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SOIL MOISTURE PREDICTION USING SHALLOW NEURAL NETWORK

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ABSTRACT

Soil moisture is the key ingredient for the growth as well as survival of the plants. Prediction of moisture in advance will be helpful for the farmers in the field of agriculture. In this paper multiple linear regression, support vector regression and shallow neural network has been used for the advance prediction of soil moisture. Also a new feature i.e. rain has been included in the analysis work for the prediction purpose to visualize the changes in the results. These regression based techniques were applied on three different datasets. The two datasets are collected from the online repositories and the third dataset is prepared by collecting the data using the sensenuts device (wireless sensor network). The predictor used for the evaluation is the MSE (mean squared error) and R^2*(co-efficient of determination). The results of shallow neural network with rain as parameter provides MSE and* R^2 *of 0.032 and 0.923 for 1 day ahead, 0.034 and 0.903 for 2 days ahead and 0.111 and 0.739 for 7 days ahead for Braggs farm dataset. For the Kyeamba dataset the MSE and* R^2 *is 0.12 and 0.97590 for 1 day ahead, 0.172 and 0.97585 for 2 days ahead and 0.19 and 0.97581 for 7 days ahead. For the third dataset the MSE and* R^2 *of 0.12 and 0.98 for 1 day ahead,0.20 and 0.96 for 2 days ahead and 0.20 and 0.95 for 7 days ahead.*

Key words: Agriculture, analysis, artificial intelligence, machine learning, multiple linear regression, prediction, shallow neural network, soil moisture, support vector regression, wireless sensor network

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1. INTRODUCTION

The monitoring and prediction of soil moisture has proven to be very useful for the farmers in the agricultural land. In many developing countries like India crop production is a source of livelihood. Soil moisture in field is variable and it changes over time. It depends on several factors like the quantity of rainfall in that particular area, irrigation and level of water in the soil and even water consumed form the soil by evaporation, transpiration etc. Balanced soil moisture can be determined by the climate, seasons, type of vegetation of that particular area.

Soil moisture content could change the amount of minerals in the water when the soil wets or dries and ultimately effects pH of the soil. MRM Kassim et. al. build a decision support system in precision agriculture. Different techniques to tackle the problems related to farming resources optimization has been discussed. Monitoring of the data is done by the software in a feedback loop based upon the set value of threshold [1]. Zhihao Hong et. al. proposed a methodology which is data-driven on precision agriculture solution for data-modelling system. For the data analysis the framework is built for the models generated by the machine learning techniques such as support vector machine and relevance vector machine[2]. It predicts the values of soil moisture for n number of days ahead on the particular soil. Analysis results showed that there was correlation of 95% and the low error rate of 15% when predicted the soil moisture two weeks ahead. Xianlei Xu et. al. designed a predictive model to measure the soil moisture content using the Multiple linear regression and RBF neural network[3]. Here it was observed that when using GPR the multiple linear regression predicted the soil moisture content better than the RBF neural network.Luca Pasolli et. al. estimated soil moisture content using the support vector regression technique[4]. The paper discusses about the two methods which are support vector regression and MLP NN network. The results showed that the SVR is a valid alternative to the more traditional MLP NN regression method. D. Shinghal et. al. designed a wireless sensor network especially for the farming of potato. The sensor network measured the parameters like water depth, overall system capacity etc. [5] and increases the irrigation efficiency system by 10%. M.Kashif Gill et. al. describes the prediction of soil moisture in advance using support vector machines.The data of soil moisture predicts in advance four days and seven days ahead using support vector machines and ANN.The results shows that SVM works better than the ANN to predicts the soil moisture[6].Yue Liu et. al. two method are compared for the prediction of soil moisture for Apple orchard i.e. ELM and SVM[7]. Based on the datasets both the models predicts the soil moisture and based on the future trends of the moisture it is useful for the decision support for the future irrigation scheduling. Here, ELM has higher prediction accuracy than SVM. Karandeep Kaur describes the various machine learning techniques that could be beneficial for the Indian Agriculture and these methods could help the farmers in advance to work on various parameters and solve them using these techniques[8].Kenny M. et. al. measures the volumetric content of the water present in the soil using the techniques known as ground penetrating Radar(GPR) but it is not commonly used technique due to having problems in determining the travel time for the unguided waves[9].Danhyang Lee et. al.[10] compares the soil moisture collected data for the five sites of Yongdam dam basin which are Jucheon, Bugui, Sangieon, Ahncheon and Cheoncheon in South Korea. Predicts the model for these sites using the support vector regression and artificial neural network. ANN model performed better than the SVR model. Sajjad Ahmad et. al. estimates the soil moisture using the remote sensing data. Results obtained from the SVM models are ANN and MLR.SVM models performs better than ANN and MLR models.Leila Esmaeelnejad et. al. develops a prediction model to estimate the soil moisture content in North Iran. MLR,ANN and Rosetta models were employed for modeling. Prediction parameters used were the RMSE and R^2 and the results showed that ANN predicts better than the other models [11].Manijesh et.al designs and develops an efficient model for the prediction of soil moisture for the precision agriculture using the wireless sensor network[12]. The sensor network technology will help the farmers to know the exact values of the requirements that they need to improve the crop productivity. Ruixiu Sui explains the irrigation scheduling using soil moisture sensors. Soil moisture sensors were evaluated and used for irrigation scheduling in humid region of the Mid-South US. Soil moisture sensors were installed at three different soil depths which are 15cm,30cm and 61 cm for scheduling of irrigation in the mid south of US which is a part of humid region[13].Rupanjali D. Baruah et. al. predicts the tea yield in the Assam region using the multiple linear regression[14]. Rain as a parameter for the analysis shows improved results for the prediction purpose [15].

