Namal University Mianwali

Department of Computer Science

Soil analysis using machine learning

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DECLARATION

The project report titled "Soil analysis using machine learning" is submitted in partial fulfillment of the degree of Bachelors of Science in Computer Science, to the Department of Computer Science at Namal Institute, Mianwali, Pakistan.

It is declared that this is an original work done by the team members listed below, under the guidance of our supervisor "Dr. Malik Jahan Khan". No part of this project and its report is plagiarized from anywhere, and any help taken from previous work is cited properly.

No part of the work reported here is submitted in fulfillment of requirement for any other degree/ qualification in any institute of learning.

Supervisor signature	May 26, 2022 Date
Student signature	May 26, 2022 Date

Contents

1 Terminologies

Following terminologies will be used in the document.

- Convolutional neural network (CNN)
- Artificial neural network (ANN)
- Phosphorus (P)
- Organic matter (OM)
- Electrical conductivity (EC)
- Decision Tree Regression (DTR)
- Random Forest Regression (RFR)
- Support Vector Regression (SVR)

2 Abstract

Agriculture is the backbone of Pakistan's economy and millions of people are directly or indirectly linked with the agriculture sector. The main source for agriculture is soil for crops production. If soil is healthy then crops production automatically boosts up. But in Pakistan average farmers cannot afford to test their soils in the laboratory which is quite time-consuming and costs a lot. So in this work, we try to facilitate the farmers with an application that can check the quality of soil by using their mobile phone images and recommend different fertilizers according to the soil sample results. About 1064 images are used for machine learning models training with laboratory-tested labels. Different machine learning models like ANN, CNN, Decision Tree Regression, Random Forest Regression, and Support Vector Regression models are trained to predict different nutrients of the soil. After machine learning model training, one of the best models are deployed on the mobile application to facilitate the farmers' use of machine learning to predict soil nutrients. Along with machine learning, we also explored soil npk sensor for soil analysis.

3 Acknowledgements

I would like to express my gratitude to my supervisor, Dr. Malik Jahan Khan, who guided me throughout this project and share his experience with me in the field of machine learning. Sir helped me at any point whenever I was stuck in my project.

4 Literature review

In the year 2014 [7], the author Vinay Kumar determined soil PH values by using digital image processing technique.In this work fifty soil samples were collected and determined their PH values using PH meter.Digital camera was used for sampling the soil images. By using below formula, PH index is calculated.

PH Index = (Red / Green) / Blue [7].

After calculating PH Index, correlation between PH values using PH meter and PH index by using RGB images are determined. [7].

In the year 2016 [8], the author CS ManikandaBabu determined physical and chemical properties of soil by using digital image analysis.For soil sampling, digital camera was used.They used fractal dimension calculation using box counting method to obtain physical recognition.They determined soil PH by using RGB colors.By using plane extraction method, each plane value is calculated and PH index is calculated.By using PH index and color of soil, PH of soil sample was calculated [8]

In the year 2019, the author Maneesha G Nair [6] proposed android application which was capable to use digital image processing. By capturing image of soil, soil PH value was determined and crop suggestion as output.After prepossessing,RGB values are extracted from image to calculate PH index. PH index value was compared with stored PH value in database. [6]

5 Project source code

Project source code which is available on the github. Source Code

6 Introduction

Pakistan economy is heavily based on agriculture.Total yield of crops is based on the quality of soil.If soil nutrients are sufficiently available than crops production automatically boosts up. Pakistani agriculture industry holds about 18.9 percents of GDP and creates about 43.3 percent jobs for labours [10].The main aim of this work to check quality of soil using machine learning.

The main motivation for using machine learning as alternative of laboratory testing is that laboratory testing of soil is time and cost consuming. Moreover farmer cannot afford such costly laboratory testing for soil because they are limited in their resources.We are developing mobile application for farmers which will take image in the input and will provide the report in the local language which will contain different soil nutrients values and recommendation of fertilizer according to the generated report.

We have 701 soil samples. Soil samples values are measured in the soil laboratory by expert using different soil laboratory tools.There are four features measured in the laboratory like pH value, phosphorous (P), electrical conductivity (EC) and organic matter (OM).There are also 1064 soil samples images are available which were captured during the collection of soil samples in the field.

Using images of soil samples, different machine learning models are trained to predict soil pH values,phosphorous (P), organic matter (OM) and electrical conductivity (EC).On the basis of predicted values of soil by machine learning models, mobile application will generate report and will suggest different fertilizers for farmer which will improve the quality of soil to get maximum yield.

6.1 Objectives

- Using machine learning to check the quality of soil
- Checking different machine learning models performance
- Recommendation system for farmers which will recommend fertilizer

7 Methodology

7.1 Dataset

We have 1064 soil images which are captured by using smartphone camera.Two images per sample are captured like outer surface image and inner surface image.Location for soil sampling are Khusab,Talagang and Mianwali.Below is the sample image captured using mobile camera.

Figure 1: Soil image captured using mobile camera

7.2 Pre-Processing

All images are captured at uncontrolled field conditions.So there is higher chances of noise in the dataset in form of light,some unwanted corners etc.In the image pre-processing, all images are resized using opencv.

7.2.1 Region of interest

After resizing, specific part of image is extracted to get region of interest (RIO).

Figure 2: Region of interest extraction

7.2.2 Applying the sharpening kernel

After extraction of region of interest (RIO), sharpening kernel is applied because there are some images which have blurr effect, contrast and shade issues. In order to tackle such issues sharpening kernel is applied on all images [1].

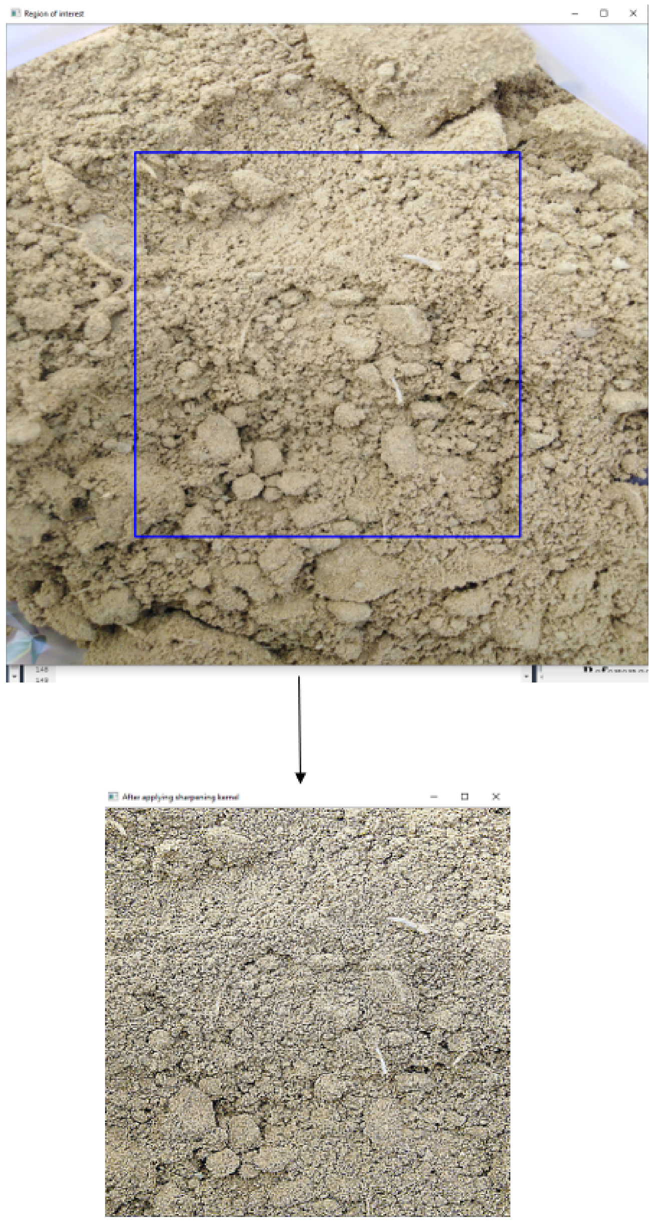

Figure 3: Image Sharpening

7.2.3 pH indexes extraction

By using the following formula [7], pH index is extracted for each image.

$$pHIndex = (Red/Green)/Blue$$

7.2.4 Features extraction using experimentation based formula

By using the following formula, feature is extracted for each image.

$$FormulaIndex = (Red + Green + Blue)$$

Feature for each image which will be used for machine learning models training and testing.Above formula is derived after experimentation like passing the extracted feature through machine learning models and results are compared with actual values.

7.3 ANN regression model on pH indexes and formula

After features extraction by using pH index and formula,each pH index and formula index is labeled with actual pH value and passed with the following ANN architecture for training and testing.

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_15 (Dense)             (None, 128)               256
_________________________________________________________________
dense_16 (Dense)             (None, 256)               33024
_________________________________________________________________
dense_17 (Dense)             (None, 256)               65792
_________________________________________________________________
dense_18 (Dense)             (None, 256)               65792
_________________________________________________________________
dense_19 (Dense)             (None, 1)                 257
=================================================================
Total params: 165,121
Trainable params: 165,121
Non-trainable params: 0
_________________________________________________________________
```

Figure 4: ANN architecture

Similarly pH index and formula index is labeled with other soil parameters like OM, EC and P separately to perform estimation on same ANN regression model.

7.4 CNN regression model on images

CNN provides feature extraction automatically.So pre-processed images are labeled with actual pH, OM, P and EC values separately because every parameter will be predicted by separate CNN model.AlexNet [11] CNN architecture is used for training and testing.AlexNet is a very famous architecture who was competed in the Image-Net Large Scale Visual Recognition Challenge on Sept 30,2012 [11].

Following is the model architecture used for predictions.In the last layer of CNN architecture, there is only neuron to predict continuous value and linear activation function is used according to problem statement.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 73, 73, 96)        34944
_________________________________________________________________
batch_normalization_5 (Batch (None, 73, 73, 96)        384
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 36, 36, 96)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 36, 36, 256)       614656
_________________________________________________________________
batch_normalization_6 (Batch (None, 36, 36, 256)       1024
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 17, 17, 256)       0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 17, 17, 384)       885120
_________________________________________________________________
batch_normalization_7 (Batch (None, 17, 17, 384)       1536
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 17, 17, 384)       1327488
_________________________________________________________________
batch_normalization_8 (Batch (None, 17, 17, 384)       1536
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 17, 17, 256)       884992
_________________________________________________________________
batch_normalization_9 (Batch (None, 17, 17, 256)       1024
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 8, 8, 256)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 16384)             0
_________________________________________________________________
dense_3 (Dense)              (None, 4096)              67112960
_________________________________________________________________
dropout_2 (Dropout)          (None, 4096)              0
_________________________________________________________________
dense_4 (Dense)              (None, 4096)              16781312
_________________________________________________________________
dropout_3 (Dropout)          (None, 4096)              0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 4097
=================================================================
Total params: 87,651,073
Trainable params: 87,648,321
Non-trainable params: 2,752
_________________________________________________________________
```

Figure 5: AlexNet CNN architecture

7.5 Discretization for classification models

For the classification models, soil parameters like pH, OM, P and EC are classified by using soil expert opinion.For example, if soil pH is less than 7.0,so it belongs to class1 and if soil pH is greater than 7.0 and less than 7.5 than it belongs to class2. Similarly all soil parameters are classified by following table .

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Classification

OM Classification	
OM	Class
<0.865	OM1
0.87 -- 1.29	OM2
> 1.29	OM3

pH Classification	
pH	Class
<7.0	pH1
7.0 -- 7.5	pH2
7.6 -- 8.0	pH3
8.1 -- 8.5	pH4
> 8.5	pH5

EC Classification	
EC	Class
<4.0	EC1
4.1 -- 8.0	EC2
8.1 -- 16.0	EC3
> 16.0	EC4

P Classification	
P	Class
<3.5	P1
3.6 -- 7.0	P2
7.0 -- 14.0	P3
> 14.0	P4

Figure 6: Discretization Process

7.6 CNN Classification Model

After discretization process, AlexNet [11] CNN architecture is used for training and testing.Following is the model network architecture.In the last layer, number of neurons are according to number of classes to predict and softmax activation function is used because it's multiclass classification problem.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 73, 73, 96)	34944
batch_normalization (BatchNo	(None, 73, 73, 96)	384
max_pooling2d (MaxPooling2D)	(None, 36, 36, 96)	0
conv2d_1 (Conv2D)	(None, 36, 36, 256)	614656
batch_normalization_1 (Batch	(None, 36, 36, 256)	1024
max_pooling2d_1 (MaxPooling2	(None, 17, 17, 256)	0
conv2d_2 (Conv2D)	(None, 17, 17, 384)	885120
batch_normalization_2 (Batch	(None, 17, 17, 384)	1536
conv2d_3 (Conv2D)	(None, 17, 17, 384)	1327488
batch_normalization_3 (Batch	(None, 17, 17, 384)	1536
conv2d_4 (Conv2D)	(None, 17, 17, 256)	884992
batch_normalization_4 (Batch	(None, 17, 17, 256)	1024
max_pooling2d_2 (MaxPooling2	(None, 8, 8, 256)	0
flatten (Flatten)	(None, 16384)	0
dense (Dense)	(None, 4096)	67112960
dropout (Dropout)	(None, 4096)	0
dense_1 (Dense)	(None, 4096)	16781312
dropout_1 (Dropout)	(None, 4096)	0
dense_2 (Dense)	(None, 3)	12291

Total params: 87,659,267
Trainable params: 87,656,515
Non-trainable params: 2,752

Figure 7: AlexNet CNN architecture for classification

7.7 Support vector regression model

By using sklearn library, support vector regression model is used for training and testing on pH and formula indexes. Following is the SVR model architecture [5].

