Internet of Things and Machine-Learning-Based Leaching Requirements Estimation for Saline Soils

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***Abstract*—Soil salinity is a soil degradation phenomenon with a severe impact on crop production. Internet of Things (IoT)-assisted solution is proposed in this article to determine soil salinity level and environment conditions to recommend irrigation water, with a purpose to leach down the salts from the root zone of crops in saline soils. IoT and machine learning (ML)-based leaching water requirements estimation for saline soils is made using the *in situ* monitoring of the salinity level and crop field temperature. The Food and Agricultural Organization (FAO)-proposed method of leaching requirement is implemented for efficient leaching water estimation. These estimations are used to train and test the Naive Bayes classifier for ML to predict the leaching requirements (LR) in future while using only temperature and soil salinity level. The performance of ML is judged in terms of accuracy, *f*-measures, precision, and recall. The proposed solution is implemented on a cotton crop in a salt-affected area, to test the agronomic impact of the proposed solution.**

***Index Terms*—Electric conductivity (EC), Internet of Things (IoT), leaching requirements (LR), Naive Bayes classifier, saline soils.**

Nomenclature

Cl^-	Chloride ions.
DSS	Decision support system.
EC	Electric conductivity.
EC_e	Crop soil salinity tolerance.
EC_w	Electric conductivity of irrigation water.
ET_0	Reference evapotranspiration.
ET_c	Crop evapotranspiration.
FAO	Food and agriculture organization.
FMIS	Farm management information system.
ICT	Information and communication technologies.
IoT	Internet of Things.
Kc	Crop coefficient.
LR	Leaching requirements.
MS	Microsoft.
Na^+	Sodium ion.
p	Day length.
PA	Precision agriculture.
UAV	Unmanned aerial vehicle.
USSL	United states salinity labs.
WR	Water requirements.
WSN	Wireless sensor network.

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I. Introduction

Soil salinity is a global environment problem of soil degradation, with severe threat to global sustainable agriculture developments [1], [2]. Soil salinity is the accumulation of different salts in the soil that can make the soil unfit for agriculture. The soils with the soluble salts in quantities above the threshold of toxicity to most of the plants are called saline soil [3]. Soil salinization is the process of accumulation of salts in soil [4]. Soil salinity is measured in terms of concentration of total soluble salts in an aqueous solution of the soil [5]. According to the United States Salinity Labs (USSL), the concentration of total dissolved salts in soil is measured as electric conductivity (EC) of soil. Soils with EC values equal to or more than 4 decisiemens per meter (dS m^{-1}) at 25 °C are called saline soils [3].

Soil salinity is a global phenomenon present in more than 100 countries with varying levels of salinity [6]. Approximately one billion hectares of the total earth surface or about 7% of the total continental surface area is affected with soil salinity [7], [8]. Soil salinity has severe impacts on crop production and sustainable agricultural resources usage due to impact on the water and nutrients uptake capabilities of the plants [9]. The uptake of water with a high concentration of sodium (Na^+) and chloride (Cl^-) ions in saline soils has negative impact on normal physiology and morphology of plants resulting in retarded growth, abnormal hormonal activities, disturbed cell membrane functions, and plant water movement [3].

In saline soil, leaching is the method to reduce the salinity in the root zones for optimal growth of the plant. Leaching is the process of application of extra irrigation water in the field to percolate down the salts from the root zone [10]. Estimation of the leaching water requirements (WRs) is crucial, when irrigation water is also scarce with soil salinity [11]. Dwindling of irrigation water reserves adds pressure on agriculture to produce more with reduced natural resources. About 70% of world fresh water is used for agriculture purpose, and the major portion of this water is wasted due to inefficient application of irrigation water [12]. There is an immense need to effectively apply leaching water according to the salinity level, crop types, and crop field environment conditions, with the conservation of irrigation water and ameliorative measure of the soil salinity [13].

Internet of Things (IoT) is an exciting paradigm with seamless integration of smart capabilities into physical objects for context oriented services [14], [15]. IoT has very promising applications in agriculture to monitor and control the environment conditions [14], [16]. The IoT-assisted context-aware applications are of great importance in precision agriculture (PA) to make recommendations based on the directly sensed data from crop fields [17], [18].

The strategy for amelioration of soil salinity requires the knowledge and information for soil salinity level at a moment, trends of salinity progress over time, and crop field environmental conditions. IoT can play a significant role in the efficient use of irrigation water for the leaching purpose by accurate estimation according to the microenvironment conditions of the crop field. The major objective of the study is the recommendation of leaching water according to the level of salinity in the crop field to gain maximum yield in saline soil by conservation of irrigation water.

The rest of this article is organized into "state-of-the-art," "proposed solution," "material and methods," and "evaluations." state of the art, the proposed solution, the material and methods, and evaluations. Finally, the work is concluded. The next section reviews different related work regarding the estimation and mapping of the salinity and crop water recommendations using information and communication technologies (ICTs).

