various research articles
[6]	Smart&Green framework	prediction of soil moisture, without sensors	data monitoring, pre-processing, fusion, synchronization, storage, and irrigation management
[7]	Low cost IoT and weather based intelligent controller system, weather prediction algorithm	soil moisture	temperature, humidity and rain drop sensors, weather parameters
[8]	Control plants watering rate	Arduino and NRF24L01	soil moisture and user requirement
[9]	Monitoring water utilization, estimate the growth	Soil moisture sensors	soil moisture, pH levels, humidity, and temperature
[10]	Predict the weather condition, predicts whether soil needs water	Sensor Data	Temperature sensor, humidity sensor, pH sensor, raspberry pi or Arduino controlled pressure sensor and the bolt IOT module.
[11]	Set up an automatic irrigation system	soil moisture sensor	soil moisture
[12]	Predict water requirements	Sensor, Ontology	KNN
[13]	DLiSA, a feedback integrated system	LSTM	volumetric soil moisture for a day ahead, irrigation period, and spatial distribution of water required
[14]	Recommendation system is proposed for efficient water usage	IoT devices are deployed	collect the ground and environmental details, own collected data and NIT, Raipur crop dataset
[15]	Precision irrigation for monitoring and scheduling	use of soil and weather conditions	Dataset of soil and weather conditions captured using sensors

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