After various literature survey done it was concluded that most of the methods on soil moisture prediction was based on the data collected through remote sensing [16],[17],[18] This gave a motivation to us to predict the soil moisture using the wireless sensors which is not much costly as the remote sensors and also the data collected through remote sensing will not go measuring the moisture in depth. Also the research has been done more on the soil moisture monitoring [19], [20], [21], [22] and not prediction. Both these facts motivate to do this analysis. After through research done including feature such as rainfall with soil moisture enhances the result [23].

The working principle of the developed model has been explained in chapter 2.The different predictive models used as multiple linear regression, support vector regression and shallow neural network has been subdivided and elaborated. The results have been discussed in chapter 3 and the paper has been concluded in chapter 4.

2. METHODOLOGY

These models are designed for the soil moisture prediction for the different datasets and to analyze the results for these datasets as well. The models have been developed to predict the soil moisture content for 1 day, 2 days and 7 days ahead. The flow graph of analysis is shown in fig.1.

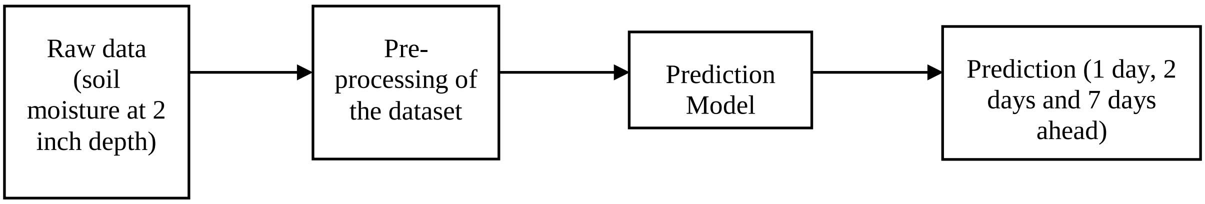

Figure 1 Flow graph of the methodology

The data collected is normalized using two techniques which are the standard scaling technique and the min-max scalar technique. Both of them have been defined respectively:

