International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

# Proactive Water Supply Management Based on Machine Learning, Sensor Reading and Weather Information

[1]Prabhat Pandey, [2] Sudhir Agarwal

**Submitted**: 22/08/2023 **Revised**: 09/10/2023 **Accepted**: 22/10/2023

**Abstract:** The global warming and climate change is a one of the main reason for shortage of water. Therefore, smart use of water resources is necessary for long-term sustainability. Among different large-scale water consumer industries, the agriculture is one of the key consumers. The utilized water in agriculture has polluted and not suitable to use. Therefore, optimization in water management systems in agricultural irrigation system is required. In this paper, we proposed an automated crop irrigation system. The system considers the real and live soil sensor readings for predicting the water treatment plan. On the other hand the weather conditions have also been considered before initiating the water supply. Therefore, decision making function has been formulated. The decision making function requires the prediction of water treatment plan and also the future weather conditions. Therefore, for making accurate prediction ANN algorithm has been trained for performing prediction of both the facts. In addition, for making dataset more effective for training with the ML algorithm a pre-processing algorithm for soil moisture sensor data set has been proposed. The experiments have been carried out and a simulation has been done. Based on the obtained performance the proposed technique of weather prediction using Artificial Neural Network (ANN) provides higher accuracy 99.4% as compared to Support Vector Machine (SVM) which provides 95% accuracy. Additionally for soil conditions this algorithm results 88.4% accurate predictions. In addition, the training and decision making time of the system has also been evaluate which demonstrate the decision can be performed in a fraction of seconds. Finally, the training time is also found acceptable and the system only needs once to train on a location specific data.

***Keywords***: *Smart Irrigation, Irrigation Automation, Machine Learning, Water Conservation, Food Security, Water Management Plan.*

## 1. Introduction

The machine learning (ML) techniques can be used in various real world problems. Mainly these techniques have employed in order to perform prediction, classification and decision making. The prediction aims to approximate a continuous value, classification perform categorization, and decision making capture and identify key insights to react on a specific

event [1]. In this presented work, the ML techniques are being used for decision making task. In precision farming it is essential to measure the requirement of crops and supply appropriate amount of water to crops for improved production and quality [2]. The aim is not only to supply the appropriate amount of water into the crops but also preserve the water during the farm irrigation process.

In traditional farming process, crop irrigation decisions are highly depends on the soil conditions such as temperature and moisture. In addition, the weather conditions are also influencing variable for accurate irrigation decision making process [3]. Therefore, in this paper, a ML based system has proposed to address this decision making complexity in an automated irrigation system.

The aim is to involve the analysis and utilization of weather information (prediction) in order to make more precise and practical decision making for crop practical decision making for crop irrigation. Therefore:

1. First explore the sensor reading dataset to correctly identify the type of prediction or classification problem.
2. Next, explore the techniques of weather data collection, analysis and utilization.
3. Third, introduce an algorithm to combine weather prediction information into the irrigation system automation.

The proposed model is trying to automate decision making and water treatment practise for more practical use. The proposed technique map the irrigation decisions based on the relationship between the soil temperature, moisture and weather conditions. Therefore, the data exploration is the essential task before proposing any method. After exploration we can decide the appropriate ML algorithm for employing with the proposed system. This section presents an overview of the work involved in this paper, next section provide a detailed investigation of the utilized dataset.

## 2. Data Collection and Exploration

In order to explore the data nature and to identify the type of problem hidden in the sensor readings analysis we utilize a predefined dataset. Thus, a Soil Moisture and

[1] *Research Scholar, Department of Electronics and Communication, SAGE University, Indore, (M.P.), India*
[2] *Professor, Department of Electronics and Communication, SAGE University, Indore (M.P.), India*
[1] *prabhat212011@gmail.com*
[2] *Sudhiragrawal2.1309@gmail.com*

Temperature - Data set is downloaded from the KBS LTER core database [4]. The dataset is consisting of sensor readings and labelled with appropriate water treatment labels. The initial dataset attributes and their description are given in figure 1.

| Variate | Description | Units |
|---|---|---|
| year | year in which sampling date occurs | |
| sample date | sampling date | |
| Trt | treatment | |
| T0-2cm | temperature, 0 to 2 cm | celsius |
| T3-15cm | temperature, 3 to 15 cm | celsius |
| W0-2cm | water content, 0 to 2 cm | cubiccentimeters/cubiccentimeters |
| W3-15cm | water content, 3 to 15 cm | cubiccentimeters/cubiccentimeters |

**Fig 1** KBS LTER core database attributes

The dataset is the collection of soil moisture and temperature readings for 10 years, each day. It contains a total of 15706 readings. The attribute “Treatment_Type” has needed to predict. There are five treatment types (i.e. 1, 2, 4, 6, 7 and 8). Figure 2 shows the raw dataset samples.

| | Years | Date | Treatment_Type | T0-2cm | T3-15cm | W0-2cm | W3-15cm |
|---|---|---|---|---|---|---|---|
| **0** | 1998 | 01/01/1998 | 1 | 1.68 | 1.77 | 0.02 | 0.18 |
| **1** | 1998 | 01/01/1998 | 2 | 1.77 | 1.87 | 0.02 | 0.19 |
| **2** | 1998 | 01/01/1998 | 7 & 8 | 1.63 | 1.72 | 0.02 | 0.18 |
| **3** | 1997 | 31/12/1997 | 1 | 1.65 | 1.73 | 0.02 | 0.18 |
| **4** | 1997 | 31/12/1997 | 2 | 1.76 | 1.85 | 0.02 | 0.19 |

**Fig 2** Raw dataset samples

The treatment type or classes are first encoded to (0, 1, 2, 3, and 4) using a label encoder function. During this we want to check is the dataset has any class imbalance problem or not [5]. Therefore, a count plot has been prepared to know the distribution of samples into the water treatment type. Figure 3 shows the class distribution of the water treatment dataset.

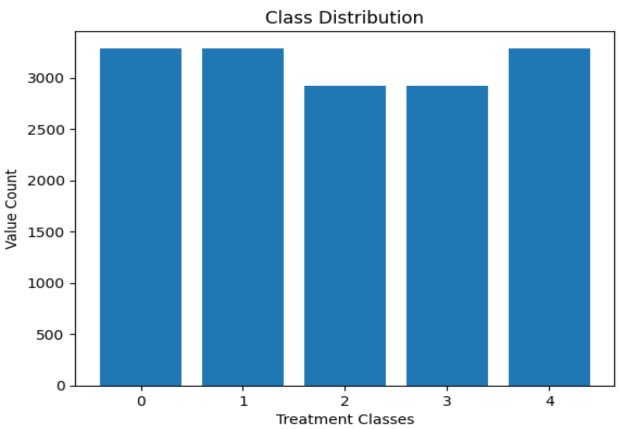



**Fig 3** water treatment class distribution

Next, we focus on the dataset, which consist of seven attributes; among them two columns is the time stamp. Therefore, initially we consider the data and problem as time series problem [6]. In this context, we eliminate the “Years” attribute and “Date” attribute is converted into the index column. The transformed dataset has demonstrated in figure 4.

