Chapter 5
IoT BASED DECISION SUPPORT SYSTEM

5.1 INTRODUCTION

Currently, agribusiness must overcome a number of obstacles to ensure food safety. One of the biggest problems for farmers in the rain fed agriculture industry, particularly during the summer, is a lack of water, which can result in significant financial and farm losses. Recently, the Internet of Things (IoT) has emerged as a potentially revolutionary method for smart farming that offers a wide range of creative uses.

The suggested research proposed an IoT Cloud platform designed with Raspberry-pi 3 module with few sensor and web camera. The system based on a deep learning methodology for tracking and forecasting farmers' capacity to meet agricultural water requirements in the event of a lack of rainfall as well as diseases inside the crop. Data about significant physical phenomena such soil moisture, air temperature, air humidity, CO2, soil temperature and light intensity can be collected using the smart farming system. Also, the same system will monitor the different stages of plant by continuously uploading leaf images of crop, to check whether crop is healthy or it has some diseases.

The majority of research projects rely their projections on easily accessible, historical data. However, the dataset is created here for more genuine findings. All parameters, including soil moisture, soil temperature, ambient temperature, and airborne CO2 levels, were continually measured in this investigation; as a result, a dataset was created. The dataset has roughly more than 5000 records for each parameter.

5.2 TOOLS AND COMPONENTS

The required Tools and components are listed below.

Tools:

- Google Colab
- Raspbian OS
- EasyEDA
- ThingSpeek

Components:

- Raspberry pi 3
- Soil Moisture Sensor
- Soil Temperature Sensor DS18B20
- Environment Temperature and humidity sensor DHT11
- CO2 sensor MG811
- Sun Light Sensor LDR
- Web Camera

5.3 SCHEMATIC DESIGN

Figure 5.1 depicts a schematic for the identical system. The proper Raspberry-Pi pins are used to connect the sensors. All parameters are continuously sensed by the sensors with a 30-second delay. The appropriate connections of sensors with pins of Raspberry Pi are listed in table 5.1.

PIN No.	Sensor
A3	Soil Moisture Sensor
D8	Environmental Temperature and Humidity Sensor
A2	CO2 Sensor
A0	LDR Module
A1	Soil Temperature Sensor
Raspberry Pi Camera Slot	Web Camera

Table 5.1 Sensor Connection with Pins of Raspberry-Pi

Deep learning algorithms can be used to monitor the health and other illnesses of plants. The best algorithm among those developed with additional layers is selected. Other photos of plants are used to generalize the model. Thus, a great model with excellent precision and less loss is created in the end. The created model is applied to various classification issues. The site map is located at 22.4690° N, 73.0763° E, at SVIT VASAD. Figure 5.2 (A) & (B) shows the physical architecture of the system. The corresponding data are sent on thingSpeak which is an IoT analytics platform service.