II. State of the Art

The soil salinity has gained much attention from researchers, farmers, communities, and international bodies that deal with these issues [19]. There are different ways to detect, monitor, and map soil salinity. The most important are laboratory analysis, ground surveys, proximal sensing, remote sensing, and unmanned aerial vehicle (UAV)-assisted ariel photography. All of these approaches have their own pros and cons [10]. Laboratory tests are a valid and proven method for mapping the soil salinity [10]. However, laboratory and chemical analysis is costly and time consuming [9]. Remote sensing using the satellite imagery is the cheap and efficient method of soil salinity mapping over a broad area [11]. The remote sensing methods are based on the principle of reflectance properties of salts and vegetation from the top layer of the soil [20], [21]. Application of remote sensing at irrigation management level is limited because of its inability to determine soil salinity at a root zone level.

Many IoT-assisted agriculture applications have emerged in recent years with a major focus on monitoring of environment parameters, control of environment, animal tracking, irrigation water applications, and zone-specific treatments [16]. This review focuses on the IoT-assisted irrigation recommendations, based on the crop field environment conditions.

Mohanraj *et al.* [22] proposed automated irrigation with real-time monitoring of the environment parameters using the humidity, temperature, and soil moisture sensor with significant conservation of water as compared to the traditional process. Nikolidakis *et al.* [23] proposed the automated irrigation system by the novel routing protocol for the wireless sensor network (WSN) with the intentions to improve the efficiency of crop water applications. Karim *et al.* [24] proposed the decision support system (DSS) for efficient irrigation application based on the real-time spatial crop field data captured with WSN. Navarro-Hellin *et al.* [25] presented an automated smart irrigation to deal with water scarcity. Brewster *et al.* [17] proposed IoT-based DSS to conserve natural resources, especially the irrigation water. Tan [26] proposed a cloud-based framework for software-defined control of equipment in PA applications. Feng *et al.* [27] proposed the machine learning (ML)-based evapotranspiration measurements in crop fields. Zhao *et al.* [28] estimated the crop water stress using the UAV. Rojo *et al.* [29] proposed the leaf temperature monitoring system to recommend site-specific irrigation. Uddin *et al.* [30] proposed a model for harnessing the data from ground sensor using the UAV for the effective implementation of the IoT system in smart agriculture. Kong *et al.* [31] proposed monitoring of water contents in sandy soil using the gravimetric soil sampling, active sensing, and electric permittivity for improvements of water measurement methods in precision agriculture applications. Cid-Garcia *et al.* [32] proposed site-specific irrigation based on the soil characteristics using the mathematical models. Rajalakshmi and Mahalakshmi [33] proposed IoT base field monitoring and irrigation management while using the soil moisture, temperature, humidity, and light intensity sensor. Ye *et al.* [34] proposed the IoT and WebGIS-based PA management system (PAMS) for efficient use of water. Ramachandran *et al.* [35] proposed IoT and cloud-based automatic irrigation system based on the soil moisture, soil type, pH, and weather conditions. Gutiérrez *et al.* [36] proposed a Web-based IoT system of irrigation automation by deploying underground sensors for temperature and soil moisture. Goumopoulos *et al.* [37] proposed a WSN bases autonomous irrigation system using the soil moisture, temperature, and humidity sensors and actuator for automatic control of irrigation valve. Ilic *et al.* [38] proposed estimation of evapotranspiration with the neuro-fuzzy approach for irrigation scheduling and water resources management in agriculture. Mazon-Olivo *et al.* [39] proposed dynamic event processing architecture for IoT application in PA. Zhuiykov [40] review solid state sensors for real-time monitoring of water quality parameters as dissolved oxygen, conductivity, turbidity pH, and dissolved metal ions. Ojha *et al.* [41] proposed a mathematical model for sensor cloud in agriculture applications. Koksal and Tekinerdogan [42] proposed IoT-based architecture of the farm management information system (FMIS).

A deep analysis of this review reveals the following.

1) Many irrigation automation systems were proposed, but not a single solution targeted the saline soil. Not a single IoT-assisted precision irrigation study was conducted

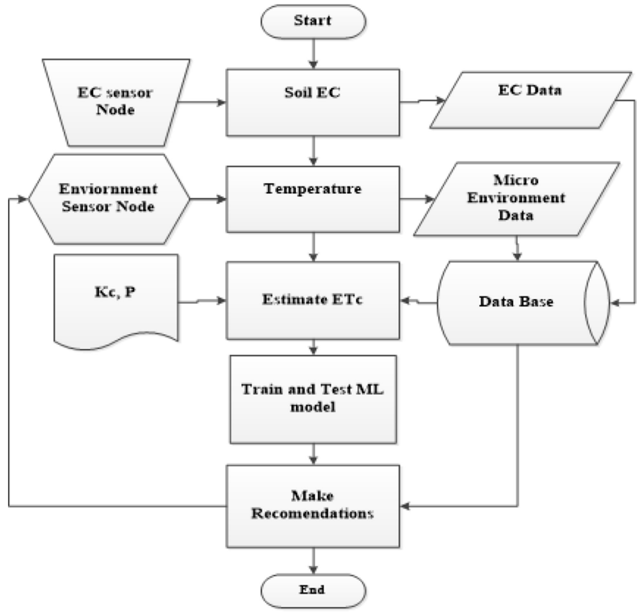

Fig. 1. Workflow of the proposed solution.