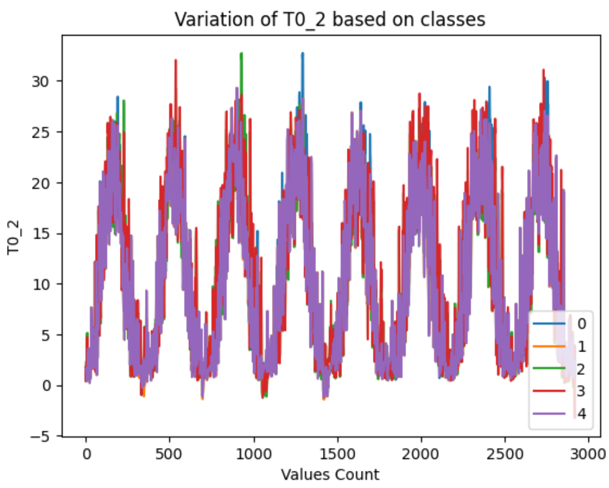
| Treatment_type | T0_2 | T3_15 | W0_2 | W3_15 |
|---|---|---|---|---|
| 0 | 1.68 | 1.77 | 0.02 | 0.18 |
| 1 | 1.77 | 1.87 | 0.02 | 0.19 |
| 4 | 1.63 | 1.72 | 0.02 | 0.18 |
| 0 | 1.65 | 1.73 | 0.02 | 0.18 |
| 1 | 1.76 | 1.85 | 0.02 | 0.19 |
| 4 | 1.60 | 1.69 | 0.02 | 0.19 |
| 0 | 1.63 | 1.70 | 0.02 | 0.18 |
| 1 | 1.75 | 1.83 | 0.02 | 0.19 |
| 4 | 1.59 | 1.65 | 0.02 | 0.19 |
| 0 | 1.59 | 1.60 | 0.02 | 0.18 |

**Fig 4** Final dataset used for analysis

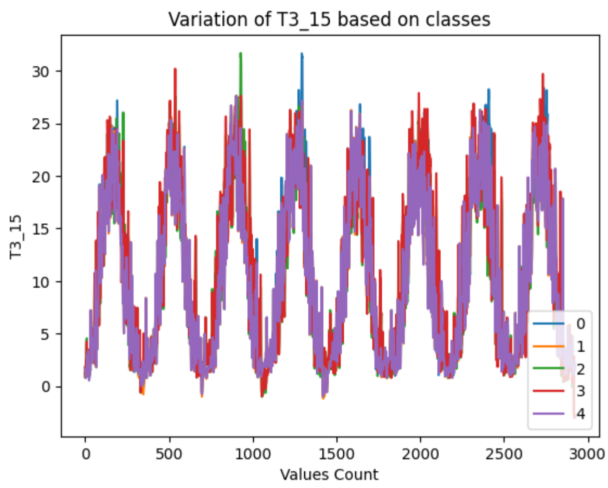
In this figure, we can see a single date has three sensor readings. Additionally, the treatment type of these readings is different from each other. Therefore, if we apply any time series operation or time series based pre-processing then data loss has been possible. Therefore, we drop the idea of analyzing the water treatment prediction problem as time series forecasting problem [7].

Thus, we consider this problem as the classification or pattern recognition problem [8]. In this context, we drop time information from the dataset to avoid over-fitting and under-fitting problem [9]. Next, we are investigating the influence of attributes over the classification. Therefore, the entire dataset has grouped according to the treatment type and prepare a line plot to understand the patterns of the data attributes for making different set of decisions. Figure 5 demonstrates the plots of the different attributes according to their class labels. In figure 5(A) and 5(B), the temperature attribute’s line plot is given, which shows high over-lapping between them. Additionally, the attributes are following a cyclic trend in temperature. On the other hand, in figure 5(C) and 5(D) shows the less overlapping according to the attribute.

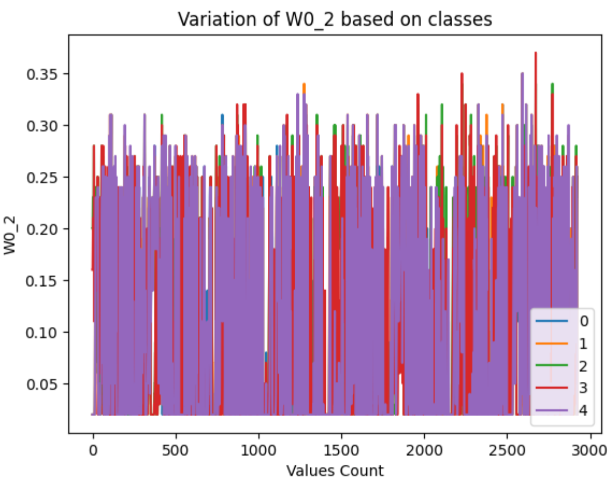
Next the data has been analysed to establish the relationship among attributes. Therefore, the scatter plot between two attributes has been prepared. The combinations of the different attribute’s plot have been demonstrated in figure 6. Based on the four attributes a total of 6 unique combinations has been prepared to evaluate the relativity among them. According to the different generated plots the most of combinations have a relationship but between attribute “T0_2” and “T3_15” data has strong relationship. Based on the visual analysis of the dataset attributes we can utilize a classification algorithm for performing more accurate classification.