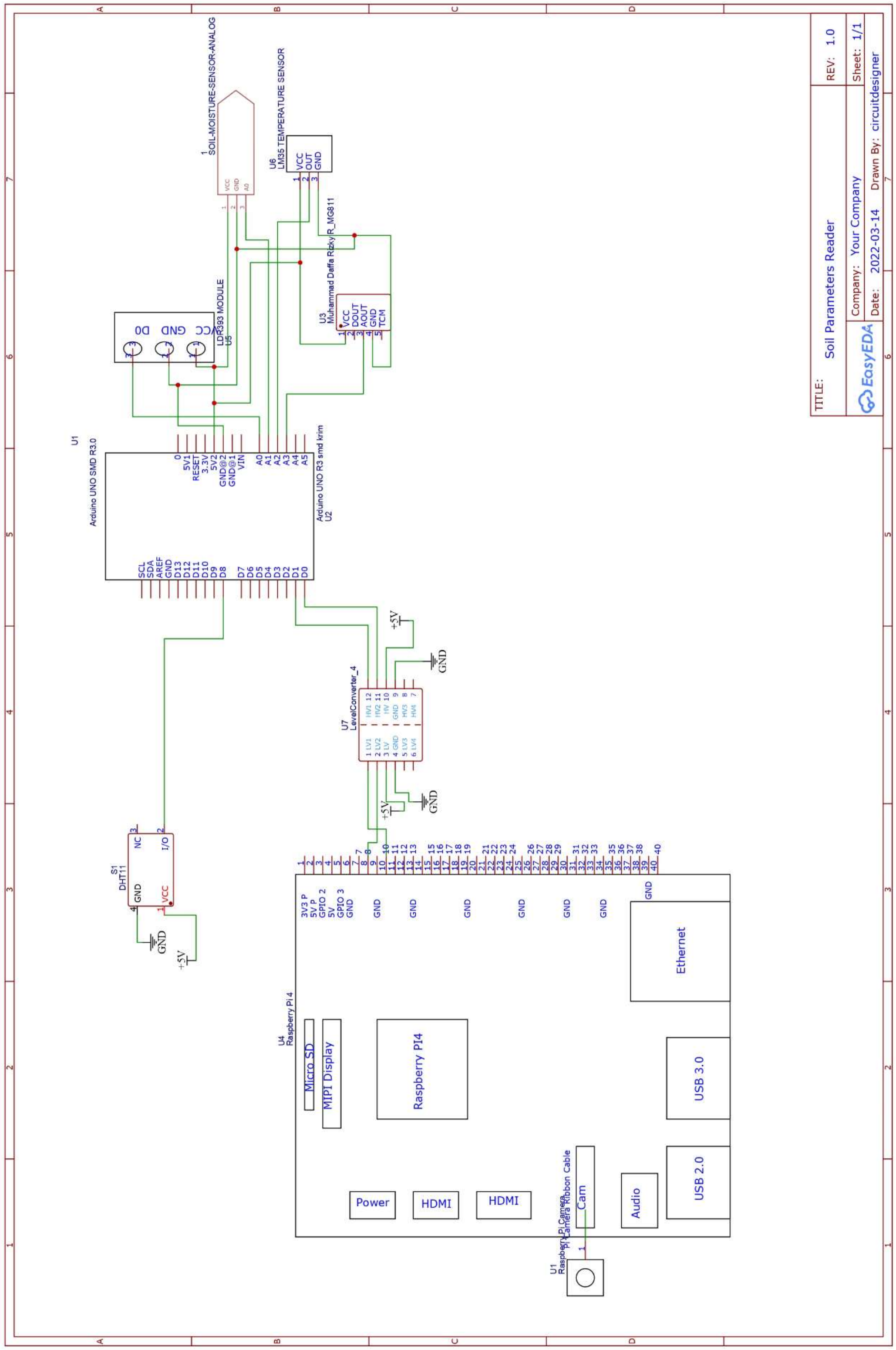
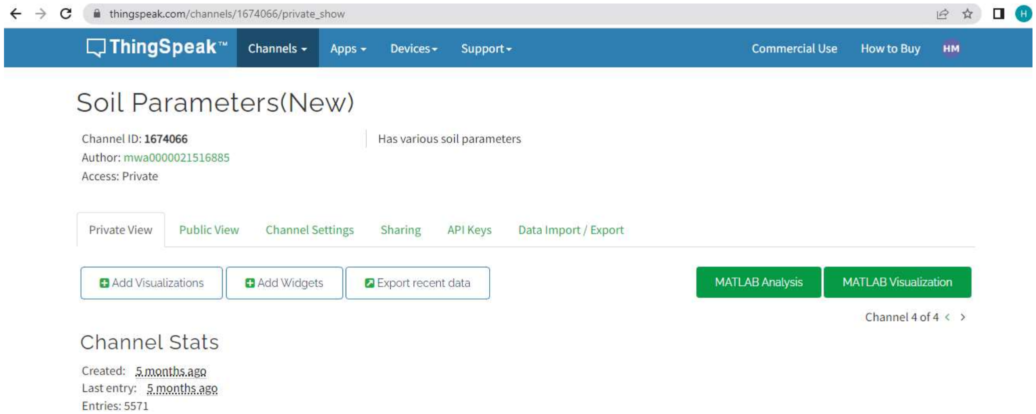


Figure 5.1 Schematic Design of Raspberry Pi based Module

[B]

[A]