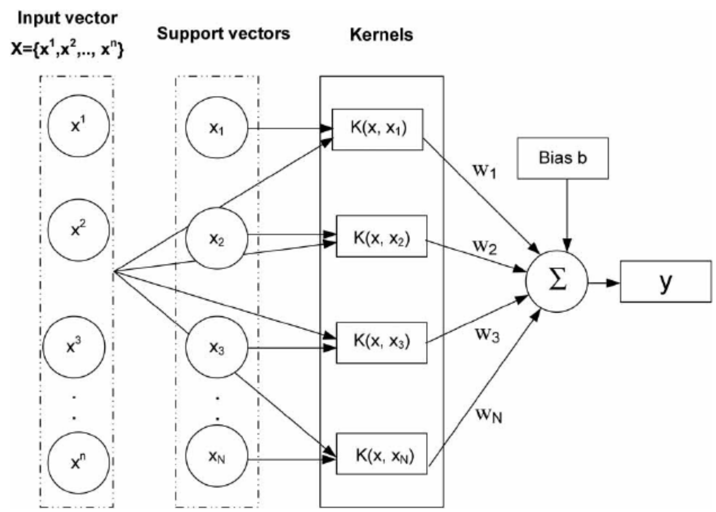

Figure 8: Support vector regression model architecture

7.8 Random forest regression model

By using sklearn library, random forest regression model is used for training and testing on pH and formula indexes. Following is the random forest regression model architecture [9].

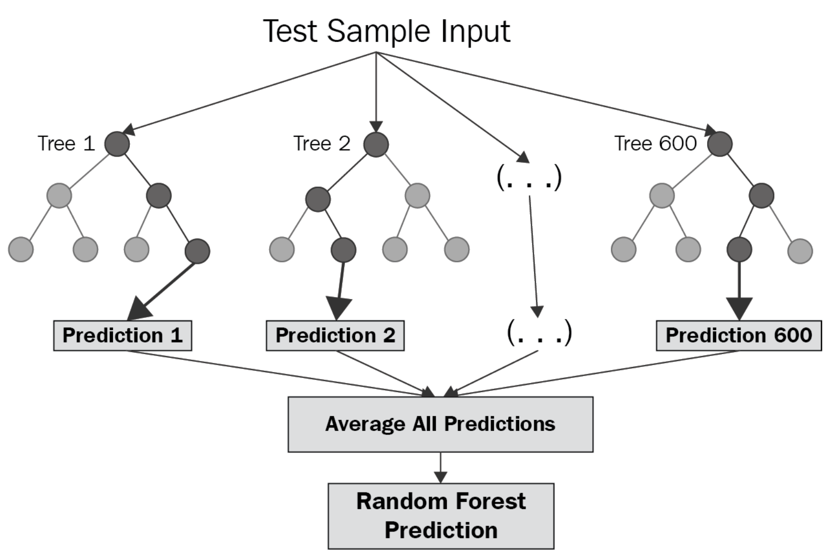

Figure 9: Random Forest regression model architecture

7.9 Decision tree regression model

By using sklearn library, decision tree regression model is used for training and testing on pH and formula indexes. Following is the example for visualization of decision tree regression model [2].

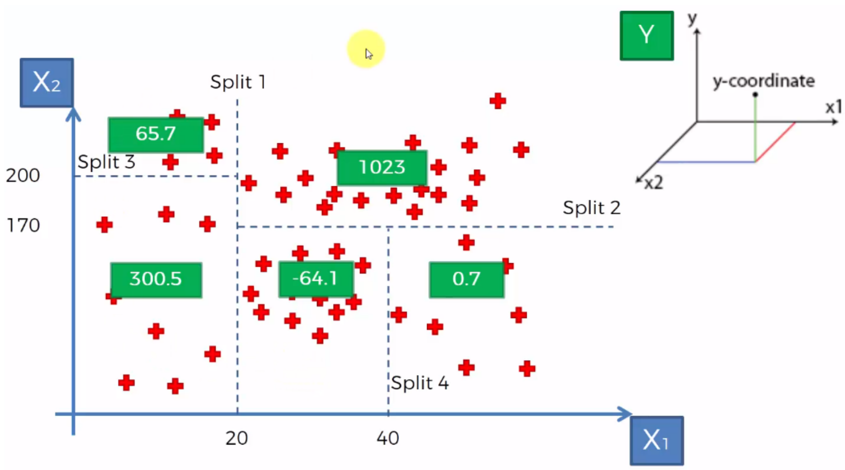

Figure 10: Dataset splits for decision tree. [2]

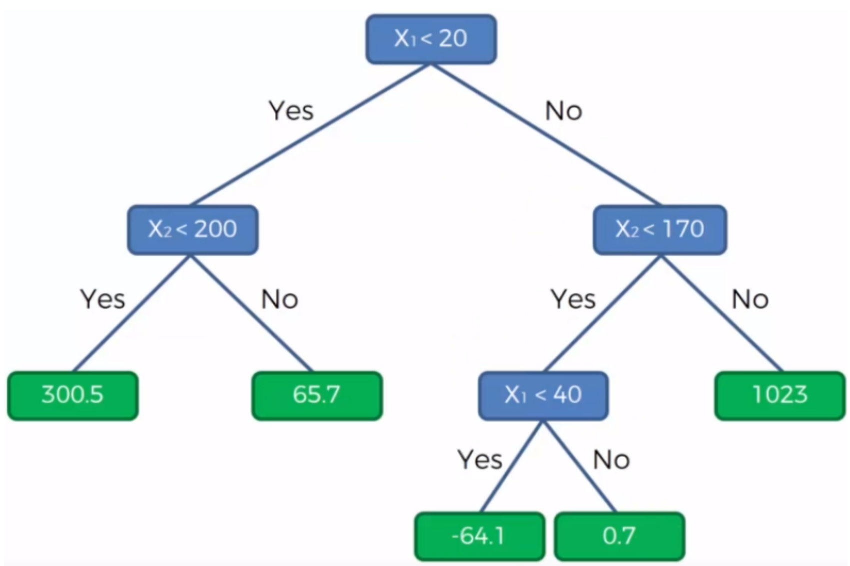

Figure 11: Decision tree. [2]

7.10 Evaluation measures for regression models

Following are measures used for evaluating the regression models.

7.10.1 Mean absolute error (mae)

Following is the formula for calculating mean absolute error (MAE) [3].

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n} = \frac{\sum_{i=1}^{n} |e_i|}{n}$$

Figure 12: Mean absolute error

7.10.2 Mean square error (mse)

Following is the formula for calculating mean squared error (MSE) [3].

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 .$$

Figure 13: Mean squared error

7.11 Evaluation measures for classification models

Following are measures used for evaluating the classification models.

7.11.1 Confusion Matrix

Following is the confusion matrix [4].

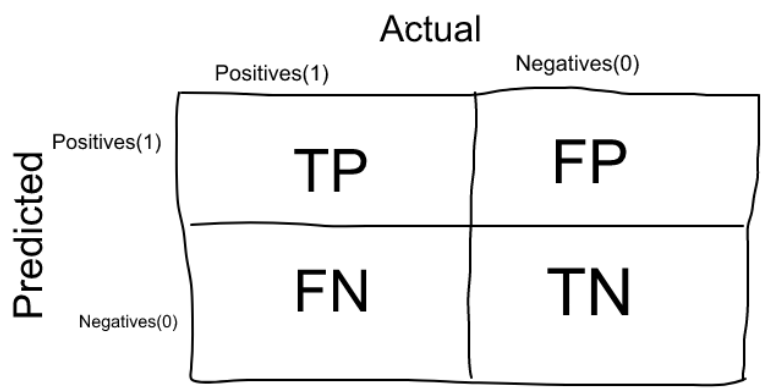

Figure 14: Confusion matrix

7.11.2 Accuracy

Following is the formula for calculating accuracy [4].

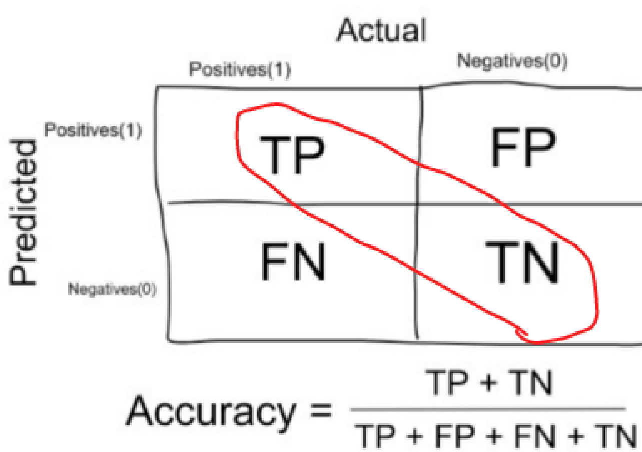

Figure 15: Accuracy

7.11.3 Precision

Following is the formula for calculating precision [4].

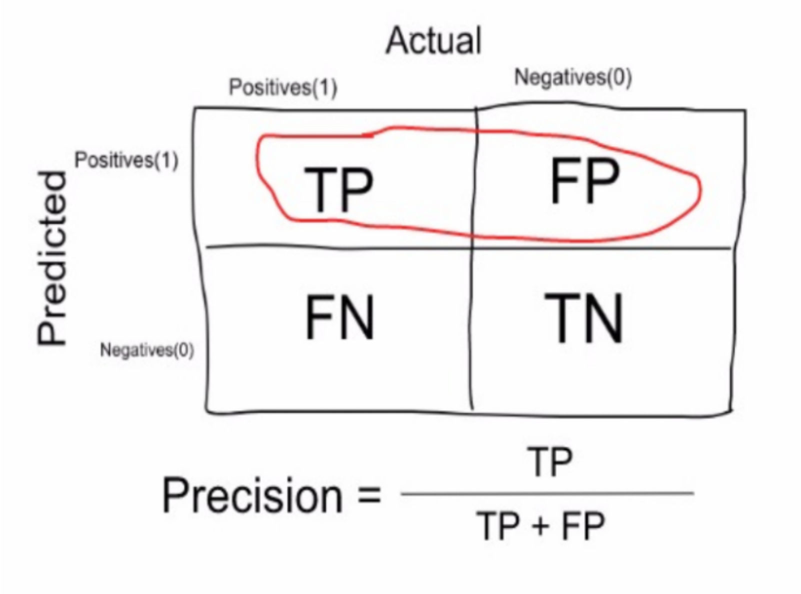

Figure 16: Precision

7.11.4 Recall

Following is the formula for calculating recall [4].

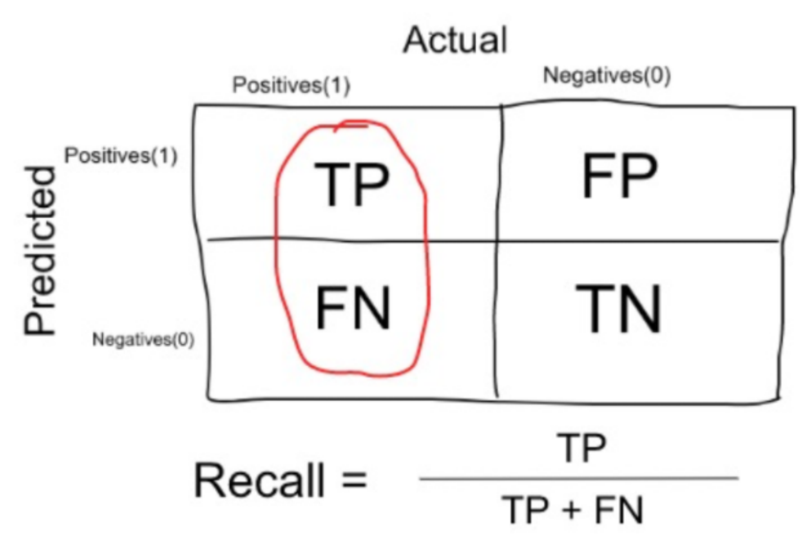

Figure 17: Recall

8 Results

Following results which are obtained on unseen datasets after training the models.

8.1 pH, P, EC, and OM prediction on pH indexes using ANN

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values by ANN regression model.