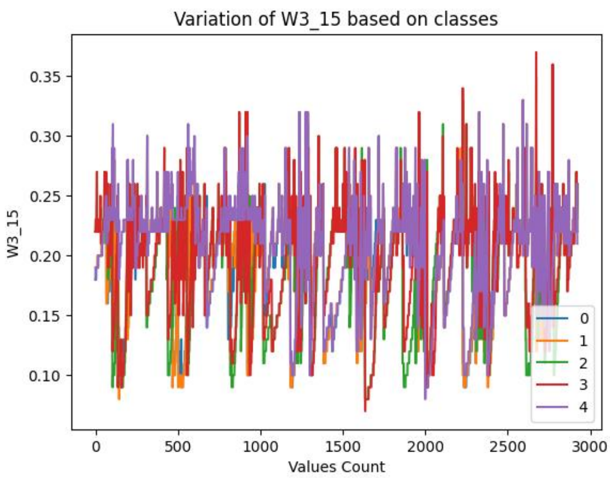

(A)




(B)




(C)




(D)

**Fig 5** Attributes plot according to the treatment type

### 2.1 Problem with Data and their solution

The dataset contains a time stamp attribute. Therefore, it is a time series problem. Most of the time series problems are configured to perform regression but the discussed problem is a multi-class classification problem [10]. The second issue is belongs to the frequency of treatment, and the type of treatment [11]. For understanding clearly, consider the figure 7 below.

| vdate | Treatment_type | T0_2 | T3_15 | W0_2 | W3_15 |
|---|---|---|---|---|---|
| 1998-01-01 | 0 | 1.68 | 1.77 | 0.02 | 0.18 |
| 1998-01-01 | 1 | 1.77 | 1.87 | 0.02 | 0.19 |
| 1998-01-01 | 4 | 1.63 | 1.72 | 0.02 | 0.18 |
| 1997-12-31 | 0 | 1.65 | 1.73 | 0.02 | 0.18 |
| 1997-12-31 | 1 | 1.76 | 1.85 | 0.02 | 0.19 |

**Fig 7** Example of data samples

In this diagram we can see the single date has multiple entries, which makes learning difficult for learning algorithms. In this context, are proposed to pre-process the data for making it effective for learning algorithm. The pre-processing algorithm follows the following steps:

**Table 1** Pre-processing Algorithm

**Input:** Dataset D

**Output:** pre-processed Dataset P

**Process:**

1. $S = D.SortValues(by\ Date)$
2. $G = S.GroupBy(Date)$
3. $for\ each\ g_i\ in\ G$
   a. // where $g_i = \{d_1, d_2, \ldots d_n\}\ instances$
   b. $M = \frac{1}{n}\sum_{j=1}^{n} d_j$
   c. $P.Add(M)$
4. End for
5. Return P

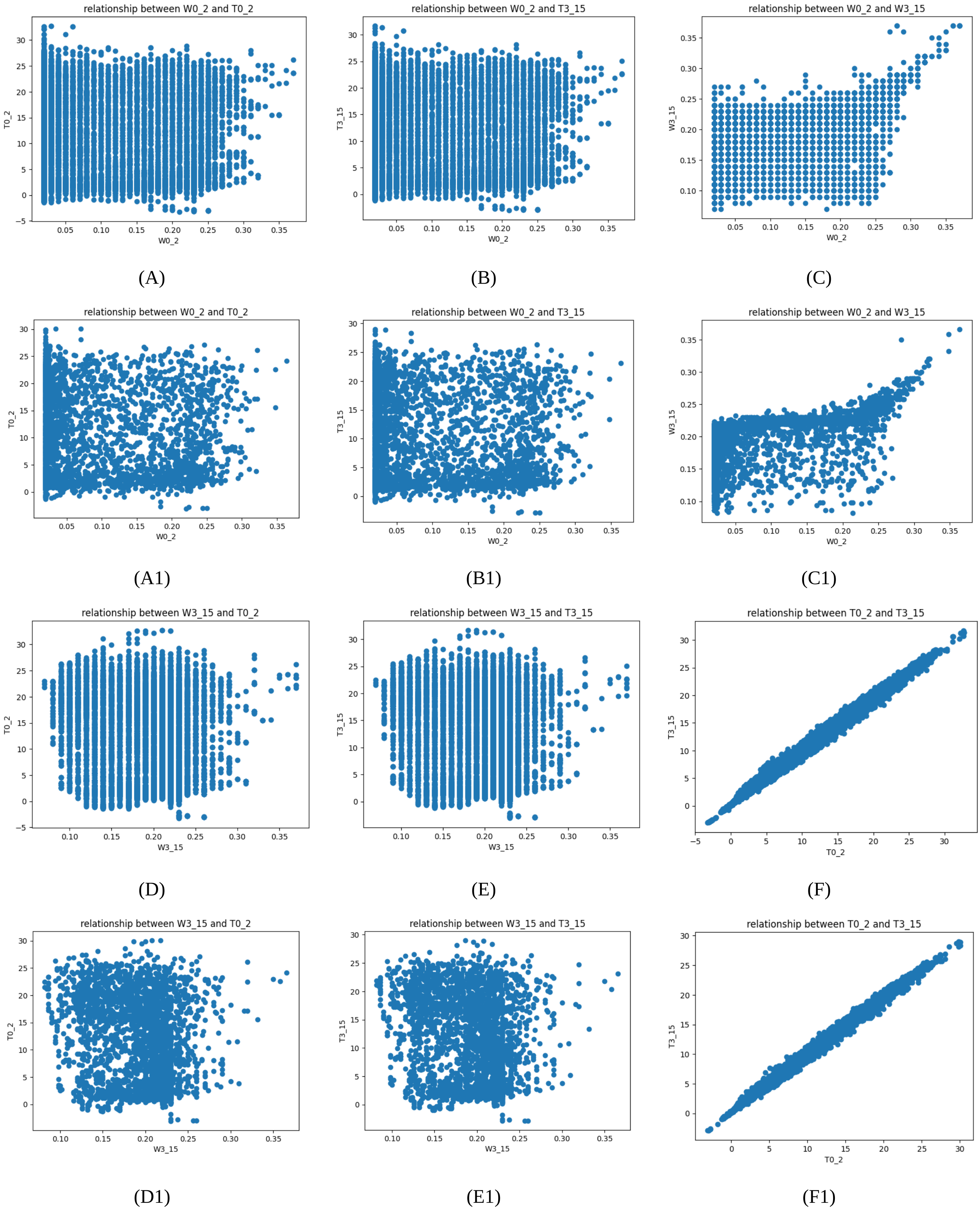
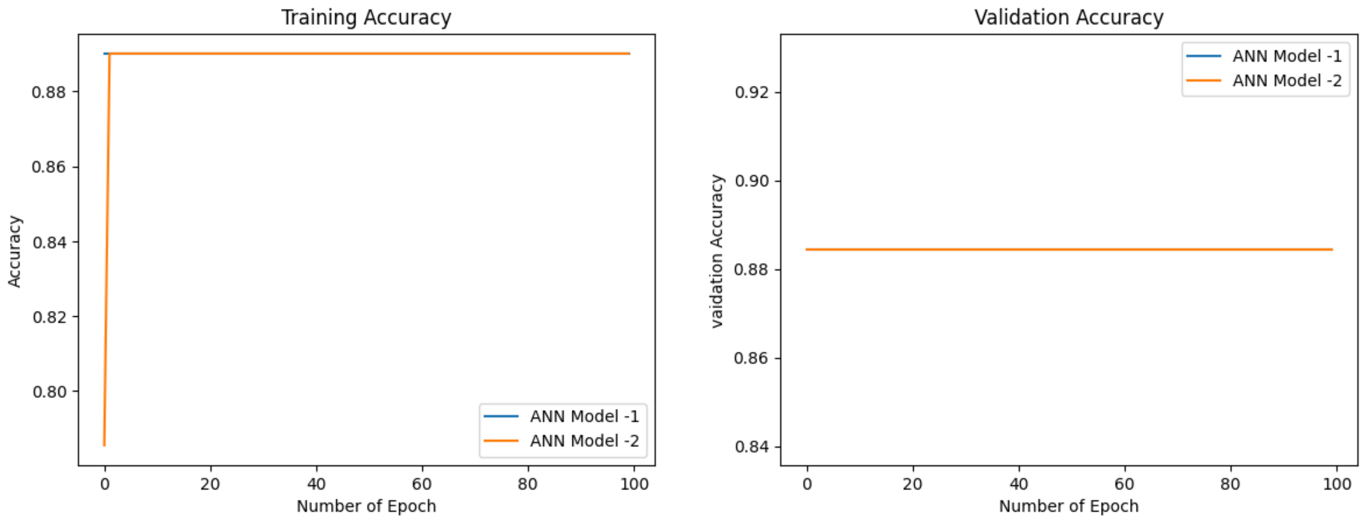