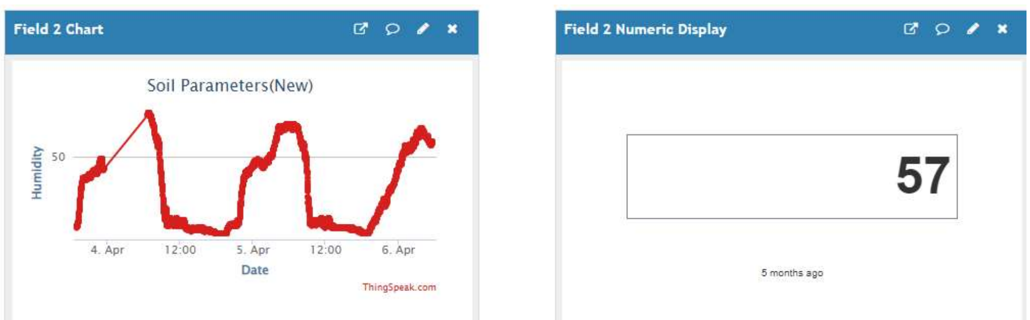
Figure 5.2 [A] & [B] Physical View of Proposed System


thingspeak.com/channels/1674066/private_show
ThingSpeak™
Channels
Apps
Devices
Support
Commercial Use
How to Buy
HM
Soil Parameters(New)
Channel ID: 1674066
Author: mwa0000021516885
Access: Private
Has various soil parameters
Private View
Public View
Channel Settings
Sharing
API Keys
Data Import / Export
Add Visualizations
Add Widgets
Export recent data
MATLAB Analysis
MATLAB Visualization
Channel 4 of 4
Channel Stats
Created: 5 months ago
Last entry: 5 months ago
Entries: 5571

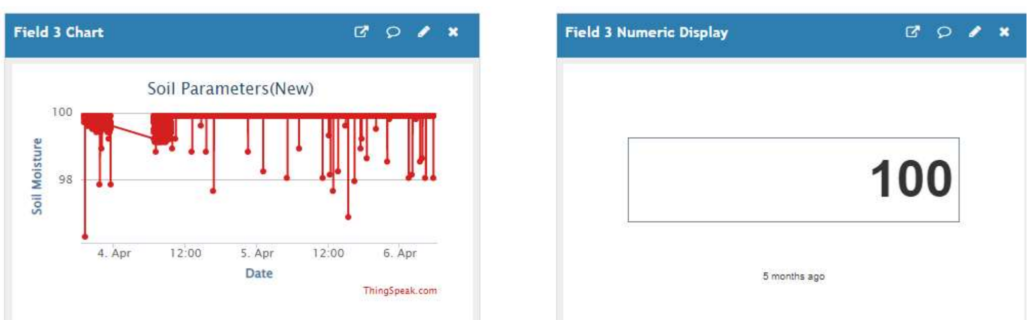
[A]


Field 1 Chart
Temperature
Temperature
40
30
4. Apr
12:00
5. Apr
12:00
6. Apr
Date
ThingSpeak.com
Field 1 Numeric Display
27
5 months ago

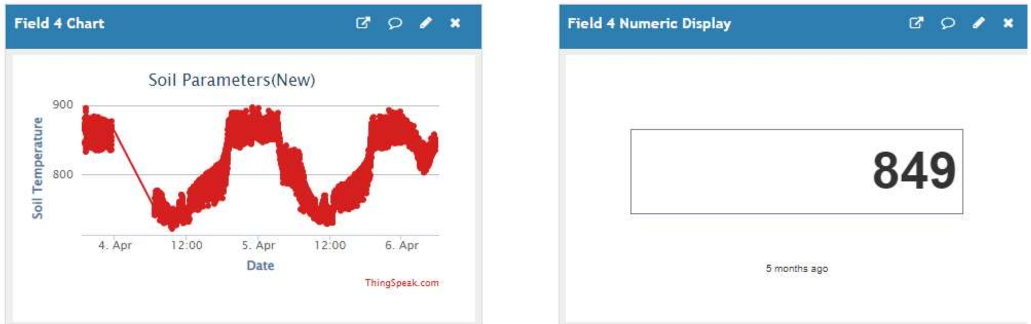
[B]


Field 2 Chart
Soil Parameters(New)
Humidity
50
4. Apr
12:00
5. Apr
12:00
6. Apr
Date
ThingSpeak.com
Field 2 Numeric Display
57
5 months ago