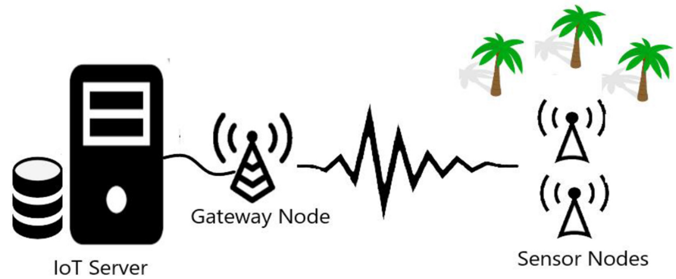

Fig. 2. Proposed solution architecture.

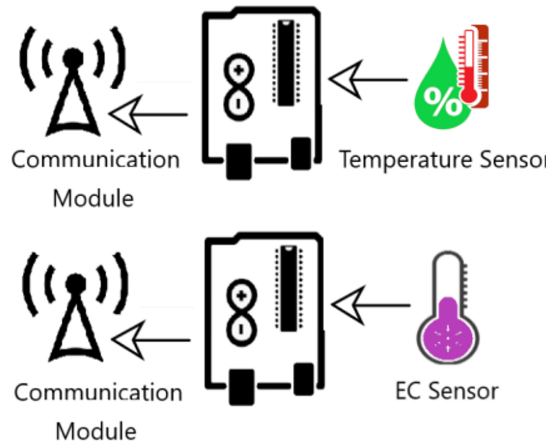

Fig. 3. Architecture of EC, and environment sensor node.

using *in situ* monitoring of field parameters related to salinity and applied the ML approach to predict such recommendation in future based on microenvironmental data.

2) Irrigation WR estimation is a complex process and needs special emphasis to adopt standard methods of calculation of irrigation water like Pen Month or the Blaney–Criddle method of crop water estimation [43]. Very few studies use these standard approaches to recommend the efficient use of irrigation water while maintaining the yield.

For effective irrigation management in saline soils, *in situ* monitoring of salinity level is necessary and there is a need of a solution that minimizes the sampling and chemical test, for characterizing the salinity condition and other environment parameters. IoT can play a significant role in the development of practical means of scheduling and control of irrigation for leaching the salts out of the root zone, according to crop field context.

III. Proposed Solution

In order to meet the objectives, the proposed solution is based on the direct sensing of the microenvironment parameters like temperature and soil EC, to estimate the leaching WR according to these parameters, for leaching down the salts from the root zones. The ML algorithm is applied to make the leaching requirement (LR) prediction in the future, based on crop field temperature and the soil salinity level. The flow chart of the proposed solution is shown in Fig. 1.

A. Architecture of the Proposed Solution

Keeping in view the objectives of the study, and present technology capabilities, the proposed architecture is based on the *in situ* sensor nodes, IoT server, gateway node, and application. The values from the sensor's node are transferred to the IoT server through gateway, for further processing and storage. The IoT server estimate, the salinity level and calculates leaching WR according to the level of salinity using the ML approach. The end user can communicate with the system using an easy to use desktop application. The proposed architecture is shown in detail in Fig. 2.

The architecture of the proposed solution is based on the environmental sensor nodes and the EC sensor node. The architecture of these sensor nodes is shown in Fig. 3.

B. Characteristics of the Proposed Solution

The major characteristics of the proposed solution are as follows.

1) The proposed solution is specifically targeted for ameliorative measures in saline soils and to implement precision irrigation practices, through proximal sensing of saline soil characteristics.
2) The study used the standard Food and Agricultural Organization (FAO)-proposed Blaney–Criddle methods of predicting the water LR for efficient use of irrigation water while maintaining the yield.
3) The study uses the soil EC and air temperature sensors directly deployed in field.
4) The proposed solution is implemented and tested in real-time scenario, rather than in protected or green houses.

Fig. 4. Pakistan location on the world map.

Fig. 5. Selected site salinity observation at the selected site.

5) The study used the ML approach to suggest the leaching WR in the future, based on temperature and the level of salinity.

IV. Material and Method

The proposed solution is implemented in the Vehari district of Pakistan. The geographical location of Pakistan in subcontinental Asia is shown in Fig. 4.

It is an arid region with frequent temperature from 45 °C to 50 °C in summer. Summer prevails from April to late October.

The intensive irrigation activities and arid climate properties make it an ideal candidate for the salinity hazard development. The selected site for experimental purpose is heavily affected by the salinity problem, shown in Fig. 5.

A. Crop and Season

Cotton (*Gossypium hirsutum*) is the major crop of the selected area and is selected for implementation of the proposed solution because of its tolerance to salinity [43]. The proposed solution can easily be extended to any other crop.

There are two cropping seasons in the selected area. For experimental purpose, the second cropping season is selected that prevails from May to November.

B. Equipments Used

Soil EC sensor, temperature, and humidity sensor are used for the prototype development to implement the proposed solution. The detailed characteristics of these sensors are described.

Fig. 6. MEC10 soil conductivity sensor.

TABLE I
Characteristics of the MEC10 EC Sensor

MEC10 Soil EC (Salinity) Sensor	
Measurement Range	0-20000 us/cm
Accuracy	±3%
Dimensions	15 cm x 5 cm

Fig. 7. DHT22 temperature sensor.