**Fig 6** Relationship between dataset attributes before and after applying the pre-processing algorithm

Basically this algorithm calculates the mean of all the attributes of the instances belongs to same date. Additionally the different treatment types are also involved in this process. After performing group based mean we found the new three type of treatments says 0, 1 and 2. Additionally, again we plot the relationship among the different dataset attributes. The figure 6 also contains the pre-processed data based attribute relationships. According to the visual analysis the data has transformed and may become more classifiable for the ML algorithms. Therefore, the pre-processed data is used with the SVM [12] and two variants of ANN models to classify the data to predict accurate treatment levels. The figure 8 demonstrates the performance of ANN based model's training and validation. Figure 8(A) demonstrates the accuracy for the training of the ANN models and Figure 8(B) shows the accuracy for validation.

## 3. Weather Forecasting

The weather data and future trend prediction is now in these available by using different Application Programming Interface (API). There are two popular APIs available for gathering location aware weather information.




(A) (B)

**Fig 8** shows the accurate of the water treatment type prediction based on ANN algorithm for (A) Training samples (B) Validation samples

According to the recorded performance of the ANN algorithms we found the accuracy of the algorithm has remained constant and results to 88.4% accuracy for both the algorithms. In addition, the SVM classifier has also used and the comparison have been done for both the conditions before and after pre-processing of the data. The figure 9 shows the accuracy of the SVM and ANN classifiers for before and after pre-processing of data.

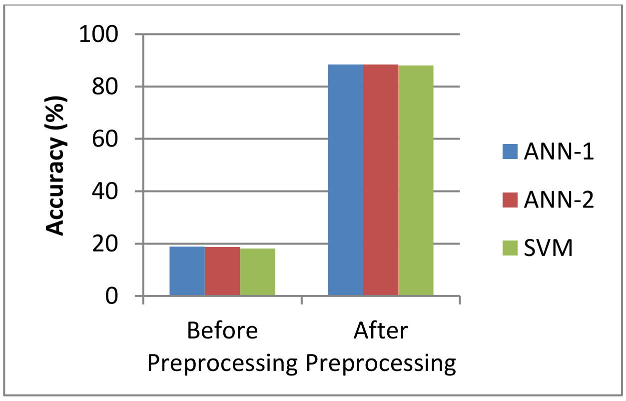



**Fig 9** Accuracy before and after data pre-processing

Based on the obtained results all the classifiers are performing similar in terms of accuracy and produces 88% accurate decisions. Thus, after obtaining the acceptable accuracy the weather forecasting modules has been studied.

### 1. OpenWeatherMap

It is a service for weather data, which includes current weather, forecasts, and historical data for developers. This API enables the utilization for web and mobile applications. API also supports JSON, XML, and HTML endpoints. A free and limited version of API is available. Additionally for more than 60 requests per minute paid subscription required. To use this API, we need an API key [13].

### 2. BeautifulSoup

It is a python library for extracting data from HTML and XML. It generates a parse tree from the page, which can be used to extract data. The Python's has used to make HTTP requests. The headers contain specific information, which is placed before the raw information. After that, we use a get() method and perform Google search with the city name to retrieve the data. Then, we use BeautifulSoup and parse the HTML data. Then, select() function is used to retrieve the information like time, info, location [14].

These two methods are providing us direct information to utilize the weather information for preparing the proactive water treatment plan. But in this work, for simulation purpose we are utilizing the weather prediction dataset obtained from Kaggle [15]. The initial raw dataset is demonstrated in figure 9. The dataset contains 96453 instances and 12 attributes. Initially, three attributes

"Summary", "Precip Type" and "Daily Summary" have the similar information. Therefore, we eliminate "Summary" and "Daily Summary". Additionally, "Precip Type" is considered as class label. There are three type of predictions involved 'rain', 'snow' and 'nan'. In order to make use this data with ML algorithms we are going to encode the "Precip Type" as three categories.

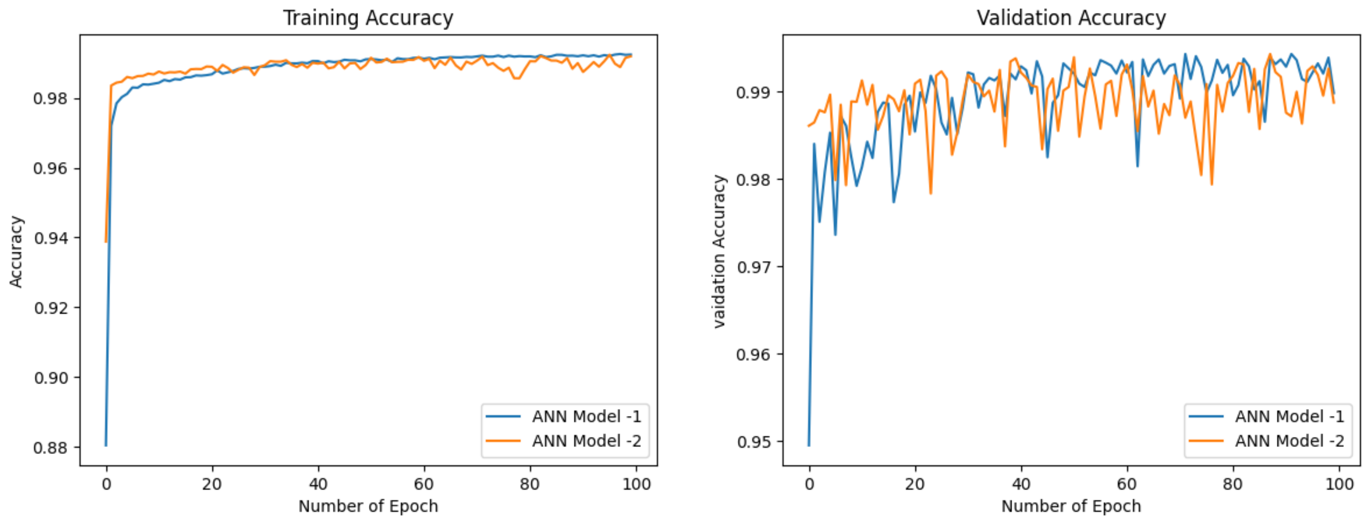
weather conditions are used as label. The similar ANN configuration has been used for performing classification of the given dataset. Additionally the SVM has also used for performing comparison.