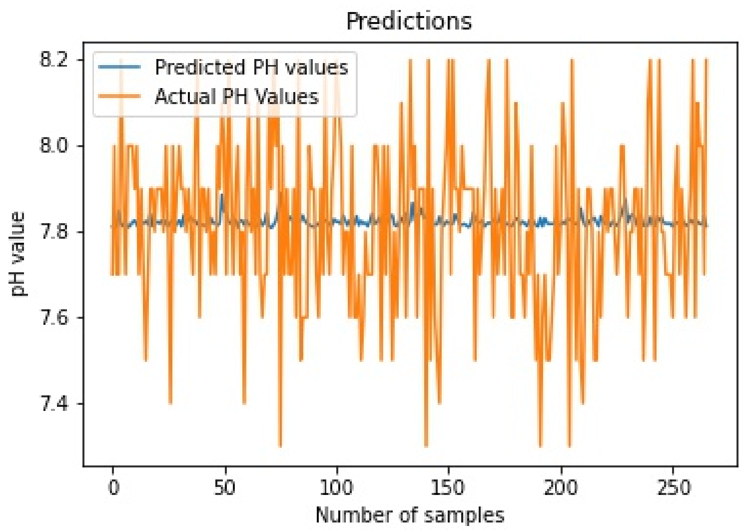

Figure 18: pH estimation using pH indexes

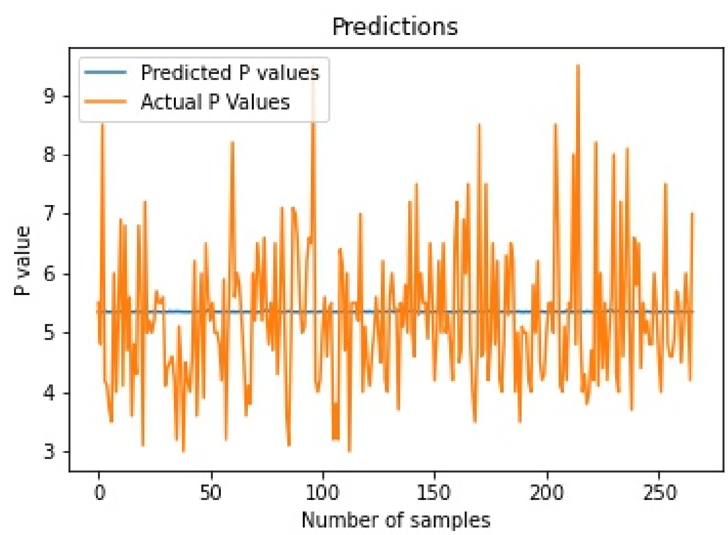

Figure 19: P estimation using pH indexes

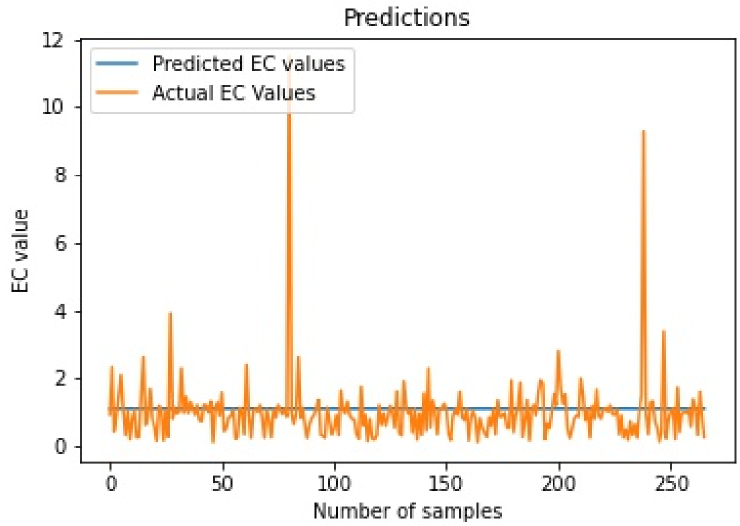

Figure 20: EC estimation using pH indexes

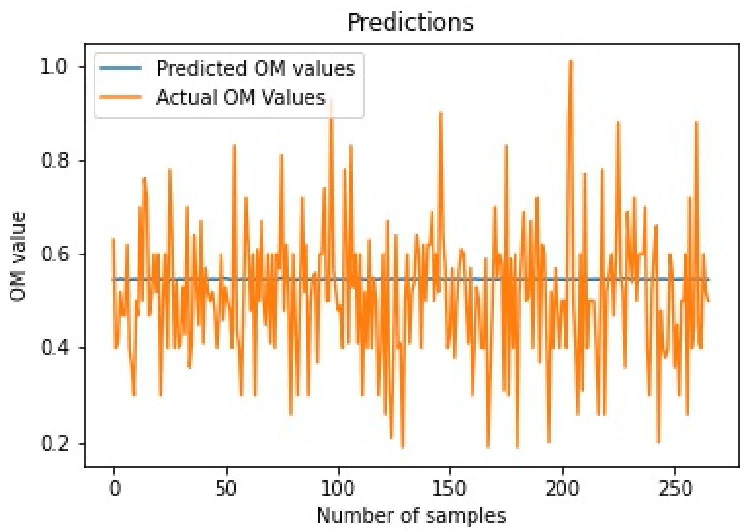

Figure 21: OM estimation using pH indexes

8.2 pH, P, EC, and OM prediction on formula using ANN

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values by ANN regression model.For this models features are extracted by experimentation based formula instead of pH indexes.

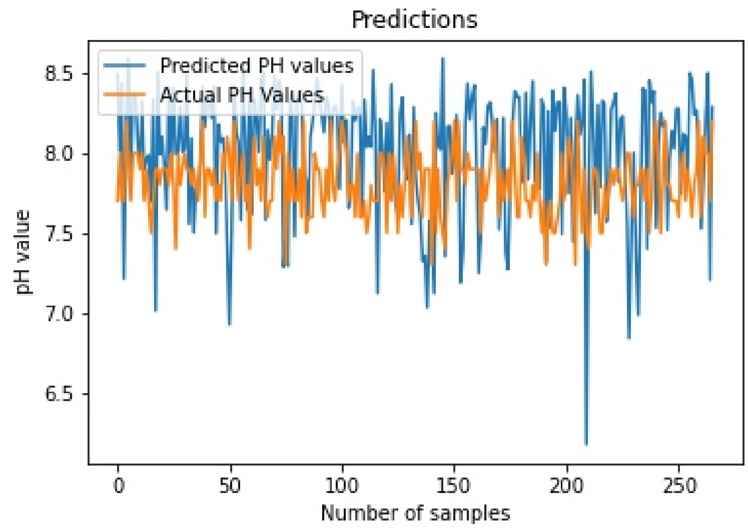

Figure 22: pH prediction using formula

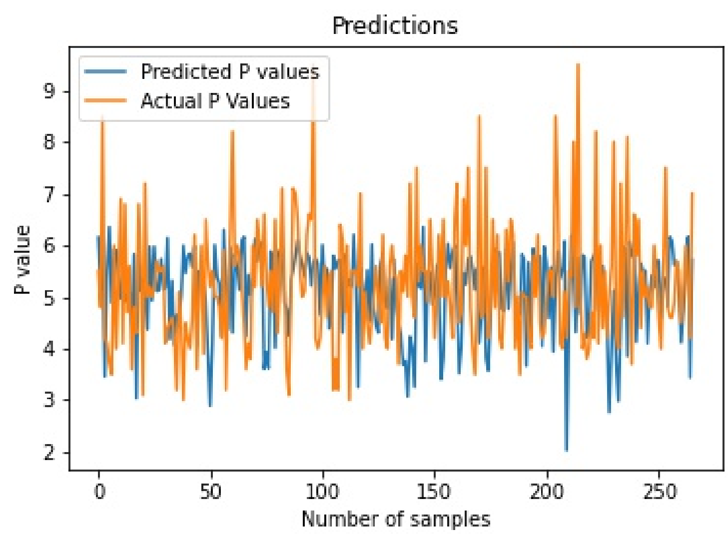

Figure 23: P prediction using formula

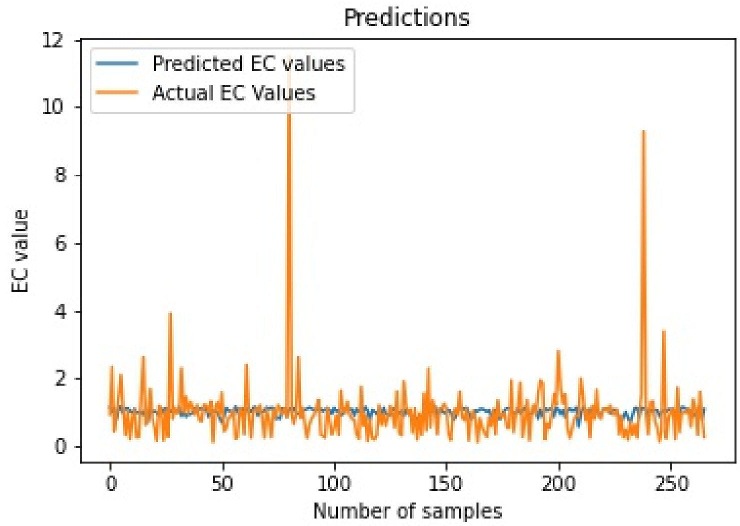

Figure 24: EC prediction using formula

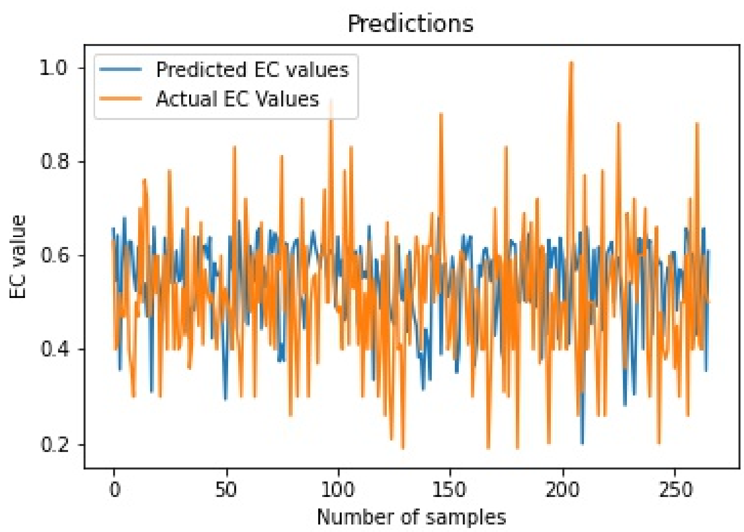

Figure 25: OM prediction using formula

8.3 pH, P, EC and OM prediction using CNN regression models

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values by CNN regression models.All CNN regression models are trained using labeled images to estimate different parameter's of soil.

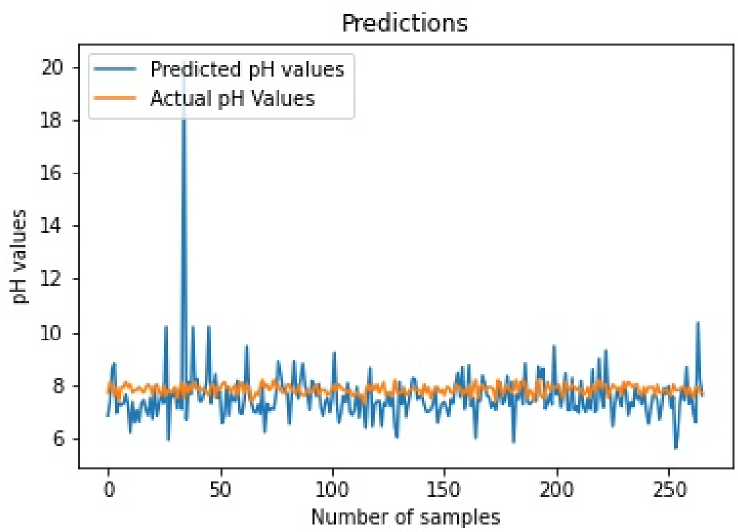

Figure 26: pH prediction using AlexNet CNN Regression model

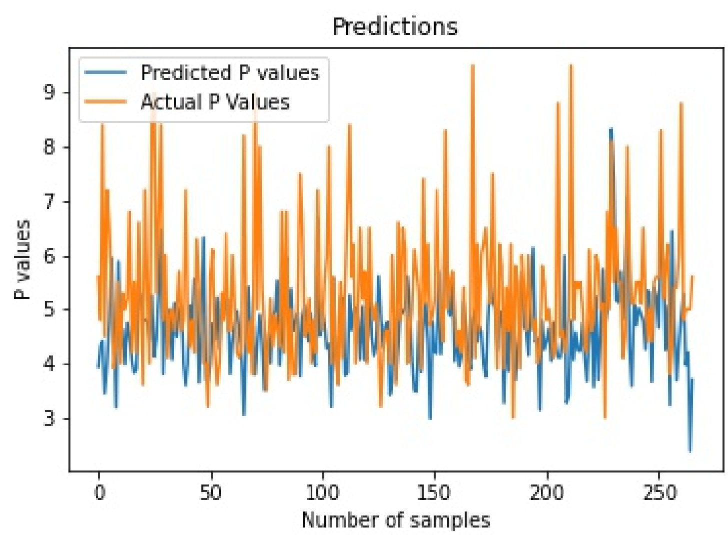

Figure 27: P prediction using AlexNet CNN Regression model

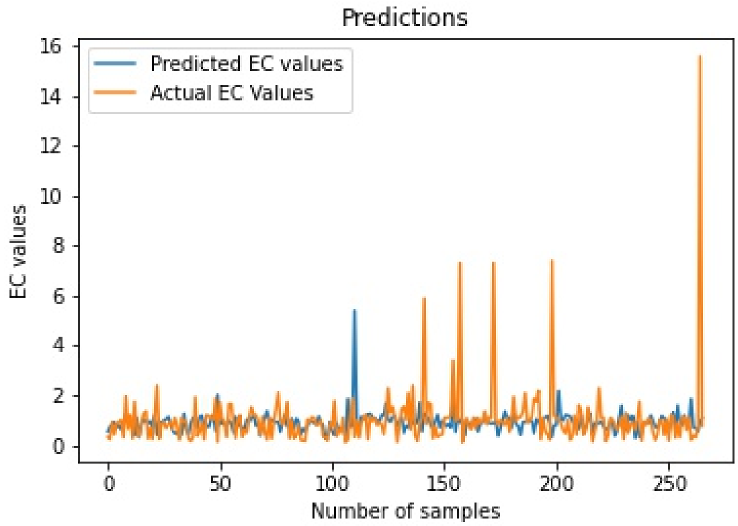

Figure 28: EC prediction using AlexNet CNN Regression model

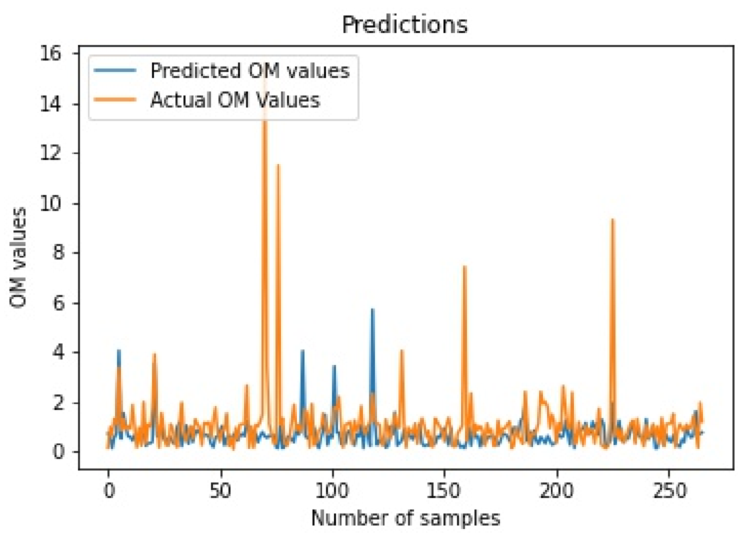

Figure 29: OM prediction using AlexNet CNN Regression model

8.4 pH, P, EC and OM prediction on pH Indexes using SVR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on pH Indexes using support vector regression models.