TABLE II
DHT22 Temperature Sensor

DHT22 Temperature Sensor	
Measuring Range	-40 ~ 80 °C
Accuracy	+/- 3°C
Dimensions	1.5 cm x 2.5 cm

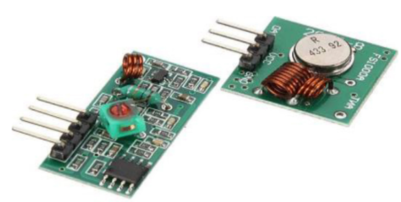

Fig. 8. Communication module.

1) Mec10 Soil EC Sensor: MEC10 is a reliable and stable sensor for estimating the salinity in soils and irrigation water. This sensor is used to measure the EC_w of the soil when irrigation water is applied and shown in Fig. 6, with characteristics in Table I.

2) Temperature and Humidity Sensor: DHT22 is low cost, low powered, lightweight, high precision, and a capacitive-type temperature sensor. This is a calibrated digital sensor with long-term stability, used to measure the maximum and minimum daily temperature, as shown in Fig. 7 with characteristics in Table II.

3) Communication Module: RF433 MHz is a low-powered communication module used to implement the gateway node in solution, and is shown in Fig. 8, with characteristics in Table III.

TABLE III
CHARACTERISTICS OF THE COMMUNICATION MODULE

RF433 Mhz - Communication Module	
Measuring Range	105Dbm
Accuracy	+- 0.2 ~ +- 0.5
Dimensions	1.7 x 1.65 cm

C. Leaching Requirements Calculations

LR estimation depends upon the crop coefficient evapotranspiration (ET_c) that is calculated using the FAO proposed Blaney–Criddle methods for determination of reference evapotranspiration (ET_0) [43]. The ET_c measurements provided by the Blaney–Criddle methods, are used to measure LR by the FAO proposed method as

$$\mathrm{WR} = \frac{\mathrm{ET}_c}{1 - \mathrm{LR}} \tag{1}$$

where ET_c is the crop evapotranspiration for a specific crop (cotton) measured in mm-day^{-1} that can be determined using (4).

LR is the minimum leaching WR to control salinity within the tolerance level of EC_e, while using the surface irrigation method, and it can be calculated using the FAO proposed [43] method as

$$\mathrm{LR} = \frac{\mathrm{ET}_w}{5(\mathrm{EC}_e) - \mathrm{EC}_w} \tag{2}$$

where:

EC_w is the EC of soil in dSm^{-1};

EC_e = Crop soil salinity tolerance;

EC_e for cotton crop at 100% yield potential is 7.7 with value $EC_w = 5.1$.

Hence, the LR can be determined as

$$\mathrm{LR} = \frac{\mathrm{ET}_w}{5(7.7) - \mathrm{EC}_w}. \tag{3}$$

ET_c is the crop evapotranspiration for a specific crop measured in mm-day^{-1} that can be determined as

$$\mathrm{ET}_c = \mathrm{ET}_0 \times K_c \tag{4}$$

where K_c is the crop coefficient for different types of crops and for different stages of the crop.

ET_0 is the reference evapotranspiration (for grass crop) measured in mm day^{-1} required for one-month period that can be calculated from temperature data using the Blaney–Criddle method. Blaney–Criddle methods consider the crop environment conditions, day length, crop type (Kc), and growth stage of the crop in estimation of the evapotranspiration for a particular crop (ET_c) [43]. The Blaney–Criddle method is a simple method to determine ET_0, with only temperature as

$$\mathrm{ET}_0 = p(0.457 \times T_{\mathrm{mean}} + 8). \tag{5}$$

P is the average day length, determined using the site latitude [43]. Vehari is situated at latitude of 30 north and "P" values for different months can be taken from Table IV.

T_{mean} is calculated as

$$T_{\mathrm{mean}} = (T_{\mathrm{max}} + T_{\mathrm{min}}) \tag{6}$$

TABLE IV
P VALUES ON BASIS OF LATITUDE OF A LOCATION [43]

Latitude	May	June	July	Aug	Sept	Oct	Nov
30	0.31	0.32	0.31	0.30	0.28	0.26	0.24

Fig. 9. Sensor deployment in field.

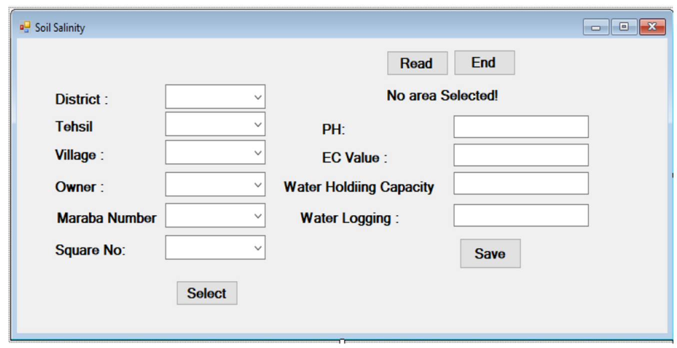

Fig. 10. EC sensor capture module.

where T_{max} = Sum of maximum daily temperature in °C, for one month/number of days in month; and T_{min} = Sum of minimum daily temperature in °C for one month/number of days in month.

The observation for the daily maximum temperature, minimum temperature, and T_{max}, T_{min}, and T_{mean} determination for the second cropping season of year 2018 and 2019 are plotted in the evaluation section.