$$X_i = \frac{x_{i} - \mathrm{mean}(X)}{\sigma^2} \quad (1)$$

$$X_i = \frac{X_i - \min(x)}{\max(x) - \min(x)} \quad (2)$$

The three dataset has been divided into a seven window system. After the division the calculation of mean and standard deviation has been carried out. In the prediction model developed nine features have been taken on the input side. Out of which, 80% of the data is used to train the model and 20% is used for independent testing. The machine learning techniques such as multiple linear regression, support vector regression and shallow neural network is used for development of the proposed model. The prediction is carried out for 1 day ahead, 2 days ahead and 7 days ahead. The prediction techniques used in this paper has been elaborated below.

2.1. Multiple Linear Regression

It is a statistical method which examines the linear relationship between the variables which are continuous or it can be a link between the dependent and independent variable. The best fitting model could be developed using the ordinary least square method [24].

2.2. Support Vector Regression

This is an adaptable technique which deals with the several limitations such as data geometry and the over fitting of the model. Support vector regression is a better and a superior model when compared with the regression models. The concept of non-linearity in the models could be easily done using this method [24].

2.3. Shallow Neural Network

The study of neural network started back in 1960s, but it has picked up recently due to the rise in enormous amount of computational power. Nowadays it is seen as a go to method for solving problems which were earlier thought to be too difficult. A neural network tries to imitate the working of an actual brain. A neural network can be perceived as a collection of artificial neurons which interact with each other to process some input and produce some output, as the same way brain neurons are thought to be interacting.

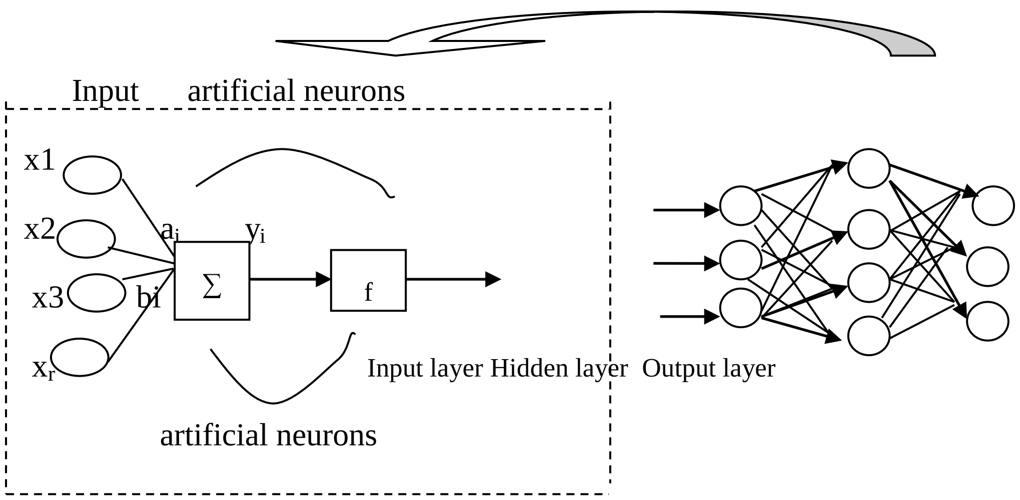

Figure 2 Structure of shallow neural network

A shallow neural network is an artificial neural network with a single hidden layer and an output layer. The number of units in input layer, hidden layer and output layer are n, h and m respectively, which can be varied according to the situation. The units of the hidden layer get their input from the input units and the output produced acts as input for the units of the next layer, which in shallow neural network is the output layer. A neural network has weights associated with each edge connecting the neurons of adjacent layers. There are bias terms associated with each layer of the ANN, except the input layer. The weights and bias terms are known as the parameters associated with that ANN.

Activation function is an important parameter in neural network which maps the input and the response variable and also adds the non-linear properties to the network. The activation function used is the tanh and the sigmoid function.