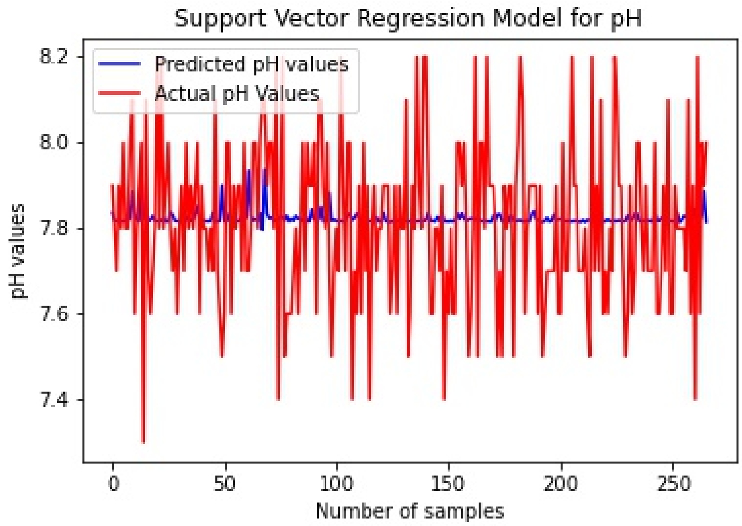

Figure 30: pH estimation using pH indexes

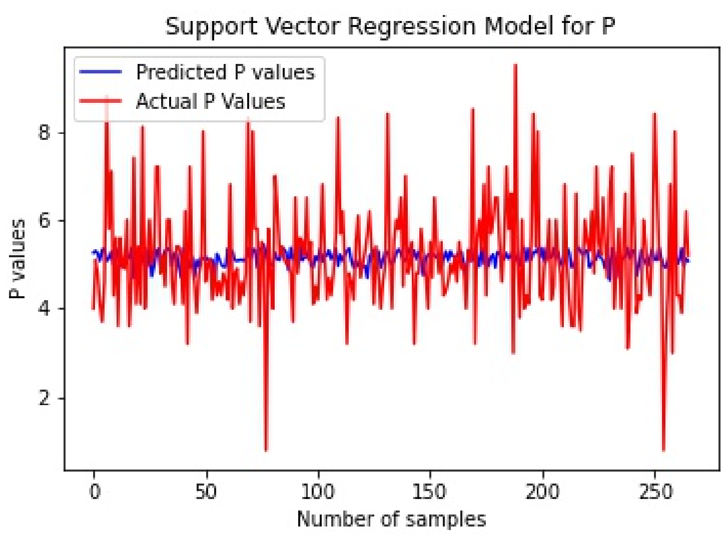

Figure 31: P estimation using pH indexes

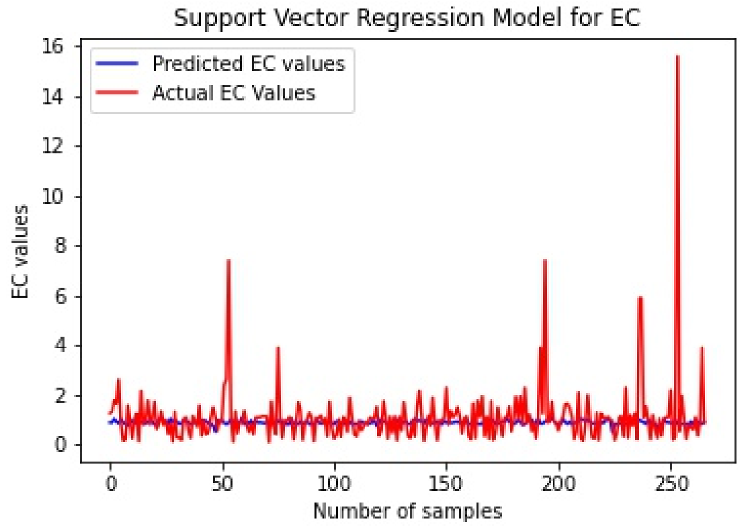

Figure 32: EC estimation using pH indexes

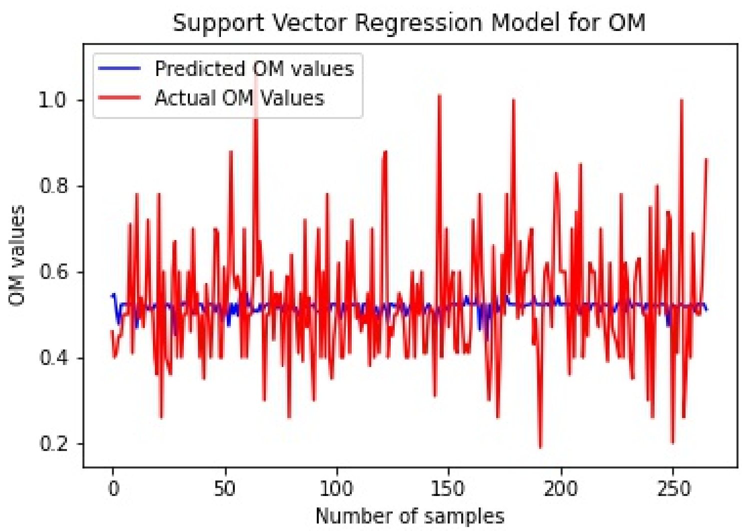

Figure 33: OM estimation using pH indexes

8.5 pH, P, EC and OM prediction on formula using SVR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on formula using support vector regression models.

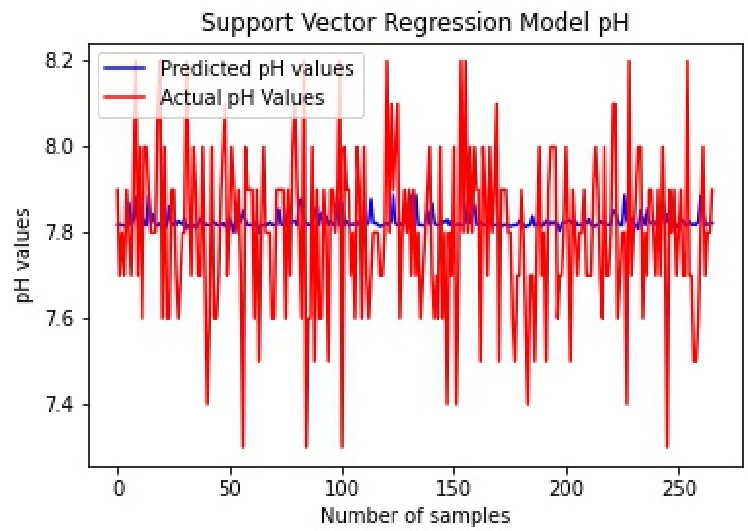

Figure 34: pH prediction using formula

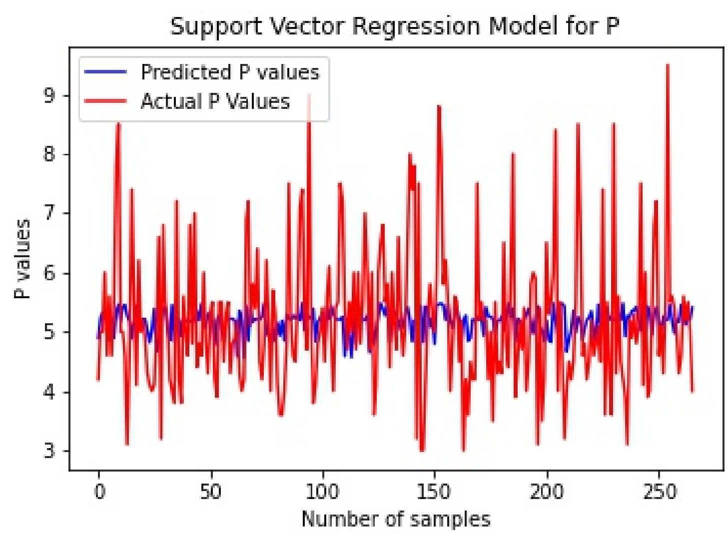

Figure 35: P prediction using formula

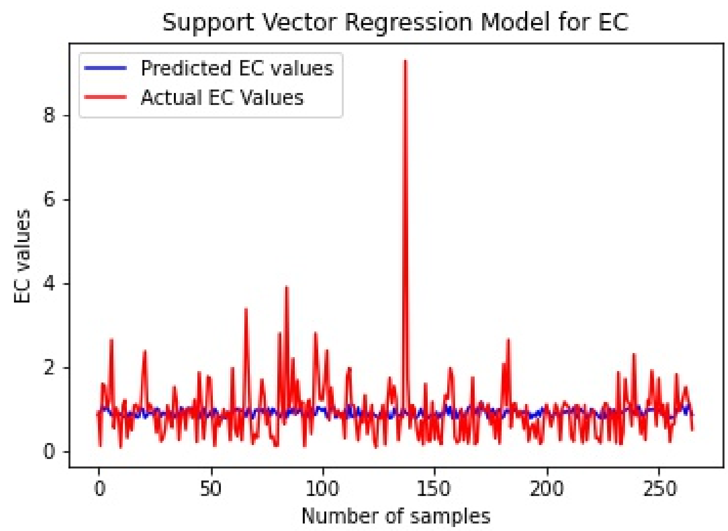

Figure 36: EC prediction using formula

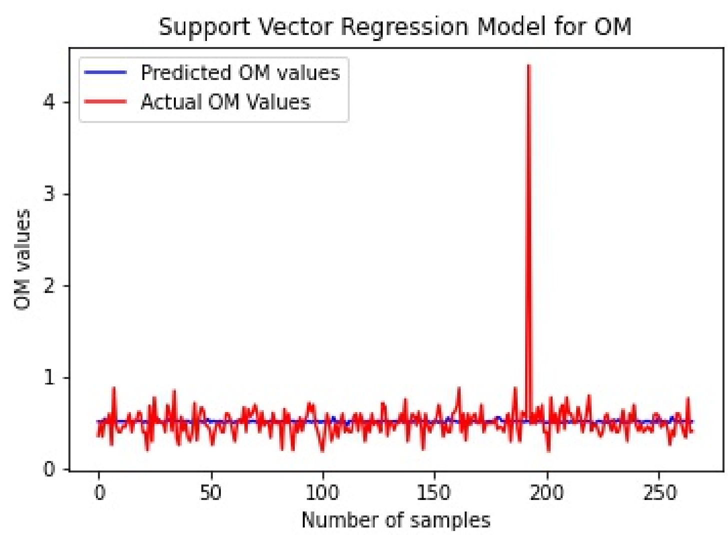

Figure 37: OM prediction using formula

8.6 pH, P, EC and OM prediction on pH Indexes using DTR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on pH Indexes using decision tree regression models.