D. Prototype Development and Deployments

The hardware part of the solution is developed using the Arduino platform. The hardware prototype is developed and deployed in the crop field as shown in Fig. 9.

A desktop application is developed using the Microsoft (MS) visual studio, MS SQL Server and deployed at IoT server. The desktop application captures the micro-environment data, processes it, and stores it. Some data capturing and analysis sessions are shown in Figs. 10 and 11.

E. Naïve Bayes Algorithm Implementation

The Naïve Bayes classifier is based on the Bayes theorem, which works on the principle that each data pair is independent and is equal in the determination of predictive feature. The Bayes theorem relies on the probability determination of

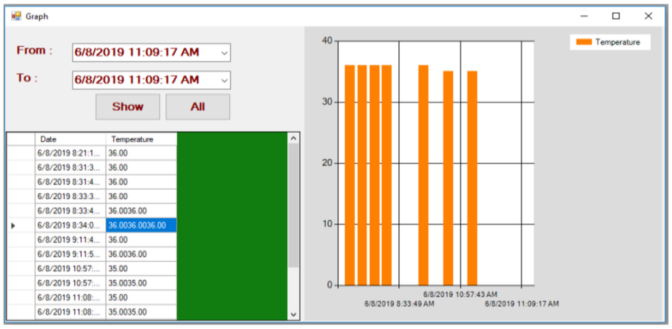

Fig. 11. Temperature sensor data analysis.

an event based on the probability of already occurred event. Mathematically it can be expressed as

$$P(A/B) = (P(A|B)P(A))/P(B) \tag{7}$$

where "A" and "B" are the events where event "B" is also called evidence. "P(A)" is the probability of event "A," also called prior probability of "A"; "P(B)" is the probability of event "B" also called posterior probability of the event "B"; and "P(A/B)" is the probability of event "A" given that event "B" has already occurred.

Each tuple of weather data set is used to classify the different conditions of leaching irrigation water ("not required," "lightly required," "medium required," "heavily required" "extensively required"). The complete data set is divided into the environment feature matrix and the predictive features vector or response vector. The environmental feature matrix consists of the vectors (row) of the data set where each vector contains the dependent feature values. In this data set, maximum daily, minimum daily temperature, and soil EC are features. The response vector is a variable of class values for making the prediction. The Bayes algorithm assumes that each data pair is independent and makes an equal contribution to the prediction made. In this case, no pair set is dependent such as the maximum daily temperature has nothing to do with the minimum daily temperature. Each feature in our data set pays an equal contribution to the prediction, and none of the feature is irrelevant.

The Bayes theorem is applied as

$$P(y/X) = \frac{P(X|y)P(y)}{P(X)} \tag{8}$$

where Y is a variable and X is the vector for dependent feature with size n when $X = (x_1, x_2, \ldots, x_n)$ for example; and $X =$ (hot, medium, slightly saline) is a dependent feature matrix; $y =$ "lightly required" is a class variable.

With the feature vector (hot, medium, slightly saline), y "lightly required," so "$P(X|y)$" means the probability of the leaching requirement "lightly required" given that maximum daily temperature is "hot," minimum daily temperature is "medium," and salinity level is "slightly saline."

In order to put independence of features in the Bayes theorem, evidence is partitioned into independent parts as

$$P(A, B) = P(A)P(B). \tag{9}$$

TABLE V
CLASSES FOR SOIL SALINITY

Soil Salinity (EC)	
EC (dSm^{-1})	Class
<2	Non saline
2 - 4	Slightly saline
4 - 8	Moderately saline
8-16	Strongly saline
>16	Very strongly saline

TABLE VI
CLASSES FOR DAILY MAXIMUM AND MINIMUM TEMPERATURE

Maximum and Minimum daily Temperature (℃)	
Temperature (℃)	Class
>35	Hot
25-35	Normal
<35	Cool

The result can be found as

$$P(y|x_1 \ldots x_n) = \frac{P(x_1|y)P(x_2|y)\ldots P(x_n|y)P(y)}{P(x_1)P(x_2)\ldots P(x_n)}. \tag{10}$$

That can also be expressed as

$$P(y|x_1 \ldots x_n) = \frac{P(y)\prod_{i=1}^{n} = P(x_i|y)}{P(x_1)P(x_2)\ldots P(x_n)}. \tag{11}$$

As the denominator is constant for any certain input, the following term can be removed:

$$P(y|x_1 \ldots x_n) \infty P(y) \prod_{i=1}^{n} = P(x_i|y). \tag{12}$$

As the objective is to develop a classifier model, probabilities of all sets of inputs for the y class variable pick the output with the highest probability as

$$y = \arg_y P(y) \prod_{i=1}^{n} P(x_i|y). \tag{13}$$

F. Classes for Implementation of Machine Learning

Different classes are developed to train and test the ML for prediction of salinity in the future. These classes are made based on real-time data from the crop field captured using the IoT capabilities. The real-time sensed EC values are used to classify the irrigated land into different salinity classes proposed by FAO, as shown in Table V.

The maximum and minimum daily temperature is classified into hot, normal, and cool, as shown in Table VI.

In order to include the Kc factor according to the growth stage, the growth stage of the crop is classified as in Table VII.