Figure 12 contains the accuracy for the implemented both the ANN models. The figure 12(A) shows the accuracy during training of the algorithm and 12(B) shows the accuracy for validation. According to the obtained results the ANN configuration 1 or model 1 shows the higher accuracy as compared to second model. The model 1 also performs better for validation samples as shown in figure 12(B). Next for comparison SVM algorithm has also implemented. The comparison of SVM and both the implemented ANN algorithms has been given in figure 13. Based on the comparison the ANN configuration 1 we found the SVM is able to predict only 95% of validation samples on the other hand ANN model 1 shows 99.4% and model 2 shows 98.9% of accurate results.

| 0 | Formatted Date | Summary | Precip Type | Temperature (C) | Apparent Temperature (C) | Humidity | Wind Speed (km/h) | Wind Bearing (degrees) | Visibility (km) | Loud Cover | Pressure (millibars) | Daily Summary |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2006-04-01 00:00:00.000 +0200 | Partly Cloudy | rain | 9.472222222222221 | 7.3888888888888875 | 0.89 | 14.1197 | 251.0 | 15.826300000000002 | 0.0 | 1015.13 | Partly cloudy throughout the day. |
| 2 | 2006-04-01 01:00:00.000 +0200 | Partly Cloudy | rain | 9.355555555555558 | 7.227777777777776 | 0.86 | 14.2646 | 259.0 | 15.826300000000002 | 0.0 | 1015.63 | Partly cloudy throughout the day. |
| 3 | 2006-04-01 02:00:00.000 +0200 | Mostly Cloudy | rain | 9.377777777777778 | 9.377777777777778 | 0.89 | 3.9284000000000003 | 204.0 | 14.9569 | 0.0 | 1015.94 | Partly cloudy throughout the day. |
| 4 | 2006-04-01 03:00:00.000 +0200 | Partly Cloudy | rain | 8.28888888888889 | 5.944444444444446 | 0.83 | 14.1036 | 269.0 | 15.826300000000002 | 0.0 | 1016.41 | Partly cloudy throughout the day. |

**Fig 10** Initial Weather dataset

Next the conversion of data set from Object to float type has been performed, to use the data set for numerical calculations by ML algorithms. Next the time stamp is used to sort the dataset and also we sort the data according to the date values. Then we performed visual data analysis of the weather dataset attributes.




(A) (B)

**Fig 11** Prediction performance of proposed weather condition system for (A) Training (B) validation

Figure 10 contains the visualization of the remaining attributes in dataset. Based on the visual analysis we found the temperature is varying throughout the year and follows a cycle each year. In addition, the attribute "Loud Cover" has a common value 0 for all the instances. Thus we eliminate the "Loud Cover" from the dataset. Finally, the dataset contains only 7 attribute as training input and the relevant