The cost function gives the measure of how accurately our neural network model predicted and how far it has predicted from the expected output. The most commonly used cost function can be denoted by:

$$J = \frac{1}{k}\sum_{i=1}^{k}(\hat{y}^{[i]} - y^{[i]})^2 \tag{3}$$

where,

k is the number of samples

$y^{[i]}$ is the actual value of the expected output

$\hat{y}^{[i]}$ is the output predicted by the model

The shallow neural network is build with first the initialization of the neural network where the weights associated with the hidden layer and the output layer are randomly initialized with values in the range (0,1] and are of dimensions (*h X n)* and *(m X h).* The bias terms are initialized with values of 0.The training of the network is done by the forward propagation and then backward propagation.The parameters are updated using the gradient descent algorithm. Here α is a hyperparameter known as the learning rate, which needs to be tuned for better performance. Too small a value of α may cause the model to be far from the global minima of the error function and a large value of α may cause it to either move away from or oscillate around the global minima of the error function. After the learning process is completed the prediction is done.

2.4. Prediction Parameters

After the prediction model developed, the prediction parameters used are the MSE and R^2 . Mean Squared Error (MSE)[24] is the evaluator tool which calculates the difference between the true values and the predicted values.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y_\imath})^2 \qquad (4)$$

where ,

n = total number of data points.

y_i = true values

$\overline{y_\imath}$= predicted values

Co-efficient of determination(R^2**)** tells how one variable differntiation could be explained using the another variable when an outcome is predicted[24]. It is calculated using the formula :

$$R^2 = 1 - \left(\frac{SS_{res}}{SS_{tot}}\right) \qquad (5)$$

$$SS_{res} = \sum_i (y_i - \overline{y_\imath})^2 \qquad (6)$$

$$SS_{tot} = \sum_i (y_i - \bar{y})^2 \qquad (7)$$

where**,**

SS_{res} = residual sum of squares

SS_{tot}= total sum of squares

y_i = true values , $\bar{y}$ = mean of actual values

3. RESULTS &DISCUSSION

3.1. Datasets

The two datasets are used for the prediction of soil moisture from the online repositories and the third one is the data collected of soil moisture in BIT Mesra Ranchi.

The first dataset used is the Braggs Farm data located in Alabama. The samples used in the prediction model is collected from June 2015 to December 2016 from the dataset. In total, there are 569 samples with a two inches depth. More details are available on https://wcc.sc.egov.usda.gov/nwcc [25].

Similarly the second dataset is taken from the Oz Net Hydrological Monitoring Network which is an Australian Monitoring Network. It contains the soil moisture data of six different regions. In this modelling Kyeamba region has been considered. Samples have been collected from March 2016 to May 2016.92 samples used in the prediction. More information can be viewed from the website [26] .

The third dataset is generated from the BIT Mesra campus using the sensenuts device which wirelessly collects the data of a particular area of R&D building .The data was collected from 1 January 2018 to 8 May 2018.In total there are 94 samples. The sensor is VH400 soil moisture sensor. The moisture sensor converts the measured capacitance between the probes into a dc voltage that can interface directly to the ADC for conversion into corresponding volumetric water content (VWC) expressed in %.

Table 1 Conversion table of Voltage measured in VWC(%).

Voltage Range	Equation (V = Sensor Output in Volts)
0-1.1V	VWC = 10 × V − 1
1.1 V to 1.3 V	VWC = 25 × V − 17.5
1.3V-1.82V	VWC = 48.08 × V − 47.5
1.82V-2-2V	VWC = 26.32 × V − 7.89

The techniques used for soil moisture prediction were MLR (multiple linear regression),SVR(support vector regression) and SNN(shallow neural network).The comparison results of all machine learning models is listed in table I of MLR and SVR for dataset 4 without rain as parameter in training with the other dataset,

Table 2 Performance results of MLR, SVR and SNN for dataset 3 without rain as parameter in training with dataset I,II.