LRs classes are made from leaching water requirement estimations made by the FAO proposed method, shown in Table VIII.

TABLE VII
CLASSES FOR COTTON CROP GROWTH STAGE

Growth Stage of Crop	
No of days from sowing	Class
30	Initial
31-80	Development
81-140	Mid-Season
>140	Late Season

TABLE VIII
CLASSES FOR LR

Leaching Requirements	
Irrigation Requirements (mm/season)	Class
<50	Not Required
51-100	Lightly required
101-150	Medium required
151-200	Heavily Required
>200	Extensively Required

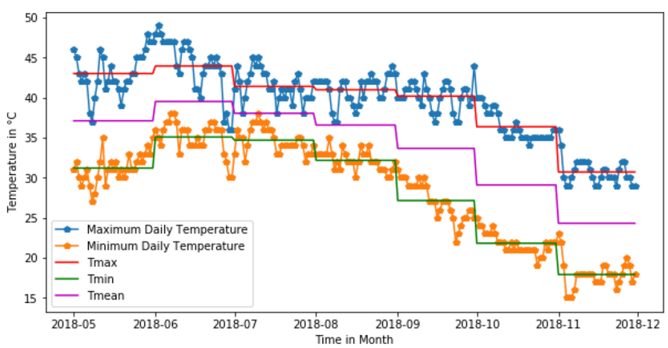

Fig. 12. Maximum and minimum daily temperature, $T_{\max}$, $T_{\min}$, T_{mean} from May to November 2018.

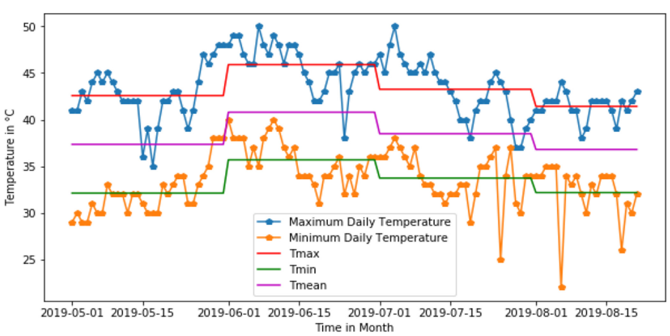

Fig. 13. Maximum and minimum daily temperature, $T_{\max}$, $T_{\min}$, T_{mean} from May to August 2019.

V. ANALYSIS AND DISCUSSION

Cotton is grown in May and the process ends in October in the selected area. Therefore, the analysis of the data is limited to May–November 2018, and to May–August 2019. The IoT-based environment captured temperature of 2018 is shown in Fig. 12, and the IoT-based environment captured temperature of 2019 is shown in Fig. 13, with $T_{\max}$, $T_{\min}$, and T_{mean}.

TABLE IX
PRECISION, RECALL, AND F1 MEASURE FOR PREDICTIVE FEATURES

Predictive Class	F1	Recall	Precision
Not Required	0.897	0.812	1.000
Slightly Required	0.688	0.846	0.579
Medium Required	0.667	0.647	0.688
Heavily Required	0.681	0.667	0.606
Extensively Required	0.941	0.935	0.946

TABLE X
COMPARISON OF AGRONOMIC MEASURES

Agronomic Measure for Cotton Crop per acre		
Characteristics	Experiment	Control
No of Plants survived	33	18
Average height of plants	5.2’	4.4’
Average bolls per plant	14	10

Fig. 14. Growth of plants in the experimental plot.

Fig. 15. Growth of plants in the control plot.

A. Performance of the Naïve Bayes Classifier

The ML model is implemented using the Scikit-learn library for python programming language. The performance of the ML algorithm is measured using the “yellow brick” library in python with an accuracy of Naive Bayes 85% and high f1, precision, and recall of different predictive features, as shown in Table IX.

B. Agronomic Measures

The performance of the proposed solution is also measured using the observation of the growth of plants and yield with application of leaching water recommendations in the experimental plot of size of one acre, with the implementation of the proposed solution. The control plot is also judged without the implementation of the proposed solution to make comparisons. The growth of the plant is measured in terms of the number of plants, average height of the plants, and average number of bolls on the plants. Comparison for the different agronomic measures with the control and experimental area is shown in Table X.

Clear improvements in plant growth are observed in the experimental plot as compared to the control plot. The experimental area shows good growth of plants as shown in Fig. 14, as compared to the control plot shown in Fig. 15.

VI. Conclusion

In this article, IoT-assisted crop field context was used to determine the leaching irrigation requirements in saline soils to leach down salts from the root zone of the crop. These requirements are used to train and test the Naive Bayes classifier for the ML model, to make LRs prediction in the future using the temperature and salinity level only. The proposed model shows 85% accuracy and high f-measure, precision, and recall for making predictions. These estimates and predictions proved to be very effective in recommendation of WRs for leaching of the salts from the root zones of the plants for better production in saline soils. The IoT-based data provided high accuracy with real-time field microenvironment conditions. The implementation of the proposed model shows significant improvements in cotton crop production in terms of the number of plants, height of plants, and fruitings.

References

[1] H. Jiang and H. Shu, "Optical remote-sensing data based research on detecting soil salinity at different depth in an arid-area oasis, Xinjiang, China," *Earth Sci. Informat.*, vol. 12, no. 1, pp. 43–56, 2019.