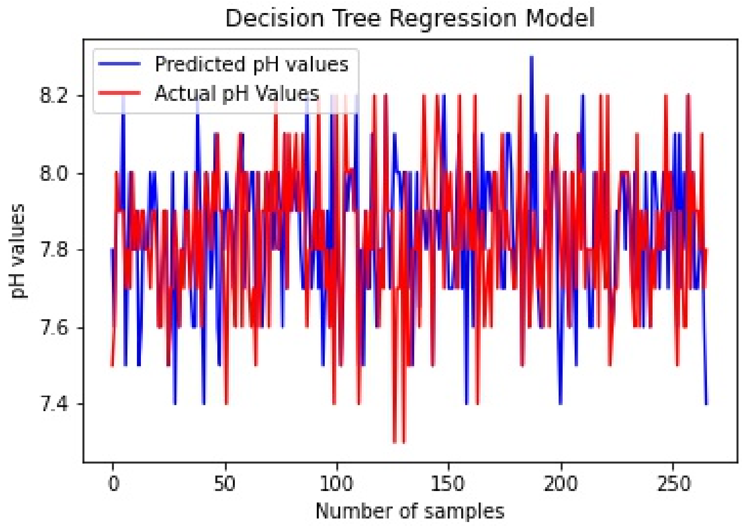

Figure 38: pH estimation using pH indexes

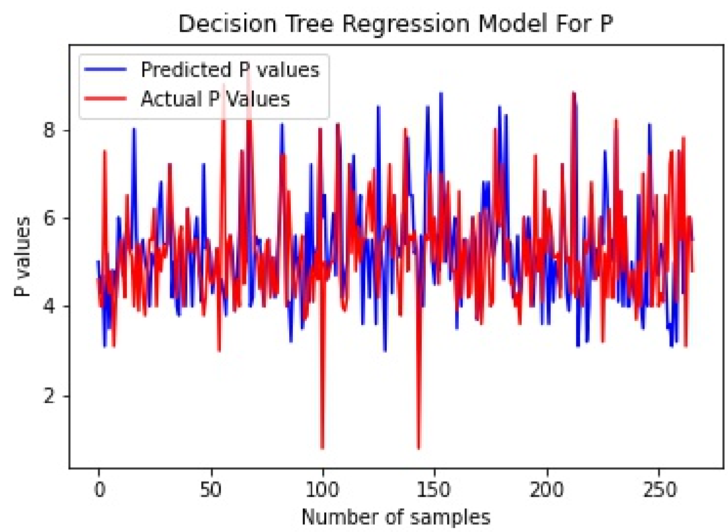

Figure 39: P estimation using pH indexes

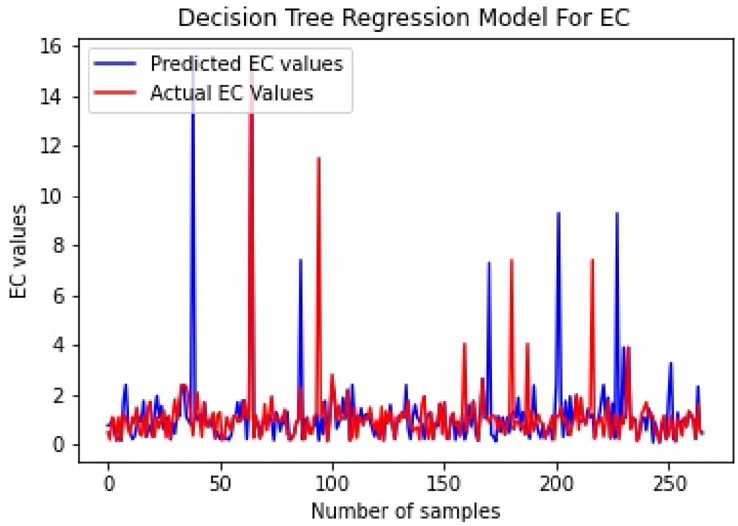

Figure 40: EC estimation using pH indexes

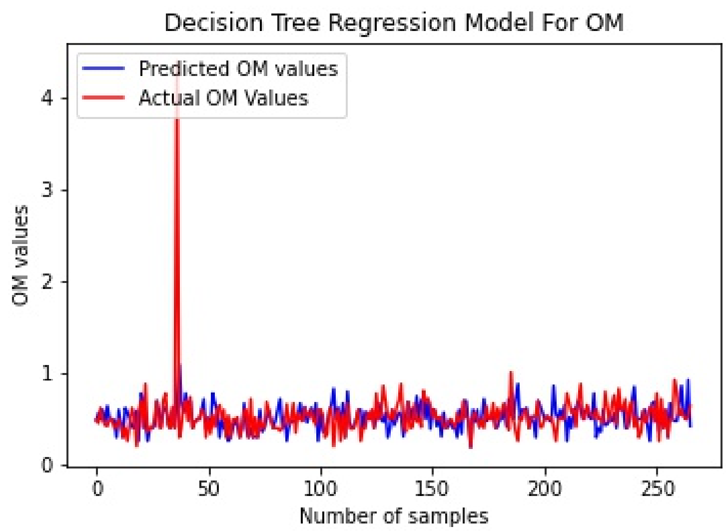

Figure 41: OM estimation using pH indexes

8.7 pH, P, EC and OM prediction on formula using DTR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on formula using decision tree regression models.

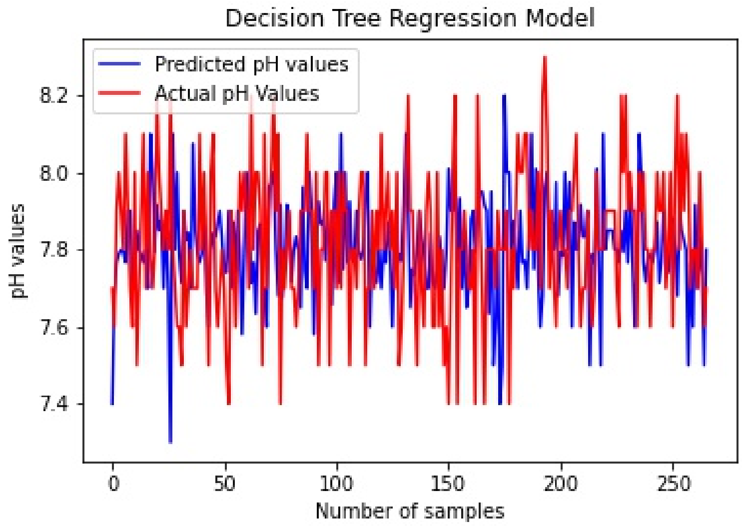

Figure 42: pH prediction using formula

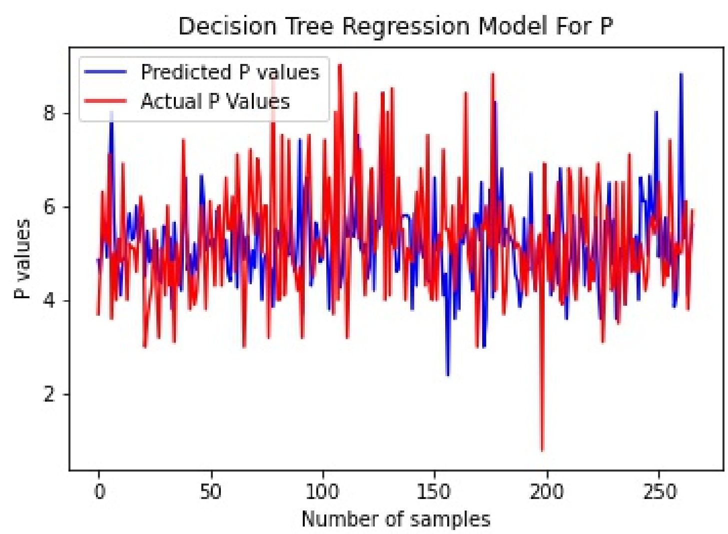

Figure 43: P prediction using formula

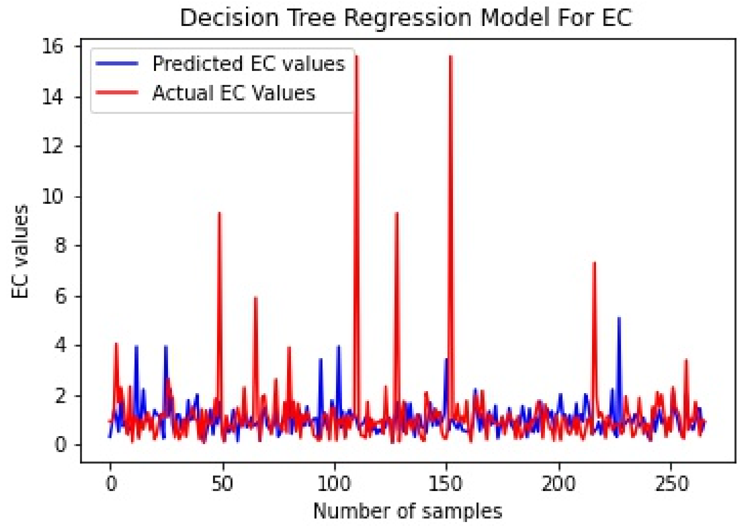

Figure 44: EC prediction using formula

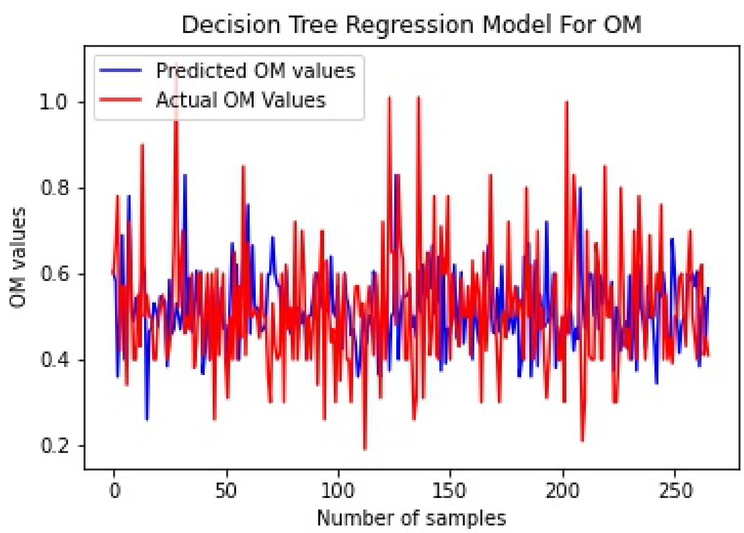

Figure 45: OM prediction using formula

8.8 pH, P, EC and OM prediction on pH Indexes using RFR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on pH Indexes using random forest regression models.

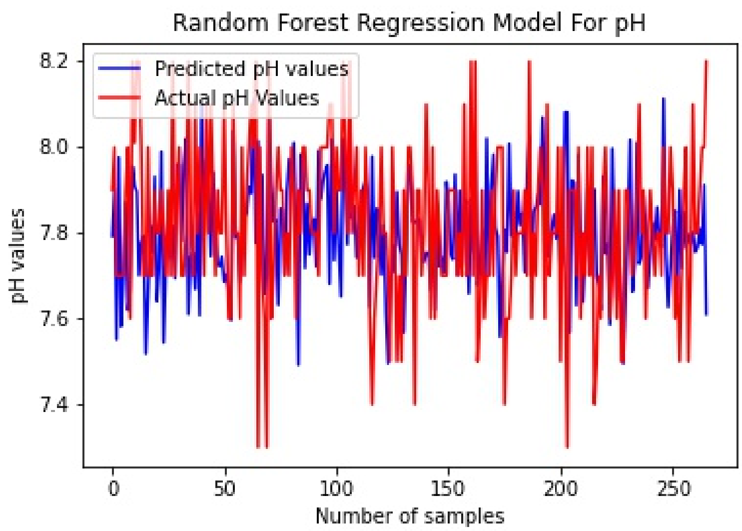

Figure 46: pH estimation using pH indexes

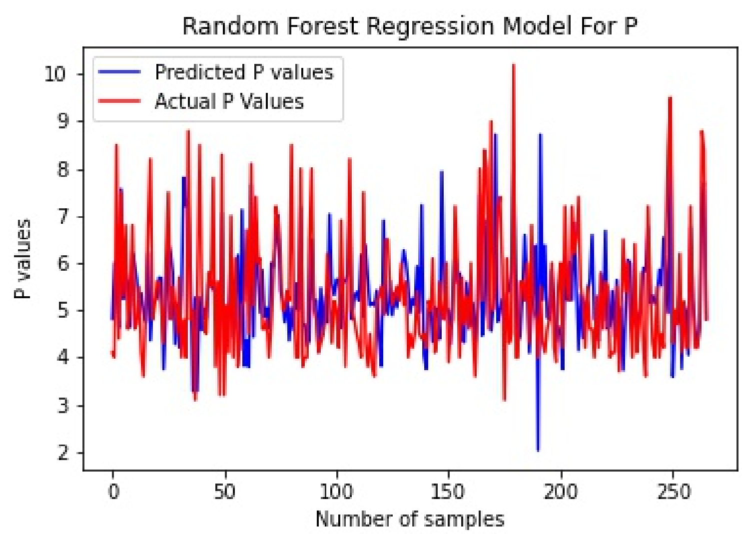

Figure 47: P estimation using pH indexes

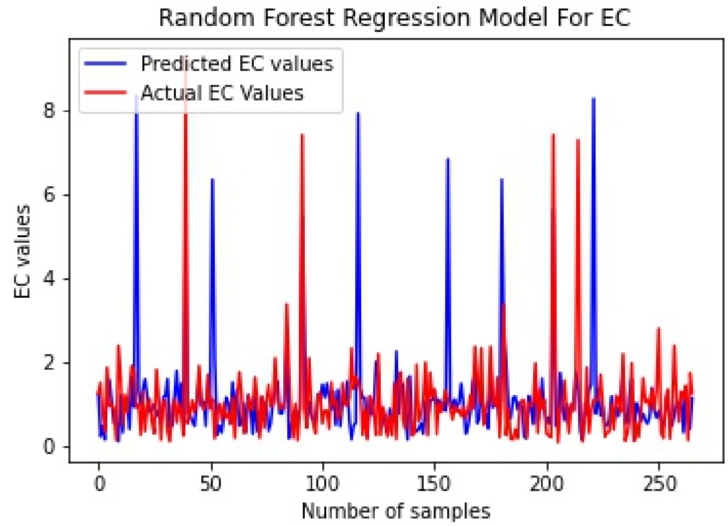

Figure 48: EC estimation using pH indexes

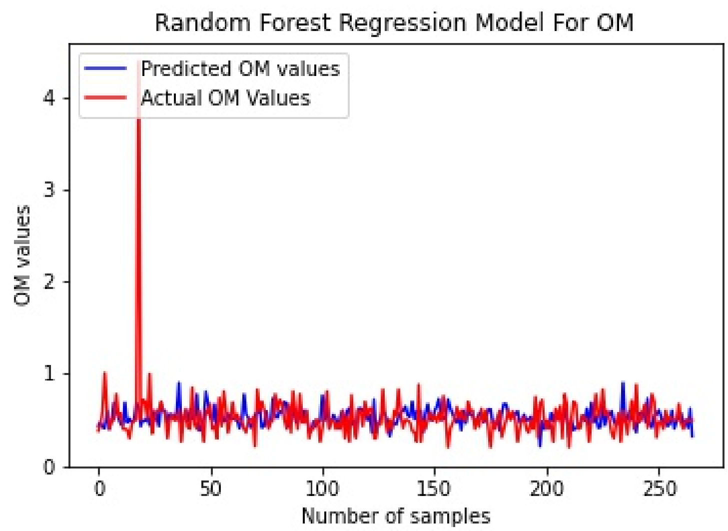

Figure 49: OM estimation using pH indexes

8.9 pH, P, EC and OM prediction on formula using RFR

Following graphs showing that actual values of pH, P, EC and OM values along with predicted value of pH, P, EC and OM values on formula using random forest regression models.