S. No.	**Techniques**	**MSE (1 day ahead)**	**MSE (2 days ahead)**	**MSE (7 days ahead)**	**R^2 (1 day ahead)**	**R^2(2days ahead)**	**R^2 (7days ahead)**
1.	Multiple linear regression	1.51	4.03	12.52	0.963	0.906	0.713
2.	Support vector regression	1.46	4.23	13.57	0.963	0.901	0.689
3.	Shallow neural network	2.8	3.2	5.6	0.88	0.80	0.72

It can be observed that the MLR has MSE of 1.51 for one day ahead, 4.03 MSE for two days ahead and 12.52 MSE for seven days ahead. Similarly the R^2 for one day ahead is 0.963, for two days ahead is 0.906and for seven days ahead is 0.713.In the same way SVR has the MSE 1.46 for one day ahead, 4.23 for two days and 13.57 for seven days ahead and for R^2 of 0.963 for one day ahead,0.901 for two days ahead and 0.689for seven days ahead. In RNN the MSE for one day ahead is 1.54, for two days ahead is 5.27 and for seven days ahead is 12.67 for R^2 it is 0.963, 0.877and 0.709 respectively.

The results clearly show that the MSE is high i.e. a large difference is there between the true and the predicted values for all the three techniques used and hence it is not a good predictive model.

So, we tried to change the analysis type with adding rain as a feature and the results were pretty good and can be concluded from the simulation results as shown in table II that by changing the type of analysis improves the result of MSE to some extent for the three techniques used i.e. multiple linear regression,support vector regression and shallow neural network neural network.

Table 3 Comparative results of MLR, SVR and SNN for dataset 3 with rain as parameter.

S. No.	Techniques	MSE (1 day ahead)	MSE (2 days ahead)	MSE (7 days ahead)	R^2(1 day ahead)	R^2 (2 days ahead)	R^2(7 days ahead)
1.	Multiple linear regression	0.18	0.23	0.32	0.97	0.94	0.92
2.	Support vector regression	0.16	0.28	0.36	0.95	0.93	0.92
3.	Shallow neural network	0.12	0.16	0.20	0.98	0.96	0.95

There is a large variation at some points in dataset 3 than the other two dataset used which has comparatively very less variations. So, a new predictive model i.e. shallow neural network has been designed for dataset 3. The results were tabulated for both the cases of taking rain as a parameter and if rain is not taken then what changes occur on the prediction analysis. The results were pretty good when taking rain as a parameter for dataset 3.

Performance results of shallow neural network with rain as a parameter for 1 day ahead,2 days ahead and 7 days ahead is shown in fig.3,fig.4,fig.5 respectively.

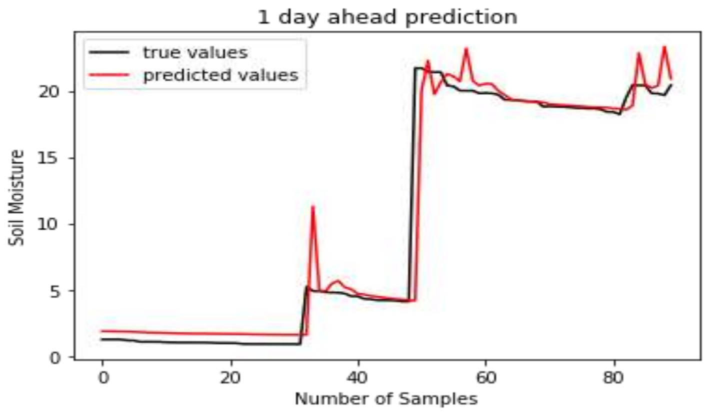

Figure 3 Performance analysis of shallow neural network with rain for 1 day ahead.