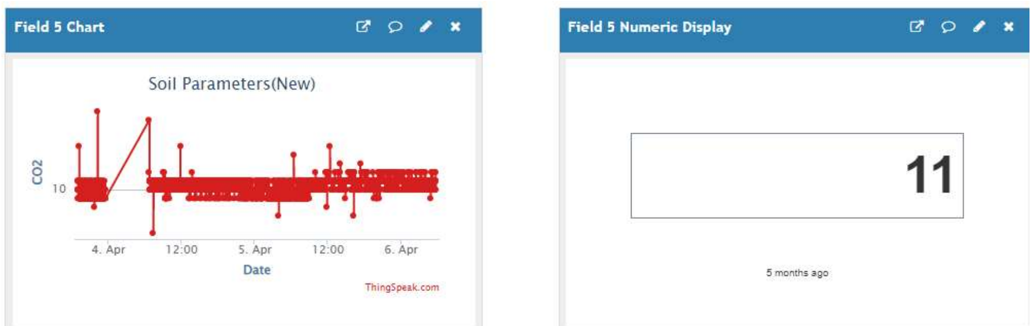
[C]


Field 3 Chart
Soil Parameters(New)
Soil Moisture
100
98
4. Apr
12:00
5. Apr
12:00
6. Apr
Date
ThingSpeak.com
Field 3 Numeric Display
100
5 months ago

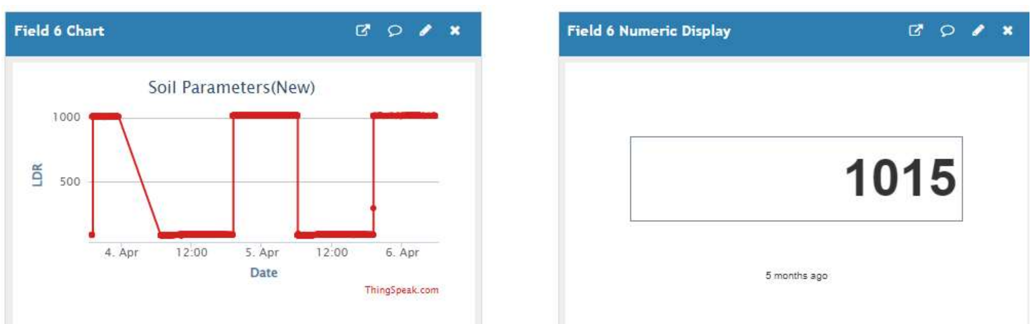
[D]



[E]



[F]



[G]

Figure 5.3 [A to G] Cloud detail with Presentation of Different Parameter for Proposed System

The Author ID is mwa000002151688 and Channel ID for the cloud is1674066, respectively. The entities are from Date-Time, 2022-04-03T07:37:44+00:00 to 2022-04-06T00:12:50+:00:00. Figure 5.3 shows the snapshot of cloud detail. Once, the CSV file is downloaded, then Splitting it in to training and testing with a standard ratio is 80% to 20%. Here the 80% data is for training and 20% data is for testing. So, there are 4456 entries are used to train the model and reaming 1115 entries for testing the model. To estimate the performance of models, we are going to find the same parameter as mentioned in table 4.5. Simultaneously, leaf images are uploaded on to the Google Drive. Approximately 1200 images are uploaded on to the cloud. Here the same techniques which are applied in chapter 3 and chapter 4 are applied, to find diseases inside the crop as well as to prediction of the soil moisture. This work establishes the generalization ability of ML\ DL algorithms derived in previous chapters.

5.4 FORECASTING SOIL MOISTURE FOR REAL TIME DATA

The suggested research initially finds the relation between target variable and covariate data. For this purpose, the correlation among all entities are found using heat map and pair plot.