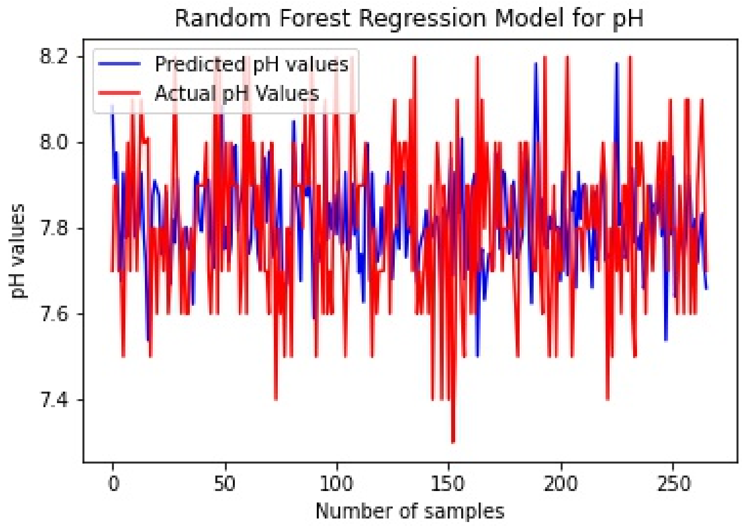

Figure 50: pH prediction using formula

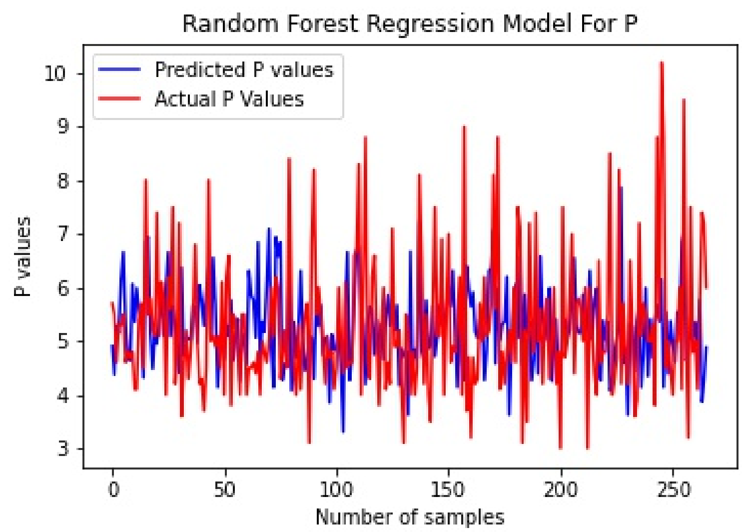

Figure 51: P prediction using formula

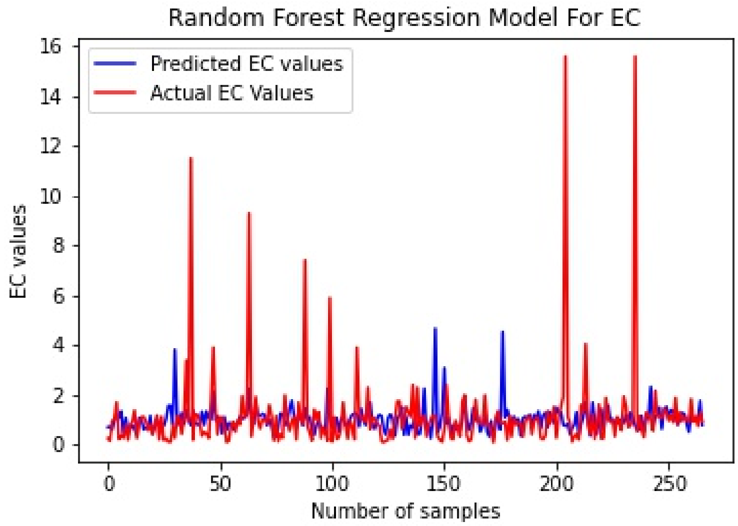

Figure 52: EC prediction using formula

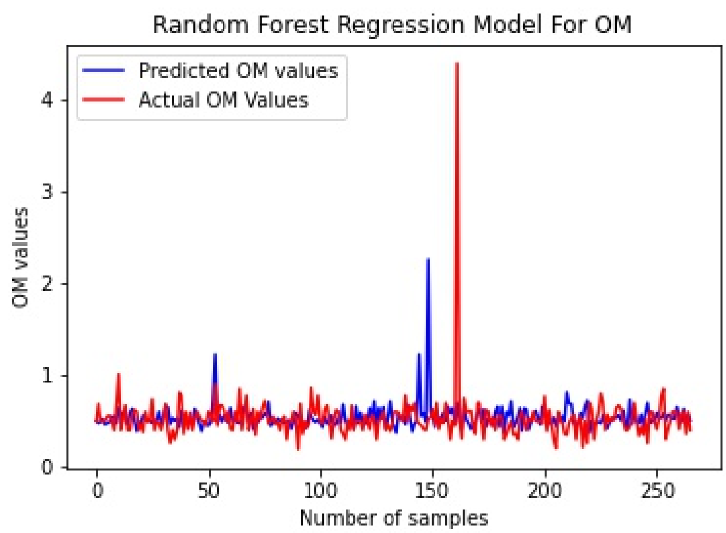

Figure 53: OM prediction using formula

8.10 pH, P, EC and OM prediction using CNN classification models

For evaluating the classification models, the most common measures which are used world widely are precision, recall and F1 score measures.Following are the results on different parameters of soil using classification models.

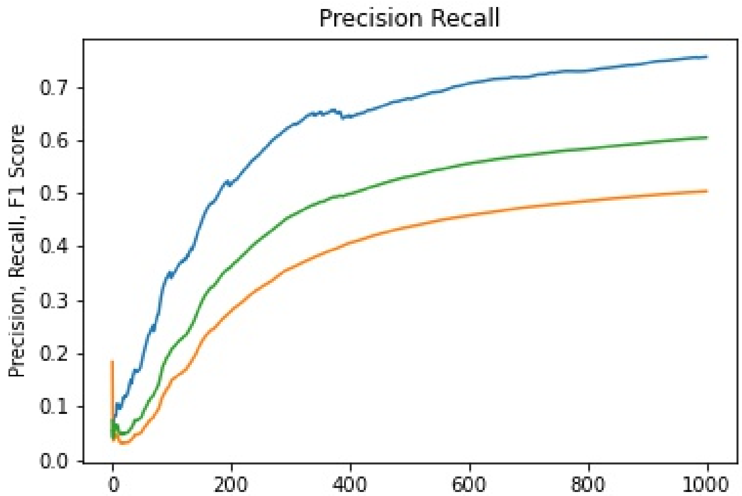

Figure 54: Precision, recall and F1 score measures for CNN classification model for pH value

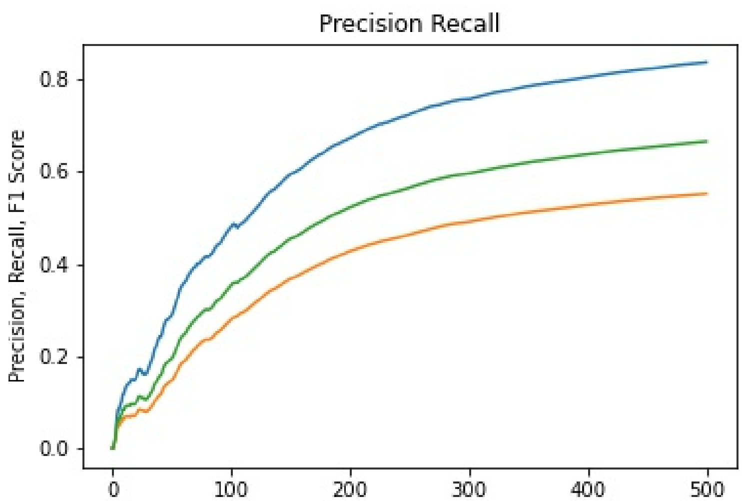

Figure 55: Precision, recall and F1 score measures for CNN classification model for P value

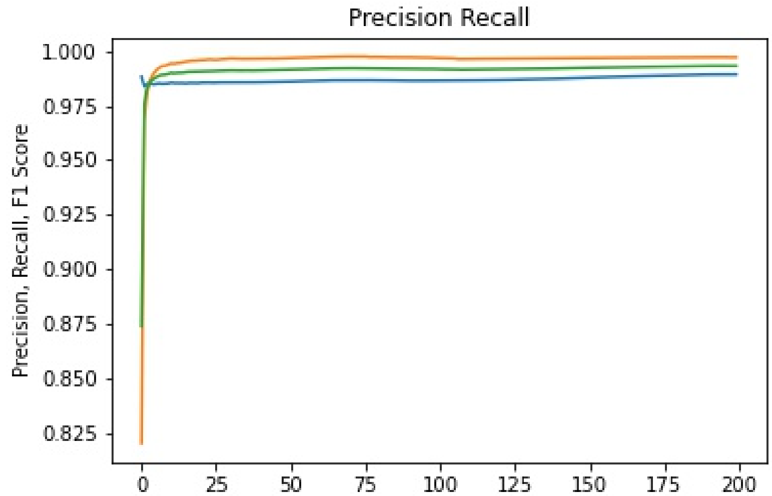

Figure 56: Precision, recall and F1 score measures for CNN classification model for EC value

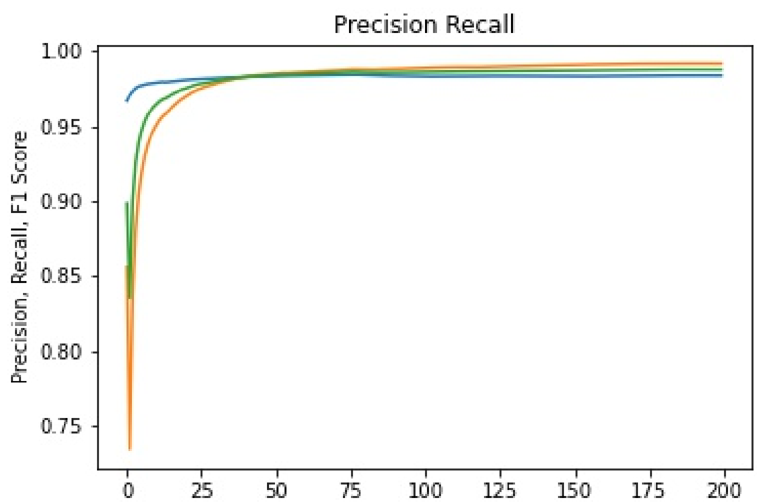

Figure 57: Precision, recall and F1 score measures for CNN classification model for OM value

8.11 Regression models evaluation results on pH Indexes

Following is the regression models evaluation results on pH Indexes for pH, Ec, P and OM

EC using pH Indexes		
	MAE	MSE
ANN	0.5039	0.9995
RFR	0.5317	1.0421
DTR	0.5157	1.7504
SVR	0.5356	1.9302

Figure 58: Regression models evaluation for Ec

pH using pH Indexes		
	MAE	MSE
ANN	0.1616	0.03999
RFR	0.15011	0.0362
DTR	0.1442	0.04284
SVR	0.1455	0.0328

Figure 59: Regression models evaluation for pH

P using pH Indexes		
	MAE	MSE
ANN	0.9171	1.37566
RFR	1.01294	1.8266
DTR	1.0253	2.1533
SVR	0.9484	1.6386

Figure 60: Regression models evaluation for P

OM using pH Indexes		
	MAE	MSE
ANN	0.1153	0.0214
RFR	0.1298	0.0332
DTR	0.1276	0.0357
SVR	0.111	0.0209

Figure 61: Regression models evaluation for OM

8.12 Regression models evaluation results on formula

Following is the regression models evaluation results on formula for pH, Ec, P and OM

EC using Formula

	MAE	MSE
ANN	0.4677	0.99401
RFR	0.6353	1.4531
DTR	0.7098	1.7848
SVR	0.4492	0.7464

Figure 62: Regression models evaluation for Ec

pH using Formula

	MAE	MSE
ANN	0.2992	0.1281
RFR	0.1599	0.0413
DTR	0.1552	0.0397
SVR	0.1432	0.0318

Figure 63: Regression models evaluation for pH

P using Formula		
	MAE	MSE
ANN	1.0795	1.8267
RFR	0.9731	1.6991
DTR	1.0696	2.0878
SVR	0.8786	1.4257

Figure 64: Regression models evaluation for P

OM using Formula		
	MAE	MSE
ANN	0.1305	0.028
RFR	0.1532	0.1368
DTR	0.1199	0.024
SVR		0.02

Figure 65: Regression models evaluation for OM

8.13 Regression models evaluation results on CNN

Following is the regression models evaluation results on CNN for pH, Ec, P and OM

CNN Regression		
	MAE	MSE
OM	0.6595	1.7062
EC	0.7585	2.5181
P	1.1773	2.3485
pH	1.0086	1.862

Figure 66: Regression models evaluation on CNN

8.14 Classification models evaluation

Following is the classification models evaluation results on CNN for pH, Ec, P and OM

CNN Classification				
	Accuracy	Precision	Recall	F1-Score
OM	0.9774	0.9837	0.9918	0.9877
EC	0.9737	0.9893	0.9972	0.9933
P	0.8745	0.8356	0.5511	0.6641
pH	0.8383	0.7555	0.5032	0.6041

Figure 67: CNN classification evaluation

9 Soil npk sensor

We tried to explore soil npk sensor to analyze the soil. Sensor have capability to output seven parameters of soil like nitrogen (N), phosphorous (P), potassium (K), electrical conductivity (EC), PH, humidity and temperature.

DC power supply (default)	DC4.5-30V
Power consumption	0.5W (24V DC power supply)
Operating temperature	-20℃~+60℃
Core chip temperature resistance	85℃
Conductivity parameter	Range: 0-20000us/cm Resolution: 1us/cm Accuracy: ±3%FS in the range of 0-10000us/cm; ±5%FS in the range of 10000-20000us/cm
Soil moisture parameter	Range: 0-100% Resolution: 0.1% Accuracy: 2% within 0-50%, 3% within 50-100%
Soil temperature parameter	Range: -40~80°C, resolution: 0.1°C, accuracy: ±0.5℃ (25℃)
Soil PH parameter	Range: 3~9PH Resolution: 0.1 Accuracy: ±0.3PH
NPK parameters	Range: 1-1999 mg/kg(mg/L) Resolution: 1 mg/kg(mg/L) Accuracy: ±2%FS
Conductivity temperature compensation	Built-in temperature compensation sensor, compensation range 0-50°C
Protection level	IP68
Probe material	Anti-corrosion special electrode
Sealing material	Black flame-retardant epoxy resin
Default cable length	2 meters, the cable length can be customized according to requirements
Dimensions	45*15*123mm
output signal	RS485 (Modbus protocol)

Figure 68: Soil npk sensor description

9.1 Sensor integration with mobile application

For interfacing soil npk sensor, we used raspberry pie as micro-controller. We used python library pymobus to read real time values of sensor from registers. After reading real time values from sensor by raspberry pie, real time values are uploaded to Firebase. Mobile application displays real time values of sensor.