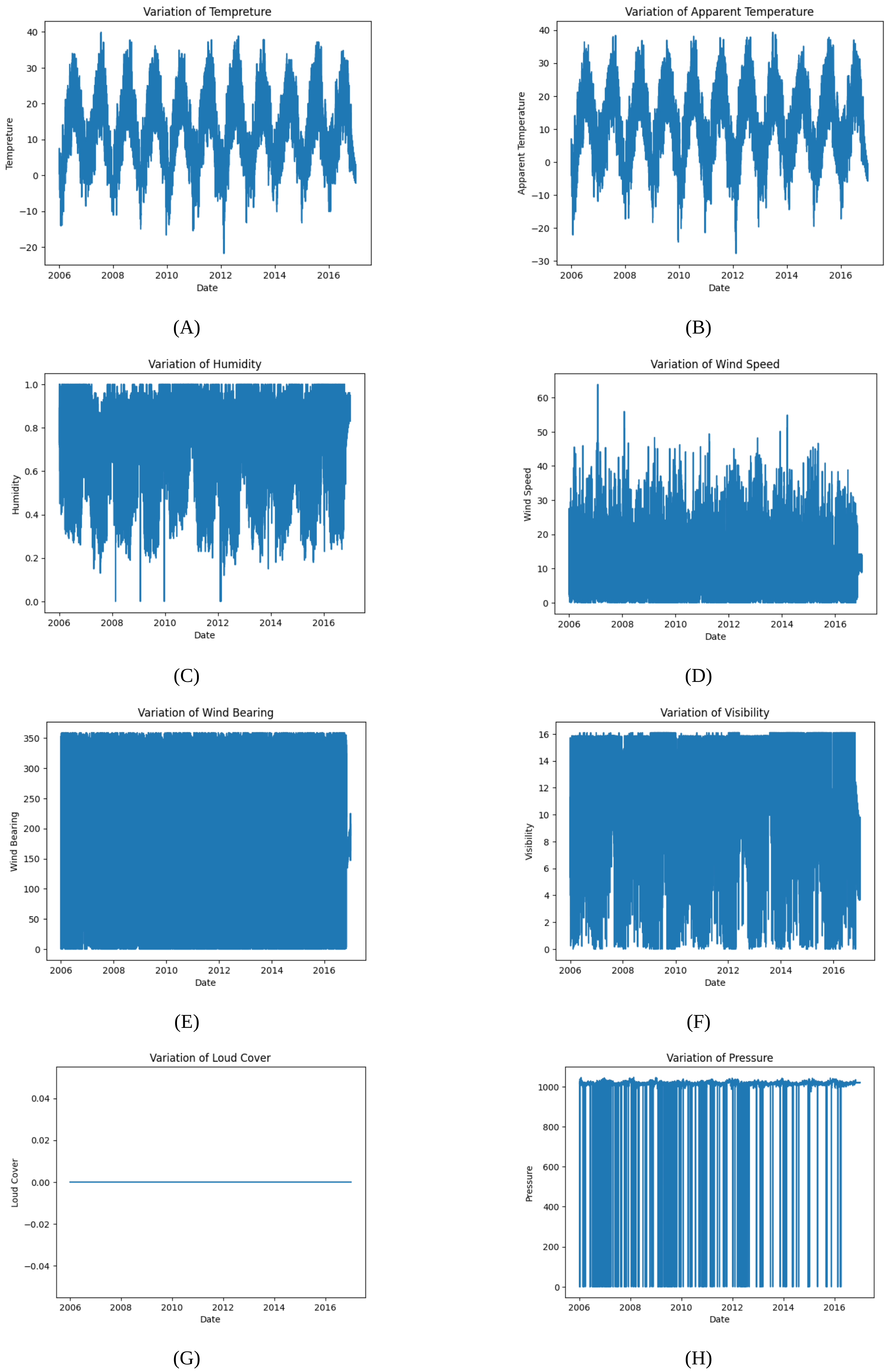



**Fig 10** Visual data analysis for the weather dataset attributes

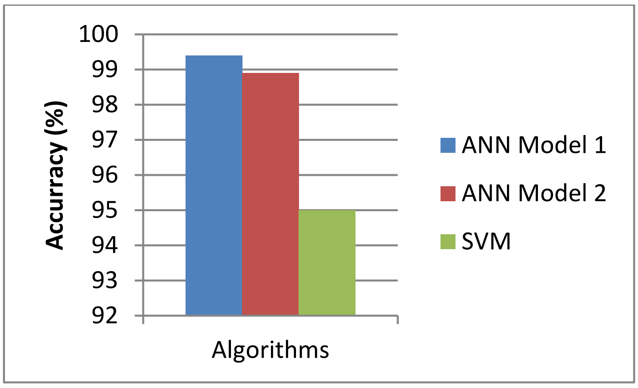



**Fig 13** Accuracy for weather prediction

## 4. Combining Decision to Make Water Supply

The system architecture of applying the weather forecasting and water treatment prediction techniques has demonstrated in figure 14. The given system can be described in three key modules:

work [16], ESP32 based hardware is used. This data collection system is works by using FC-28, which is a used for measuring the moisture in soil. It can be directly used with different microcontrollers. Additionally the hardware contains ESP32, which is a feature-rich processor or microcontroller (MCU) with Wi-Fi and Bluetooth connectivity. The FC-28 is a soil moisture sensor connected with the ESP32. The total cost of the unit is very low and can be built less than 600 INR. A farmer can put these sensors according to their own located points or for better results we discuss the location estimation technique in our recent work.

In these experimental scenarios in place of collecting data directly from farmland by using sensors we have utilized a temperature and moisture sensor reading dataset. In addition, in place of taking weather data from API or any other source, we have considered the weather dataset obtained from Kaggle. The detailed study about the dataset has been

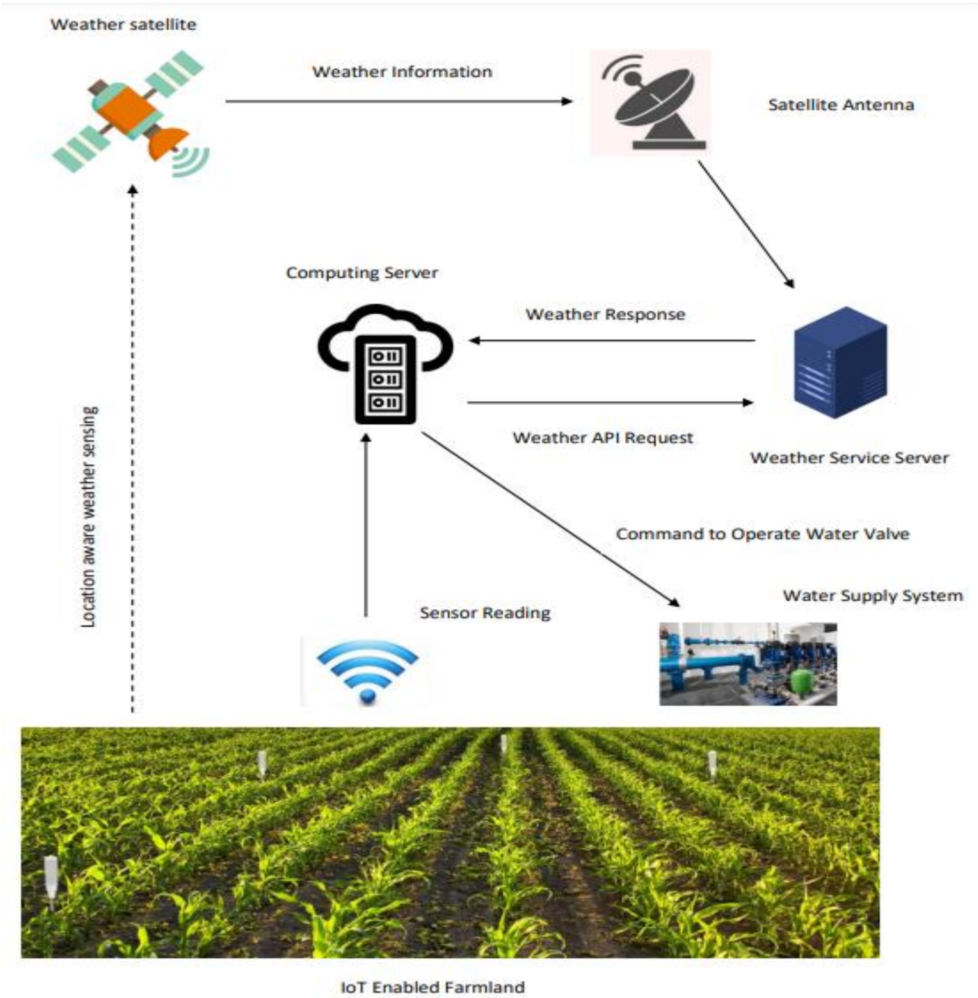



**Fig 14** shows the system architecture to configure both the components weather and water treatment prediction

### 4.1 Data Collection

Basically, the data is generated from the agricultural activity. In this work, the problem of water irrigation has considered thus the data can be collected from the farm land. In recent

discussed in previous section. In next section, we are discussing how the computational server has utilizing the weather and sensor reading to predict the water treatment plan automatically. Additionally how the weather condition is changing the water treatment plan has also been discussed.