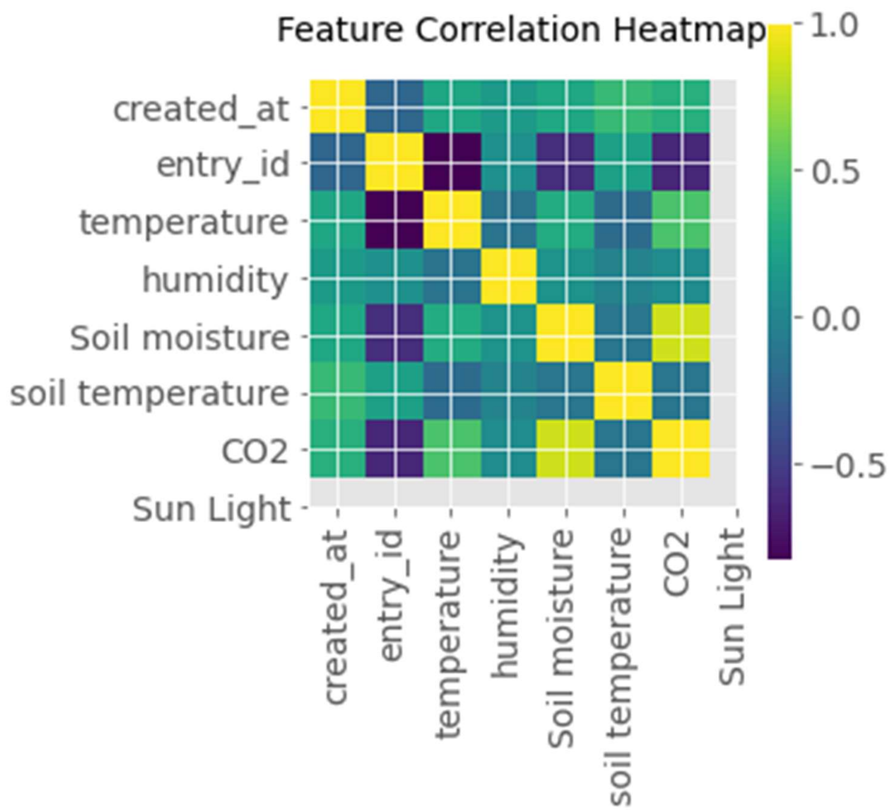


Figure 5.4 Heatmap of Real Time Data for Proposed System

Figure 5.4 and 5.5 show the heat map and pair plot respectively. From the analysis it is quite evident that data are linear and hence regression technique performs excellent as compare to SVM and ANN. Despite the widespread usage of wireless sensor networks (WSNs), data loss and corruption due to poor network performance, limited sensor bandwidth, and node failure during transmission seriously undermine the veracity of monitoring data. Due to these factors the input data becomes non-linear and hence regression model fails to performs best. It is desirable to develop a model based on SVM or ANN which can handle this issue efficiently.