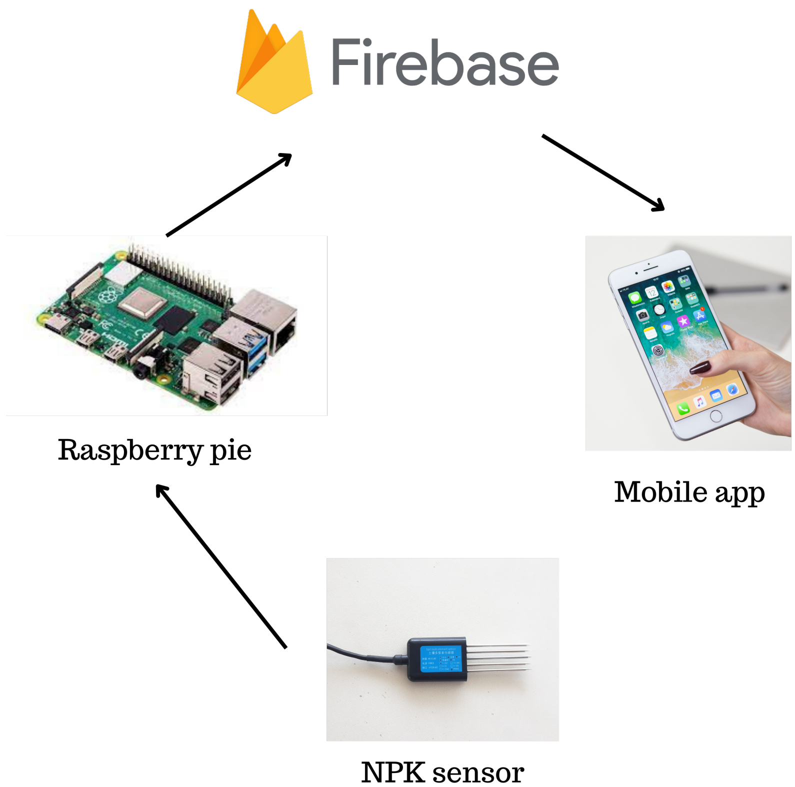

Figure 69: Architecture for interfacing

10 Mobile application

Mobile application is developed using java.There are two main functionalities of mobile application like image analysis using machine learning and sensor analysis. Mobile application is available in English and Urdu language.

10.1 Splash screen

Following is the splash screen of mobile application.

Figure 70: Splash screen

10.2 Image analysis using machine learning

In this functionality part, user can predict soil parameters using images.After prediction, user can generate soil quality report.

10.2.1 Default home screen

Figure 71: Default home screen in English

10.2.2 Home screen in urdu

When user clicks on Urdu button than home screen changes into following screen.

Figure 72: Home screen in Urdu

10.2.3 Image analysis button

When user clicks on image analysis button than following screen is displayed where user can select image for predictions.

10.2.4 Image selection screen in English

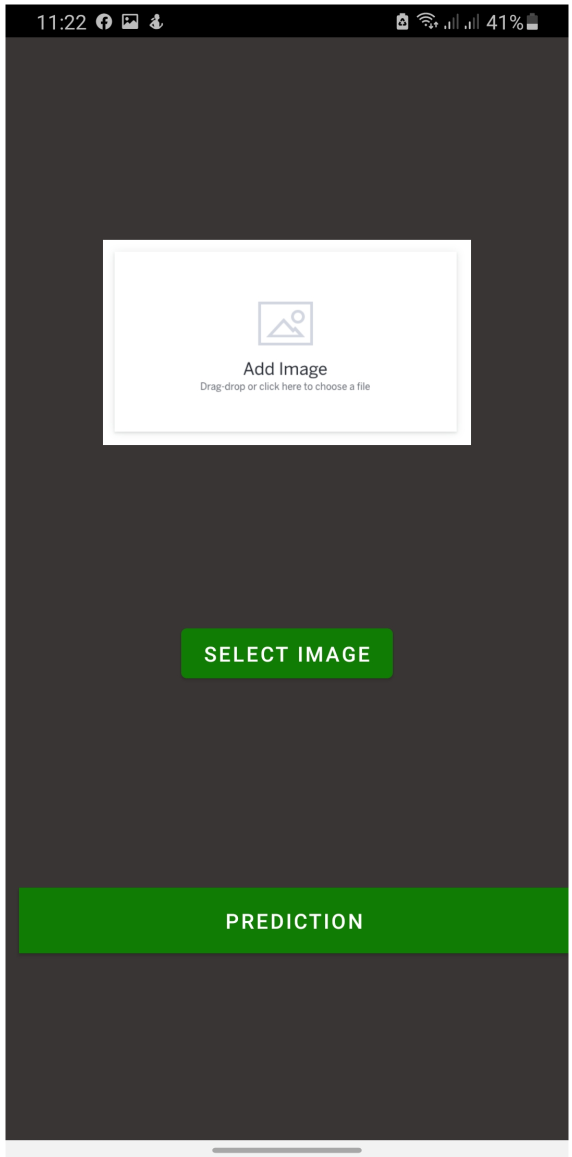

Figure 73: Image selection screen in English

10.2.5 Image selection screen in Urdu

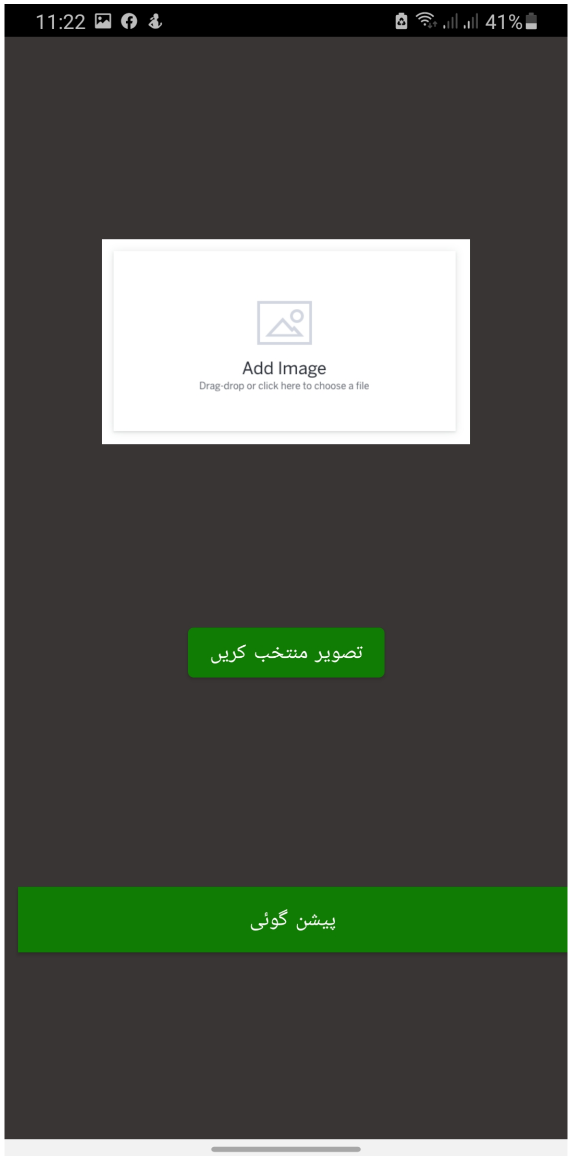

Figure 74: Image selection screen in urdu

10.2.6 Prediction by image

When user select image from local storage or capture real time image of soil and click on prediction button than following screen is displayed. When user clicks on prediction button, image is uploaded to flask server which is deployed on Heroku. Flask server returned back the machine learning results in form json which are displayed on table.

10.2.7 Report generation

When user clicks on generate report than report is generated according to predicted results.

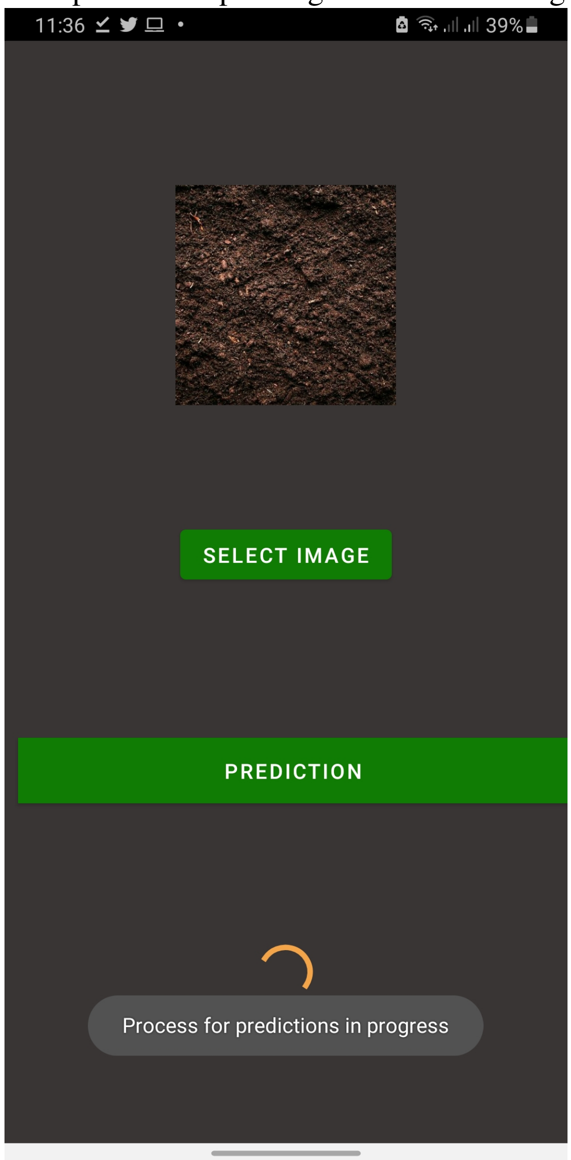

Figure 75: When user clicks on prediction button

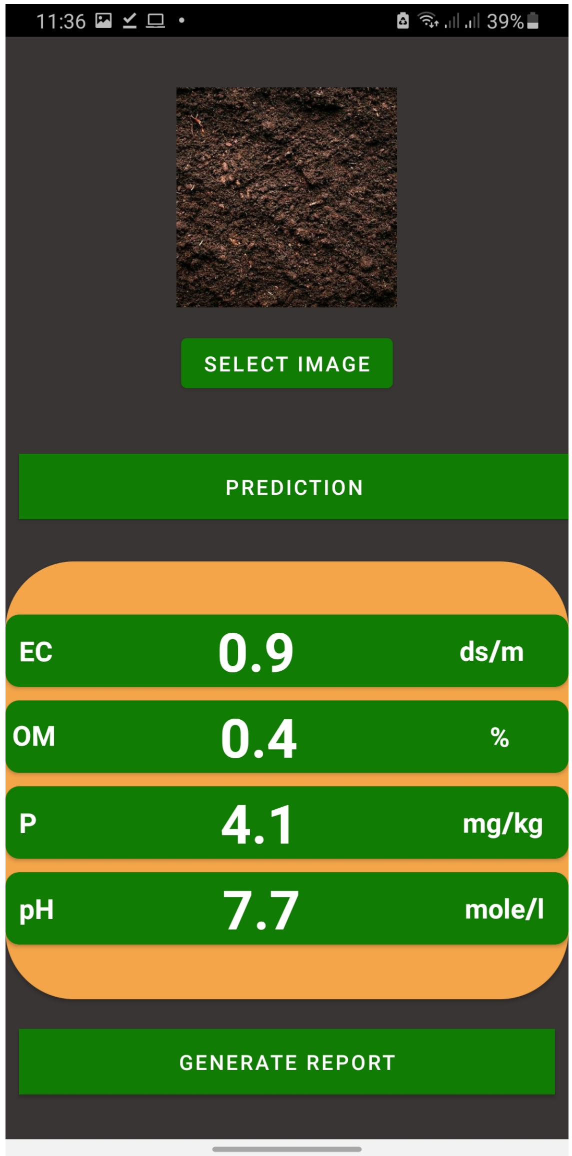

Figure 76: Predictions results

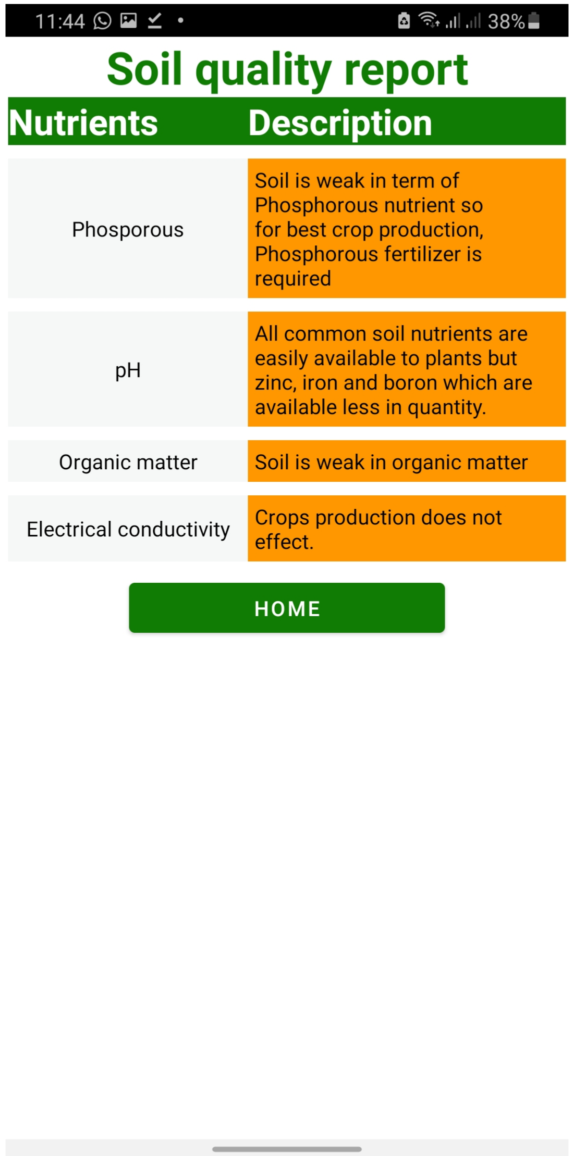

Figure 77: Report in English

Figure 78: Report in Urdu

10.3 Sensor analysis

When user clicks on sensor analysis button than following screen is displayed where user have to login or signup to use the sensor functionality.