[2] H. Yu, M. Liu, B. Du, Z. Wang, L. Hu, and B. Zhang, "Mapping soil salinity/sodicity by using landsat OLI imagery and PLSR algorithm over Semiarid West Jilin province, China," *Sensors*, vol. 18, no. 4, pp. 1–17, 2018.

[3] *Handbook for Saline Soil Management. Food and Agriculture Organization of the United Nations and Lomonosov Moscow State University*, FAO-Food Agri. Org. United Nations, Rome, Italy, 2018.

[4] R. M. A. Samra and R. R. Ali, "The development of an overlay model to predict soil salinity risks by using remote sensing and GIS techniques: A case study in soils around Idku Lake, Egypt," *Environ. Monitor. Assessment*, vol. 190, no. 12, p. 706, 2018.

[5] M. Zaman, S. A. Shahid, and L. Heng, *Guideline for Salinity Assessment, Mitigation and Adaptation Using Nuclear and Related Techniques*. Cham, Switzerland: Springer, doi: 10.1007/978-3-319-96190-3.

[6] S. Zewdu, K. V. Suryabhagavan, and M. Balakrishnan, "Geo-spatial approach for soil salinity mapping in Sego Irrigation Farm, South Ethiopia," *J. Saudi Soc. Agricult. Sci.*, vol. 16, no. 1, pp. 16–24, 2017.

[7] D. G. Metternicht and D. A. Zinck, *Remote Sensing of Soil Salinization: Impact on Land Management*, 1st ed. New York, NY, USA: CRC Press, 2008.

[8] S. J. Muller and A. van Niekerk, "An evaluation of supervised classifiers for indirectly detecting salt-affected areas at irrigation scheme level," *Int. J. Appl. Earth Observ. Geoinf.*, vol. 49, pp. 138–150, Jul. 2016.

[9] N. Pouladi, A. A. Jafarzadeh, F. Shahbazi, and M. A. Ghorbani, "Design and implementation of a hybrid MLP-FFA model for soil salinity prediction," *Environ. Earth Sci.*, vol. 78, no. 5, pp. 1–10, 2019.

[10] J. D. Rhoades, F. Chanduvi, and S. Lesch, "Soil salinity assessment methods and interpretation of electrical conductivity measurements," Food Agricult. Org., Rome, Italy, Rep., p. 57, 2002.

[11] J. Peng *et al.*, "Estimating soil salinity from remote sensing and terrain data in southern Xinjiang Province, China," *Geoderma*, vol. 337, pp. 1309–1319, Mar. 2019.

[12] R. Mulenga, J. Kalezhi, S. K. Musonda, and S. Silavwe, "Applying Internet of Things in monitoring and control of an irrigation system for sustainable agriculture for small-scale farmers in rural communities," in *Proc. IEEE PES/IAS PowerAfrica*, 2018, pp. 841–845.

[13] M. Kashiha *et al.*, "Automatic weight estimation of individual pigs using image analysis," *Comput. Electron. Agricult.*, vol. 107, pp. 38–44, Sep. 2014.

[14] O. Elijah, T. A. Rahman, I. Orikumhi, C. Y. Leow, and M. N. Hindia, "An overview of Internet of Things (IoT) and data analytics in agriculture? Benefits and challenges," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3758–3773, Oct. 2018.

[15] F. K. Shaikh, S. Zeadally, and E. Exposito, "Enabling technologies for green Internet of Things," *IEEE Syst. J.*, vol. 11, no. 2, pp. 983–994, Jun. 2017.

[16] X. Shi, X. An, Q. Zhao, H. Liu, and L. Xia, "State-of-the-art Internet of Things in protected agriculture," *Sensors*, vol. 19, no. 8, 2019, Art. no. E1833.

[17] C. Brewster, I. Roussaki, N. Kalatzis, K. Doolin, and K. Ellis, "IoT in agriculture: Designing a Europe-wide large-scale pilot," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 26–33, Sep. 2017.

[18] N. Ahmed, D. De, and I. Hussain, "Internet of Things (IoT) for smart precision agriculture and farming in rural areas," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4890–4899, Dec. 2018.

[19] X. Wang *et al.*, "Science of the total environment estimation of soil salt content (SSC) in the Ebinur lake wetland national nature reserve (ELWNNR), Northwest China, based on a bootstrap-BP neural network model and optimal spectral indices," *Sci. Total Environ.*, vol. 615, pp. 918–930, Feb. 2018.

[20] A. Memon, K. Ansari, A. Ashraf, M. M. Babar, and A. G. Soomro, "Projected rainfall variability based on PRECIS regional model," *Mehran Univ. Res. J. Eng. Technol.*, vol. 38, no. 2, pp. 513–524, 2019.

[21] A. A. A. Aldabaa, D. C. Weindorf, S. Chakraborty, A. Sharma, and B. Li, "Combination of proximal and remote sensing methods for rapid soil salinity quantification," *Geoderma*, vols. 239–240, pp. 34–46, Feb. 2015.

[22] I. Mohanraj, K. Ashokumar, and J. Naren, "Field monitoring and automation using IoT in agriculture domain," *Procedia Comput. Sci.*, vol. 93, pp. 931–939, Sep. 2016.