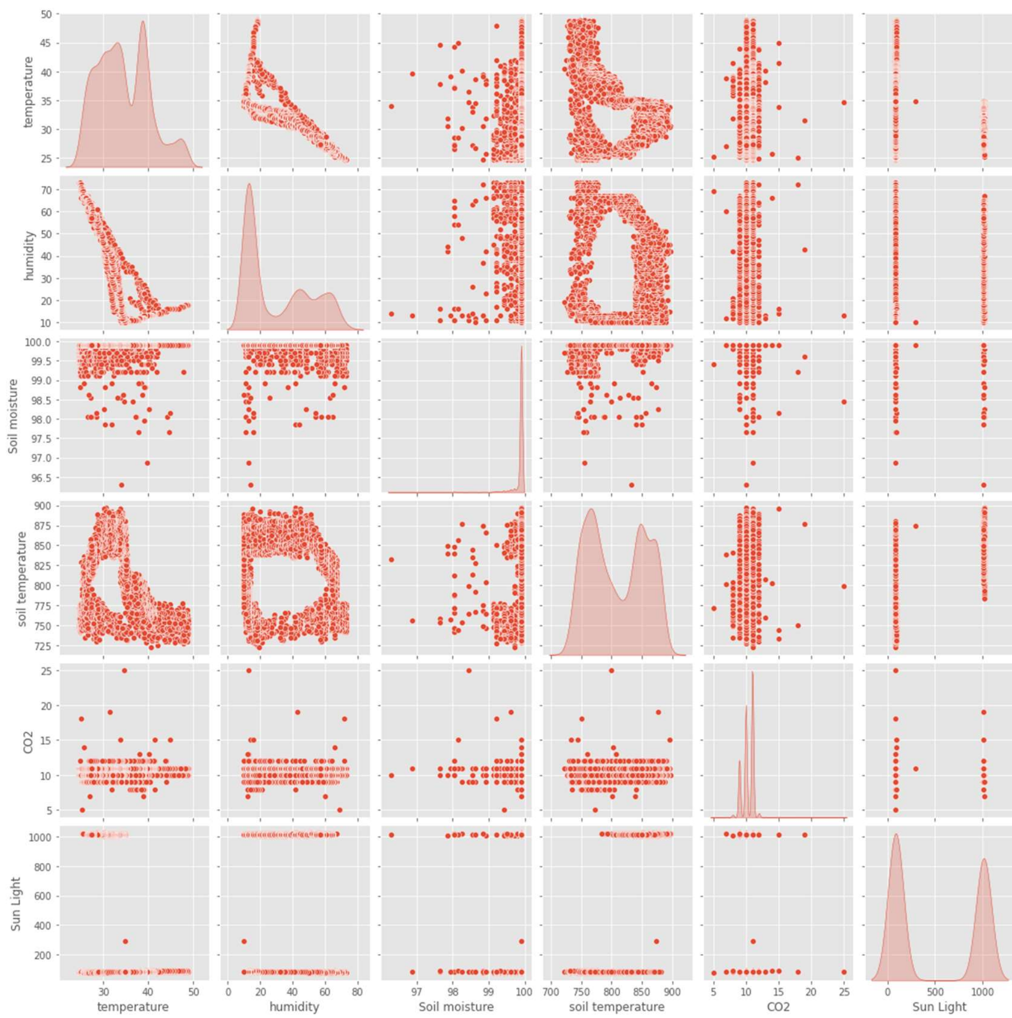


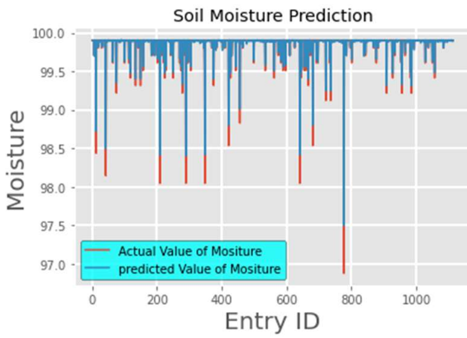
Figure 5.5 Pair plot of Real Time Data for Proposed System

The statistical analysis of CSV file is shown in table 5.2. this analysis is same as we have done section 4.8. this work helps to check whether the prepared technique is suitable for this real time data or not. From the entities of table 5.2 it is clear that the method suggested in section 4.8 is applicable without any hesitations. This outcome reflects the strength of ML / DL approach which proves the generalization ability of models with different dataset.

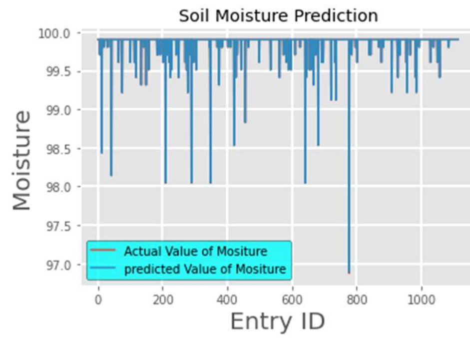
	count	Mean	Std	Min	25%	50%	75%	Max
Entry ID	5571	2786.000000	1608.353506	1.000	1393.500	2786.000	4178.500	5571.000
Temperature	5571	34.480505	5.726476	24.700	30.000	33.799	38.700	48.900
Humidity	5571	30.376593	20.139718	10.000	13.000	18.000	48.000	73.000
Soil Moisture	5571	99.864428	0.171356	96.289	99.902	99.902	99.902	99.902
Soil Temperature	5571	809.052773	46.584250	722.000	766.000	804.000	851.000	897.000
CO2	5571	10.301562	0.8494277	5.000	10.000	10.000	11.0000	25.000
Sun Light	5571	507.532579	462.479521	76.000	86.000	88.000	1015.000	1023.000