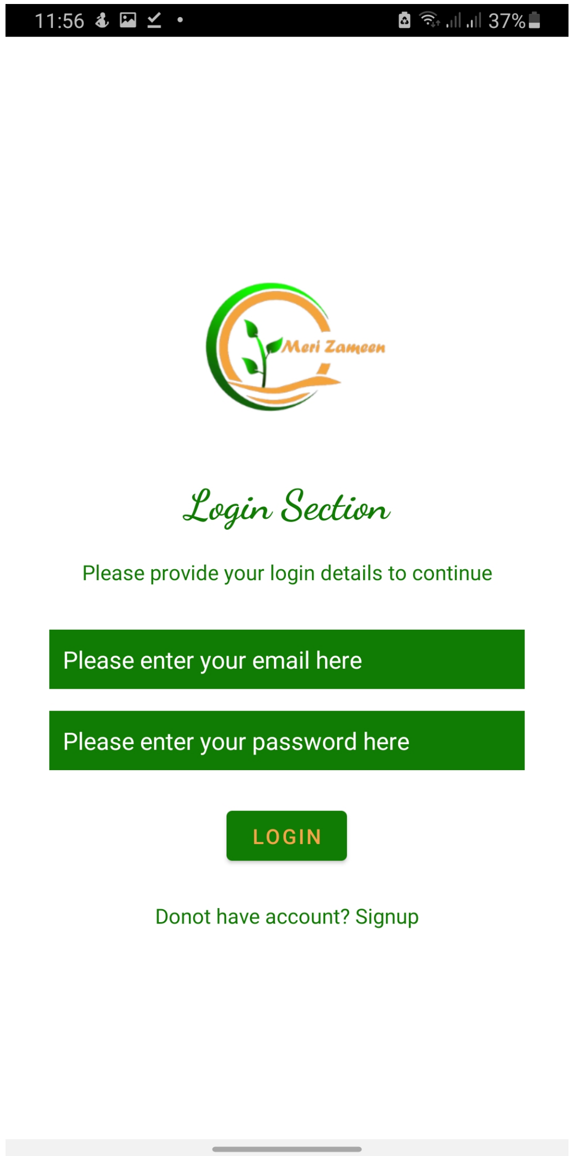

Figure 79: Login section in English

Figure 80: Login section in Urdu

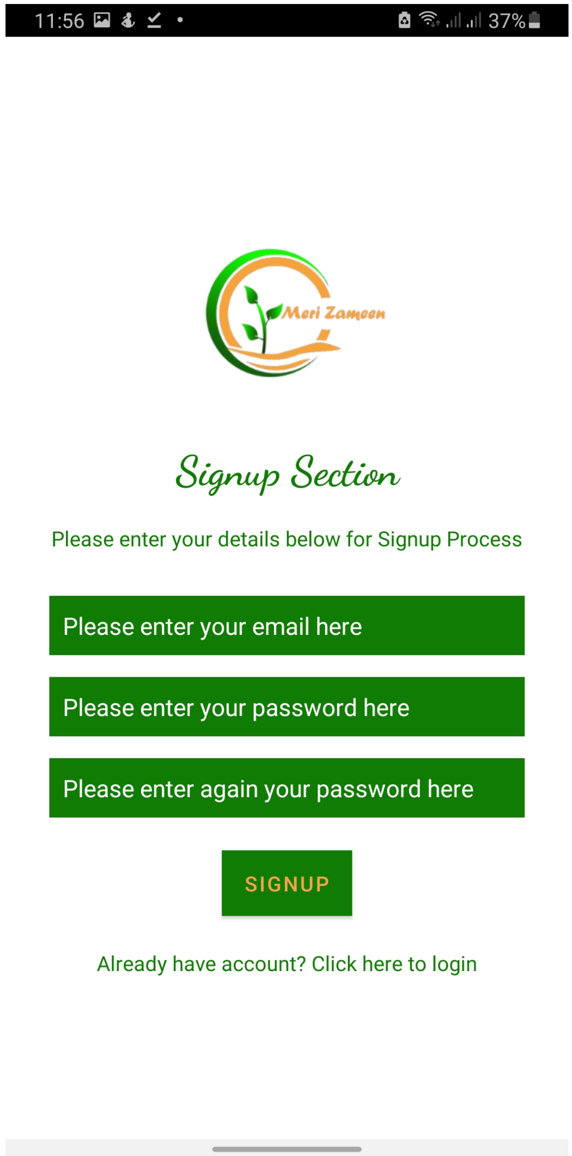

Figure 81: Sign Up section in English

Figure 82: Sign Up section in Urdu

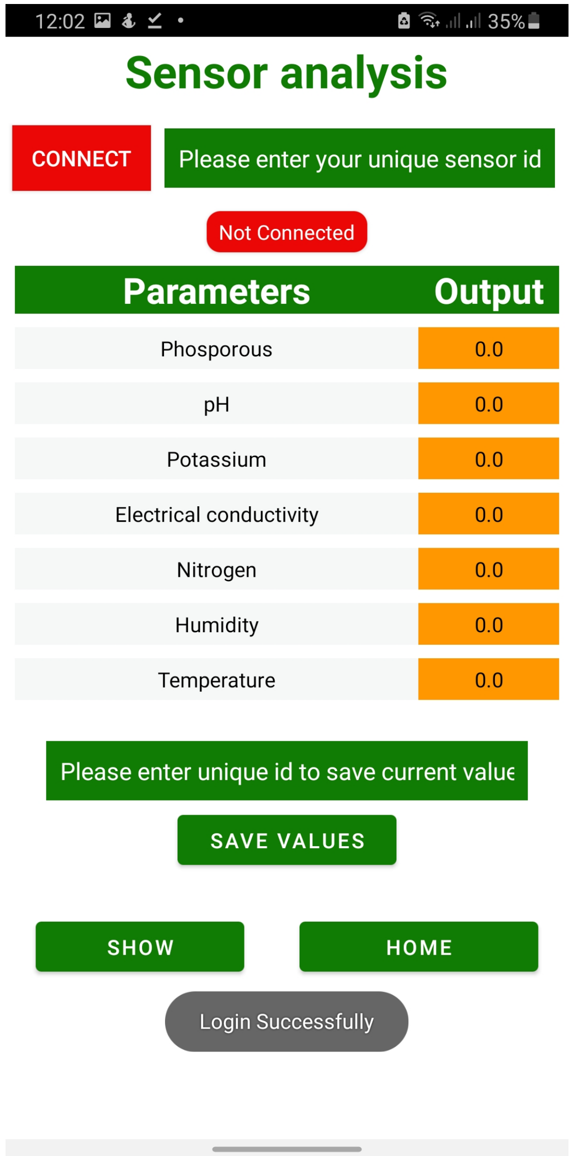

Figure 83: Default sensor home screen

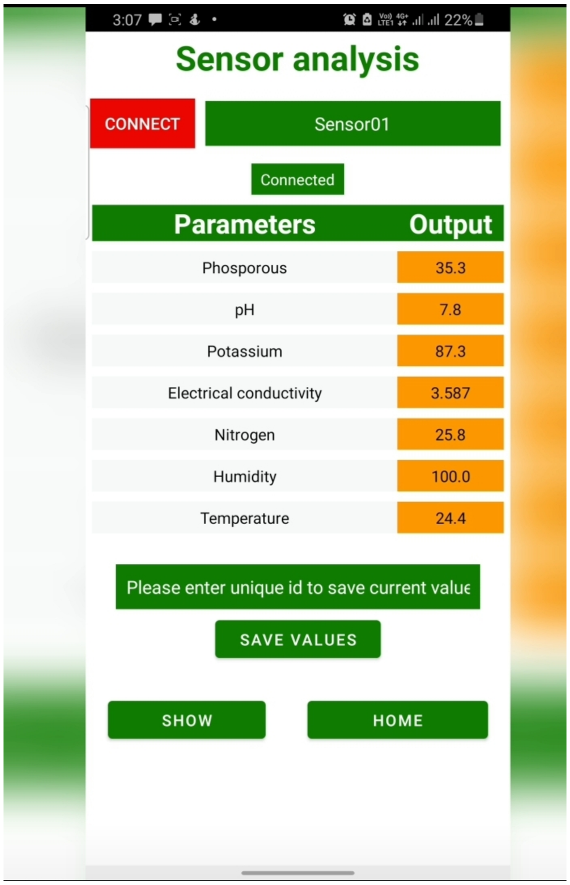

Figure 84: Sensor is connected

10.3.1 Display previous records

When user clicks on show button than all previous records will displayed and user can also query displayed records by using search bar to filter out the results

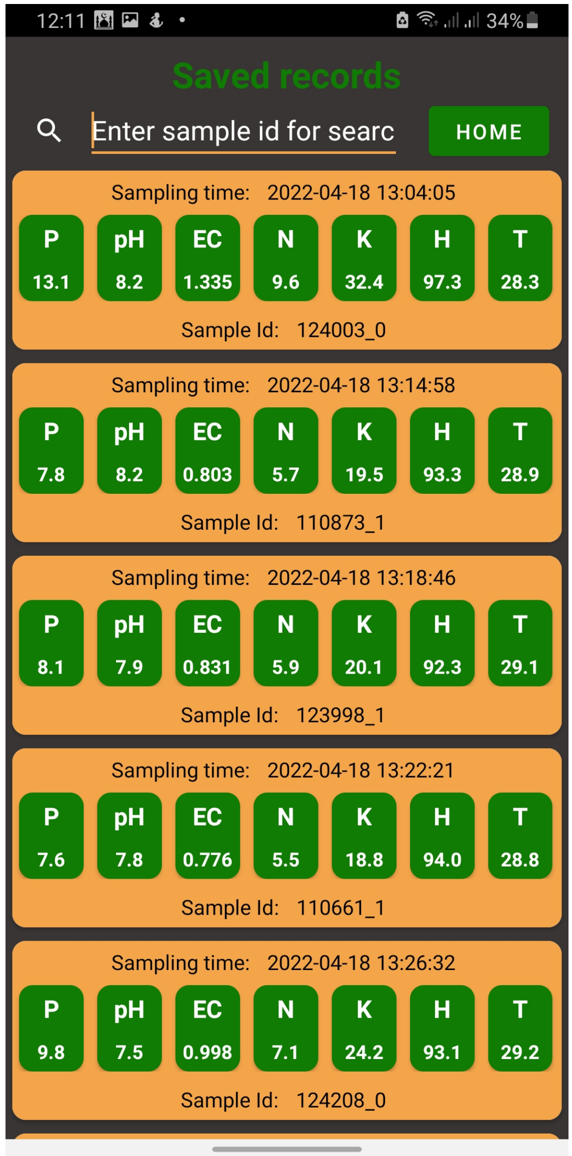

Figure 85: Sensor previously recorded values

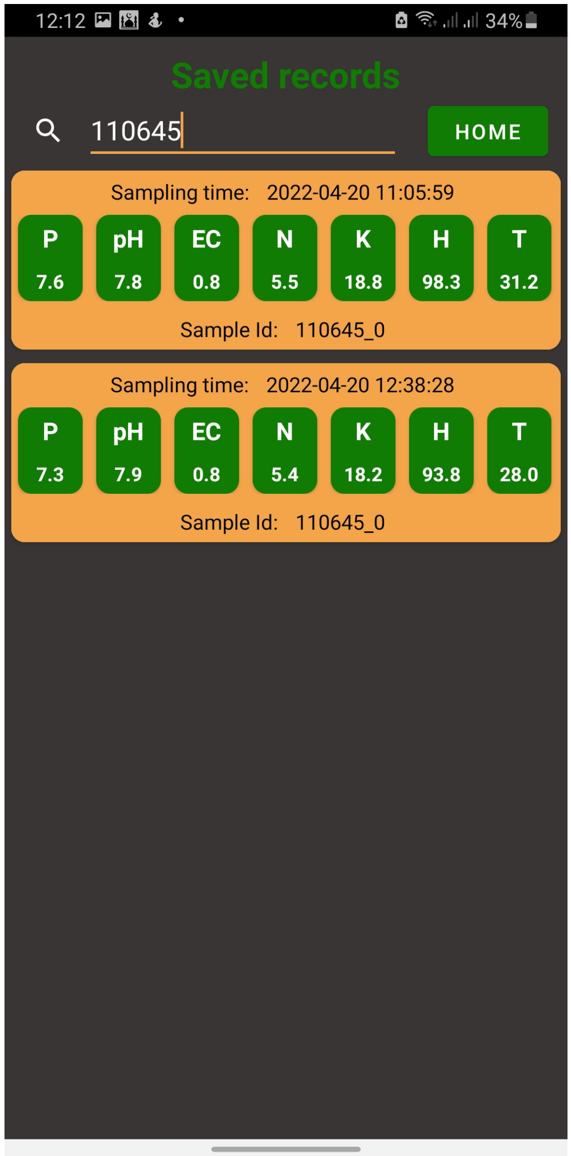

Figure 86: Searched values in the results

11 Conclusion

The main aim of this project was to facilitate the farmers with an mobile application which are enough capable to use machine learning to provide complete soil quality report. We have 1064 soil sample images with labels in order to train different machine learning algorithms. There were 40 different models are trained and tested.But decision tress and random forest algorithm were able to find some pattern from data to predict unseen soil parameters.We deployed best machine learning models on mobile application. Sensor is successfully integrated with mobile application and we are still working on sensor to validate values in order to deploy it on fields.

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