[23] S. A. Nikolidakis, D. Kandris, D. D. Vergados, and C. Douligeris, "Energy efficient automated control of irrigation in agriculture by using wireless sensor networks," *Comput. Electron. Agricult.*, vol. 113, pp. 154–163, Apr. 2015.

[24] F. Karim, F. Karim, and A. Frihida, "Monitoring system using Web of Things in precision agriculture," *Procedia Comput. Sci.*, vol. 110, pp. 402–409, Jul. 2017.

[25] H. Navarro-Hellin, J. Martínez-del-Rincon, R. Domingo-Miguel, F. Soto-Valles, and R. Torres-Sánchez, "A decision support system for managing irrigation in agriculture," *Comput. Electron. Agricult.*, vol. 124, pp. 121–131, Jun. 2016.

[26] L. Tan, "Cloud-based decision support and automation for precision agriculture in Orchards," *IFAC PapersOnLine*, vol. 49, no. 16, pp. 330–335, 2016.

[27] Y. Feng, Y. Peng, N. Cui, D. Gong, and K. Zhang, "Modeling reference evapotranspiration using extreme learning machine and generalized regression neural network only with temperature data," *Comput. Electron. Agricult.*, vol. 136, pp. 71–78, Apr. 2017.

[28] T. Zhao, B. Stark, Y. Q. Chen, A. Ray, and D. Doll, "More reliable crop water stress quantification using small unmanned aerial systems (sUAS)," *IFAC PapersOnLine*, vol. 49, no. 16, pp. 409–414, 2016.

[29] F. Rojo *et al.*, "A leaf monitoring system for continuous measurement of plant water status to assist in precision irrigation in grape and almond crops," *IFAC PapersOnLine*, vol. 49, no. 16, pp. 209–215, 2016.

[30] M. A. Uddin, A. Mansour, D. Le Jeune, and E. H. M. Aggoune, "Agriculture Internet of Things: AG-IoT," in *Proc. 27th Int. Telecommun. Netw. Appl. Conf. (ITNAC)*, 2017, pp. 1–6.

[31] Q. Kong, H. Chen, Y. L. Mo, and G. Song, "Real-time monitoring of water content in sandy soil using shear mode piezoceramic transducers and active sensing—A feasibility study," *Sensors*, vol. 17, no. 10, 2017, Art. no. E2395.

[32] N. M. Cid-Garcia, A. G. Bravo-Lozano, and Y. A. Rios-Solis, "A crop planning and real-time irrigation method based on site-specific management zones and linear programming," *Comput. Electron. Agricult.*, vol. 107, pp. 20–28, Sep. 2014.

[33] P. Rajalakshmi and S. D. Mahalakshmi, "IoT based crop-field monitoring and irrigation automation," in *Proc. 10th Int. Conf. Intell. Syst. Control (ISCO)*, 2016, pp. 1–6.

[34] J. Ye, B. Chen, Q. Liu, and Y. Fang, "A precision agriculture management system based on Internet of Things and WebGIS," in *Proc. Int. Conf. Geoinformat.*, 2013, pp. 1–5.
[35] V. Ramachandran, R. Ramalakshmi, and S. Srinivasan, "An automated irrigation system for smart agriculture using the Internet of Things," in *Proc. 15th Int. Conf. Control Autom. Robot. Vis. (ICARCV)*, 2018, pp. 210–215.
[36] J. Gutiérrez, J. F. Villa-Medina, A. Nieto-Garibay, and M. A. Porta-Gandara, "Automated irrigation system using a wireless sensor network and GPRS module," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 166–176, Jan. 2014.
[37] C. Goumopoulos, B. O'Flynn, and A. Kameas, "Automated zone-specific irrigation with wireless sensor/actuator network and adaptable decision support," *Comput. Electron. Agricult.*, vol. 105, pp. 20–33, Jul. 2014.
[38] M. Ilic, S. Jovic, P. Spalevic, and I. Vujicic, "Water cycle estimation by neuro-fuzzy approach," *Comput. Electron. Agricult.*, vol. 135, pp. 1–3, Apr. 2017.
[39] B. Mazon-Olivo, D. Hernández-Rojas, J. Maza-Salinas, and A. Pan, "Rules engine and complex event processor in the context of Internet of Things for precision agriculture," *Comput. Electron. Agricult.*, vol. 154, pp. 347–360, Nov. 2018.
[40] S. Zhuiykov, "Solid-state sensors monitoring parameters of water quality for the next generation of wireless sensor networks," *Sensors Actuators B Chem.*, vol. 161, no. 1, pp. 1–20, 2012.
[41] T. Ojha, S. Misra, and N. S. Raghuwanshi, "Sensing-cloud: Leveraging the benefits for agricultural applications," *Comput. Electron. Agricult.*, vol. 135, pp. 96–107, Apr. 2017.
[42] O. Koksal and B. Tekinerdogan, *Architecture Design Approach for IoT-Based Farm Management Information Systems*. New York, NY, USA: Springer, 2018.
[43] FAO. (2019). *Crop Water Needs*. Accessed: Aug. 30, 2019. [Online]. Available: http://www.fao.org/3/s2022e/s2022e07.htm#3.1_influence_of_climate_on_crop_water_needs_(eto)

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