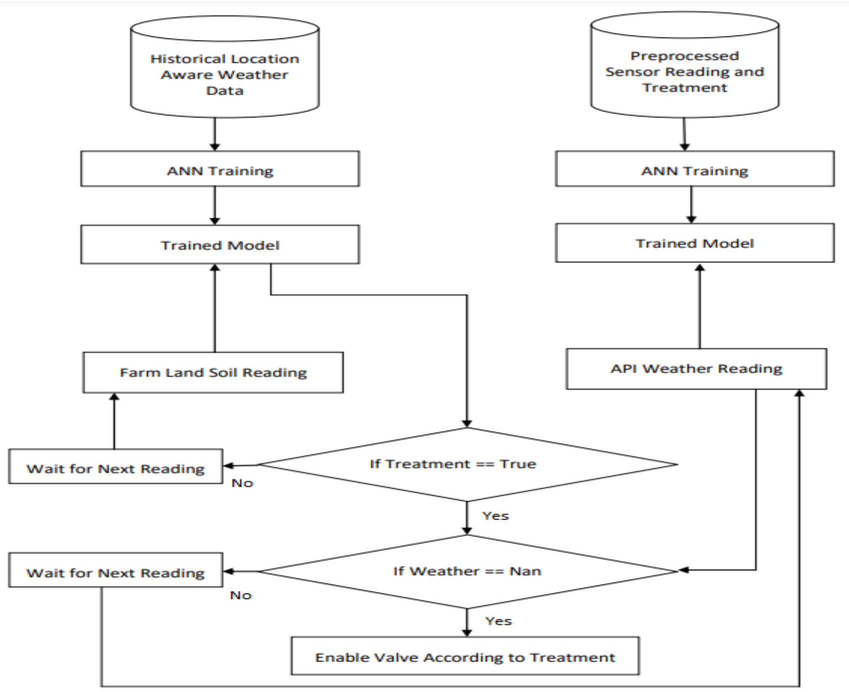



**Fig 15** Process of utilizing the weather forecast and soil moisture readings in automation of irrigation system

### 4.2 Data Processing

The steps of utilizing the weather and sensor reading in the proposed proactive management system have been demonstrated in this section. Figure 15 demonstrate the computational system work flow for obtaining the accurate and automated water supply decision making processing. According to the diagram, the system consists of two historical databases. First, dataset is termed here as weather dataset W and second dataset is termed as Soil condition dataset S. The dataset W is used with the ANNM-1 model to train the network. Similarly by using the defined pre-processing technique ANNM-1 the model is trained with sensor reading dataset S. Let first model trained with weather conditions is named as $M_W$ and model for soil condition is named as $M_S$. The model $M_W$ accepts the 7 weather parameters for making prediction. Similarly model $M_S$ requires 5 parameters to make predictions. The predicted values are used with the next section for making decision.

### 4.2.3 Decision making

According to the datasets used the input for $M_W$ is a 7 parameter input which is defined as:

$$I_W = \{i_T, i_{AT}, i_H, i_{win}, i_{WB}, i_V, i_P\} \ldots\ldots (1)$$

Where, $i_T$ is the current temperature, $i_{AT}$ is providing Apparent Temperature, $i_H$ is given as humidity, $i_{win}$ is showing wind speed, $i_{WB}$ is showing wind bearing, $i_V$ is visibility and $i_P$ is pressure.

Similarly the model $M_S$ input tuple is defined as:

$$I_S = \{i_{T0_2}, i_{T3_{15}}, i_{W0_2}, i_{W3_{15}}\} \ldots\ldots (2)$$

Where, $i_{T0\_2}$ is temperature for 0-2 cm, $i_{T3\_15}$ is temperature for 3-15 cm, $i_{W0\_2}$ is water content for 0-2 cm, and $i_{W3\_15}$ is temperature for 3-15 cm.

These inputs are provided to trained ANN algorithms which are given as $M_S$ and $M_W$ . On the given inputs these algorithms are working as the following function.

$$M_S(I_S) = \begin{cases} 0 & Return\ False \\ 1, 2 & Return\ True \end{cases} \ldots\ldots\ldots (3)$$

Similarly, for the second algorithm

$$M_W(I_W) = \begin{cases} 0, 1 & Return\ False \\ 2 & Return\ True \end{cases} \ldots\ldots\ldots (4)$$

Where, in equation (3), the output related to the water treatment, additionally the output of 1 and 2 represents the water treatment and amount of water to supply. On the other hand in weather conditions out 0 and 1 represents the happening of rain or snow. Thus, system returns false. Let, the output of the equation is denoted by $O_S$ and $O_W$. Then we need a function f such that:

$$f(O_S, O_W) = \begin{cases} if\ O_S = T\ and\ O_W = F\ Then\ N \\ if\ O_S = F\ and\ O_W = F\ Then\ N \\ if\ O_S = T\ and\ O_W = T\ Then\ Y \\ if\ O_S = F\ and\ O_W = T\ Then\ N \end{cases} \ldots\ldots (5)$$

The equation enable and disable the water supply based on T(True) or F(False) decision made by the system.

## 5. Results Analysis

The proposed work is aimed to design an automated decision making system for applying in irrigation of crops.

Therefore, the historical sensor readings are used to train ML algorithm, and based on future sensor readings the algorithm predicts the water treatment plans. But, the weather conditions are also influencing the water treatment. Therefore, one more ML algorithm has been trained to monitor the weather conditions. Additionally, with the change in atmospheric conditions it utilizes the appropriate function to change in irrigation plan. Therefore, a decision making function has been developed. That performs the decision making task for enable or disable the water supply valves. Thus the performance or quality of service of the presented work has been significantly depends on prediction components.

During the investigation we have implemented and experimented with the two versions of ANN algorithm's configuration and SVM algorithm for selecting appropriate prediction technique. Based on experimental accuracy we have selected ANN algorithm for utilizing in prediction task. The considered prediction algorithm provides 88.4% accurate prediction for soil moisture and temperature sensors additionally producing 99.4% accurate results for weather prediction task. However, the system required to train only once for initialization of prediction algorithm. The training time of the selected ANN algorithm and SVM algorithm is also measured and reported in figure 16. The training time of the algorithm has been given in terms of seconds (sec). According to the training time of the algorithms the weather data takes higher time due to large number of parameters to learn as compared to soil moisture dataset.

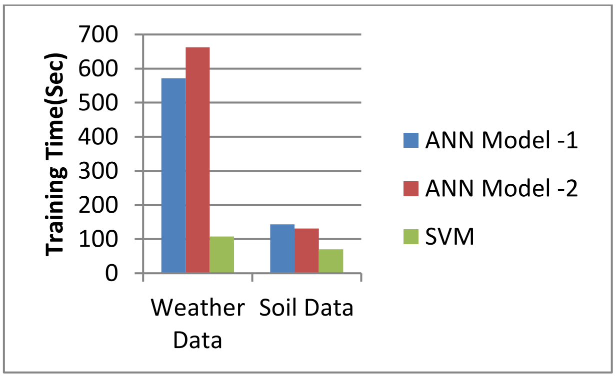



**Fig 16** Training Time of used ML algorithms

Next, the decision making time of the algorithms has also been measured. The decision making time ($D_t$) is calculated based on the following equation:

$$D_t = \frac{V_t}{N} \dots \dots \dots \dots (6)$$

Where, $V_t$ is the validation time for N number of samples.