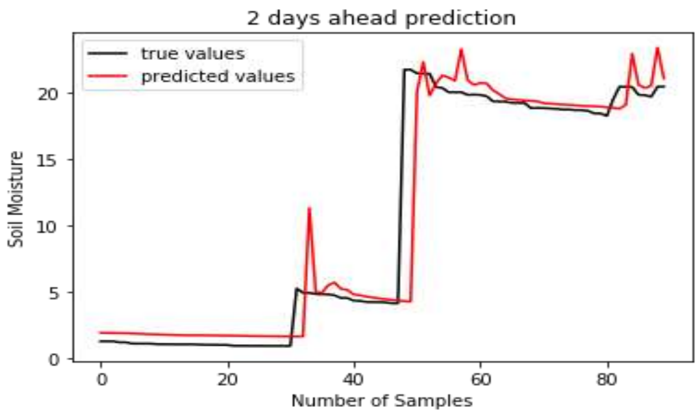

Figure 4 Performance analysis of shallow neural network with rain for 2 days ahead.

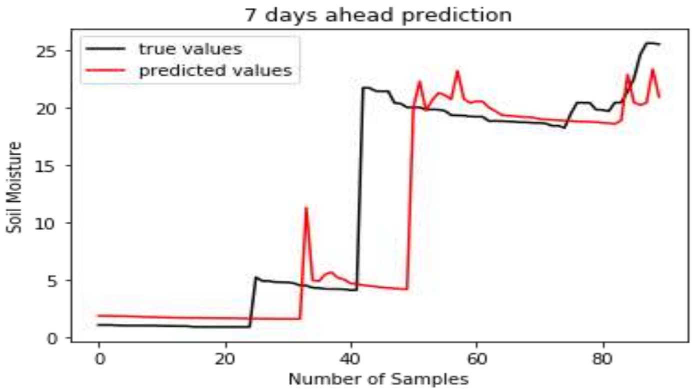

Figure 5 Performance analysis of shallow neural network with rain for 7 days ahead.

Table 4 Testing results for shallow neural network in the three dataset collected from online repositories i.e. dataset I,II.

S. No.	Dataset	MSE (1 day ahead)	MSE(2 days ahead)	MSE (7days ahead)	R^2 (1 day ahead)	R^2 (2 days ahead)	R^2 (7 days ahead)
1.	Bragg's farm data	0.032	0.034	0.111	0.923	0.903	0.839
2.	Kyeamba dataset	0.00029	0.00229	0.00229	0.97590	0.97585	0.97581

From the results shown in table III for the Braggs farm data MSE of 0.032 for one day ahead, 0.034 MSE for two days ahead and 0.111 MSE for seven days ahead. Similarly the R^2 for one day ahead is 0.923, for two days ahead is 0.903 and for seven days ahead is 0.839. In Kyeamba dataset the MSE for one day ahead is 0.12 , for two days ahead is 0.172 and for seven days ahead is 0.19 for R^2 it is 0.97590, 0.97585and 0.97581 respectively.It can be seen that the shallow neural network is a good predictive model for all the four datasets used by us for the prediction purpose.

Hence from all tabulated results it can be concluded that taking rain as a parameter for the regression shows an improved result over the other ones and also shallow neural network designed works for the dataset used.

After all the simulation results tabulated above it can be concluded that change in the data analysis also has an impact on the prediction of soil moisture. Also designing a predictive model that suits for all the three datasets discussed above is overall a good predictive model.

4. CONCLUSION

In this paper regression based machine learning techniques has been used for the prediction of soil moisture in advance for 1day, 2days and 7 days ahead. Here, multiple linear regression, support vector regression and shallow neural network has been used for the prediction purpose**.** From the above results it can be stated that shallow neural network is superior to the other two techniques which are support vector regression and multiple linear regression. More focus is to be given on an increased number of days, here it is 7 days. Also change in the prediction analysis such as rain improves the result of all the four datasets also. The strategy developed maybe useful for the farmers in the coming years.

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