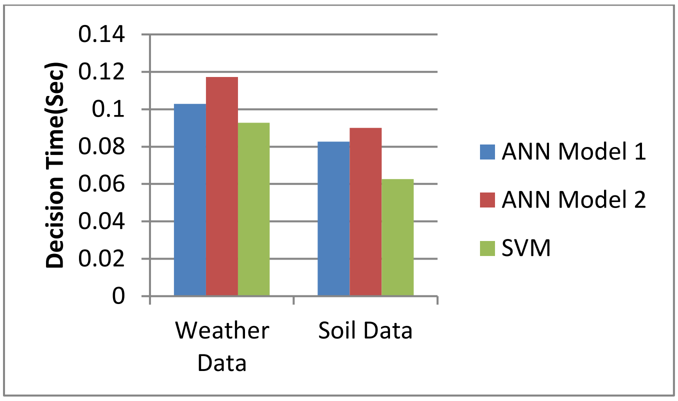



**Fig 17** Decision making time of algorithms

Figure 17 demonstrate the decision making time of the algorithms. The models are providing decisions in a fraction of seconds. Therefore, the system is not only accurate it is efficient for making decision and also has fewer training time. Due to fast processing and efficient decision making it requires fewer server (cloud) resources thus the user need to pay low cost of the service developed using this strategy.

## 6 Conclusions

The agricultural use of fresh water is never recovered again. Additionally, recycling needs a significant amount of time and artificial process are expensive. Therefore, fresh conservation is a challenging task in agriculture. In this paper, we are aimed to minimize the utilization of water without affecting the crop yield. Therefore, an automated water treatment system has been proposed. Additionally, it various components has been discussed. The model consists of three main parts data collection, data analysis and decision making. First, we discussed how the data can be collected from farm land by using the sensor hardware which is influenced by our recent work [16]. After collecting the localized sensor readings the pre-trained ANN algorithm has been used to decide water treatment decisions. These sensor readings are indicating the water requirements of the crop or farmland. Next the weather conditions are also influencing the water treatment decisions. Therefore, a weather forecasting system is also incorporated to predict the possible weather conditions.

Finally, a decision function has been introduced to make decisions of water supply enabling and disabling. This function accepts the predictive outcomes of the ANN algorithms. Additionally, on changing the sensor readings and weather condition parameters the decisions may change accordingly. The predictive algorithm has a great influence on entire system performance and required quality of service. Therefore, most accurate ANN technique among a comparison of prediction is selected. For weather conditions ANN perform 99.4% accurate predictions and for soil condition before data pre-processing is predicts only 21% correct treatment. Additionally, after performing a pre-processing step the same algorithm provides 88.4% accurate results. Additionally the algorithm also produces faster data analysis in terms of algorithm training and decision making. Thus the proposed system is acceptable to demonstrate how we can perform precise irrigation automation with limited sensor deployments and low cost server.

## References


[1] I. H. Sarker, "Machine Learning: Algorithms, Real-World Applications and Research Directions", SN Computer Science volume 2, Article number: 160 (2021)

[2] A. Monteiro, S. Santos, P. Gonçalves, "Precision Agriculture for Crop and Livestock Farming—Brief Review", Animals 2021, 11, 2345

[3] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, R. Kaliaperumal, "Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture", Agriculture 2022, 12(10), 1745

[4] "Soil Moisture and Temperature - Modeled — Main Cropping System Experiment (MCSE)", https://lter.kbs.msu.edu/datatables/81

[5] S. Sarkar, A. Pramanik, J. Maiti, G. Reniers, "Predicting and analyzing injury severity: A machine learning-based approach using class-imbalanced proactive and reactive data", Safety Science 125 (2020) 104616

[6] A. Zeroual, F. Harrou, A. Dairi, Y. Sun, "Deep learning methods for forecasting COVID-19 time-Series data: A Comparative study", Chaos, Solitons and Fractals 140 (2020) 110121

[7] M. Saeed, "A Guide to Obtaining Time Series Datasets in Python", in Python for Machine Learning, March 29, 2022, https://machinelearningmastery.com/a-guide-to-obtaining-time-series-datasets-in-python/

[8] Ezio Preatoni, Stefano Nodari, Nicola Francesco Lopomo, "Supervised Machine Learning Applied to Wearable Sensor Data Can Accurately Classify Functional Fitness Exercises Within a Continuous Workout", Front. Bioeng. Biotechnol. 8:664, July 2020

[9] X. Ying, "An Overview of Overfitting and its Solutions", IOP Conf. Series: Journal of Physics: Conf. Series 1168 (2019) 022022

[10] S. Ruberto, V. Terragni, J. H. Moore, "Towards Effective GP Multi-Class Classification Based on Dynamic Targets", GECCO '21, July 10–14, 2021, Lille, France, ACM

[11] J. Bernard, T. Ruppert, O. Goroll, T. May, and J. Kohlhammer, "Visual-Interactive Preprocessing of Time Series Data", SIGRAD 2012

[12] D. C. T. Pérez, J. R. Reséndiz, R. A. G. Loenzo, J. C. J. Correa, "Support Vector Machine-Based EMG Signal Classification Techniques: A Review", Appl. Sci. 2019, 9, 4402 openweathermap.org

[13] M. Breuss, "Beautiful Soup: Build a Web Scraper With Python", https://realpython.com/beautiful-soup-web-scraper-python/

[14] https://www.kaggle.com/datasets/ananthr1/weather-prediction

[15] P. Pandey, S. Agarwal, "A Low Cost Smart Irrigation Planning Based on Machine Learning and Internet of Things", Curr Agri Res 2023; 11(2).

[16] Rajendra, K. ., Subramanian, S. ., Karthik, N. ., Naveenkumar, K. ., & Ganesan, S. . (2023). Grey Wolf Optimizer and Cuckoo Search Algorithm for Electric Power System State Estimation with Load Uncertainty and False Data. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 59–67. https://doi.org/10.17762/ijritcc.v11i2s.6029

[17] Kshirsagar, P.R., Reddy, D.H., Dhingra, M., Dhabliya, D., Gupta, A. Detection of Liver Disease Using Machine Learning Approach (2022) Proceedings of 5th International Conference on Contemporary Computing and Informatics, IC3I 2022, pp. 1824-1829.

[18] Martínez, L., Milić, M., Popova, E., Smit, S., & Goldberg, R. Machine Learning Approaches for Human Activity Recognition. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/146