Table 5.2 Statistical Analysis of Real Time Data

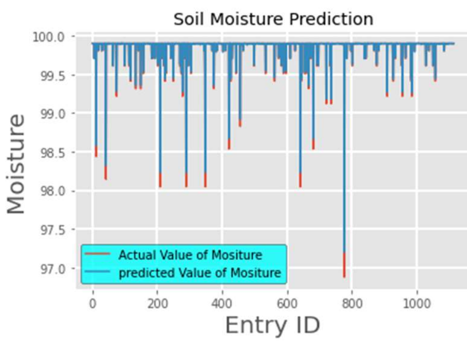
5.5 UPSHOTS FOR THE REAL TIME DATA



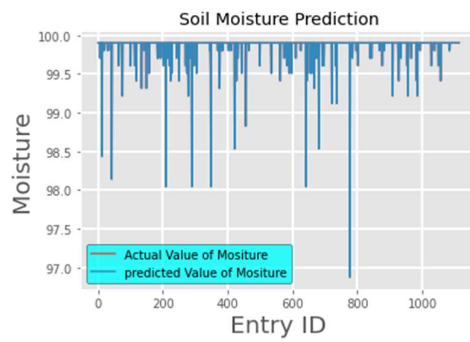
[A] Lasso Regression



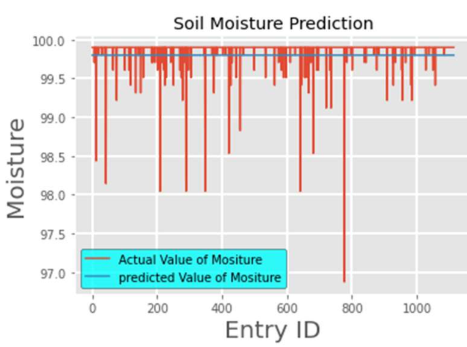
[B] Ridge Regression



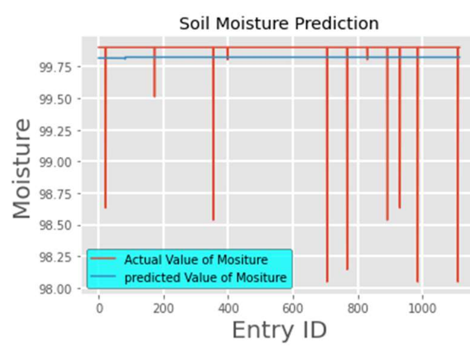
[A] ElasticNet Regression



[D] Bayesian Ridge Regression



[E] SVM



[F] ANN

Figure 5.6 [A to F] Plots of Outcomes of the Real Time Data with different Linear Regression Techniques, SVM, and Proposed ANN Model

Techniques		MAE	MSE	RMSE
Regression	Lasso	0.0127	0.0014	0.0385
	Ridge	0.0002	0.5 e-6	7.6 e-6
	ElasticNet	0.0063	0.00037	0.0194
	Bayesian Ridge	0.2 e-8	6.44 e-17	8.02 e-09
Support Vector Regression		0.121	0.0416	0.2040
Proposed Artificial Neural Network		0.1013	0.0414	0.1935

Table 5.3 Outcomes of the Real Time Data with Linear Regression, SVM and Proposed ANN Model

From the figure 5.6 (A to F) and table 5.3, quietly it can be seen that Bayesian Ridge regression give excellent performance amongst all. Although the results of SVM and proposed ANN are optimum to forecasting soil moisture. The suggested ANN Architecture performs little bit good as compare to SVM technique. If some nonlinearity occurs, like failure of sensors or some missing entities inside the dataset, then the recommended ANN model still performs well.

5.6 DISEASES IDENTIFICATION BY PROPOSED DSS

For plant disease identification, suggested system continuously upload the images of crop-leaf on google drive. Then from the image it is classifying the crop whether it healthy or diseased for an experiment, the proposed research applied on Jasminum sambac (Mogra) crop leaves with different stages. Known as the "Belle of India" or the "Queen of fragrance," jasmine is revered as the queen of flowers and is known for its wonderful scent, which is said to be calming and revitalizing. Since ancient times, jasmine has held a special place in religion and is used to fulfil both the senses of beauty and adoration. In Karnataka, a variety of jasmine species are grown. In India, jasmine is utilized for a variety of things and is revered greatly in Hinduism. In addition, the plant is a powerful relaxant and is used in Ayurvedic treatment. In addition, it is employed in the creation of fragrances and perfumes. India mostly supplies this oil to the European Union, England, the United States of America, Holland, Sweden, Japan, and Norway. Because jasmine flowers are extremely perishable and need to be handled carefully and thrown out quickly, the market is still regional. Aside from location, perishability makes the flower trade complicated and dangerous. The demand for flowers is also not consistent and steady. The link between supply and demand in the flower industry is influenced by elements such as geography, season, and socioreligious events.

5.7 SYSTEM INVESTIGATION FOR JASMINUM SAMBAC

5.7.1 Image Collection and Scrutinization

In suggested research the images of Jasmine sambac with different stages are taken and uploaded. Three different stages are considered namely, ‘Healthy’, ‘Leaf Blight’, and ‘Rust’. Three class are created for three different stages. Total 600 images are collected with each class contains 200 no. of images. Figure 5.7 shows the different stages of Jasminum sambac.

[A] Healthy **[B] Leaf Blight** **[C] Rust**

Figure 5 .7: Original Jasminum Sambac Crop Leaves Images

In this case, the system is trained with 480 photographs, and the remaining 120 shots are divided in to validation and test dataset, which is utilized to evaluate the procedure. To test the algorithm, we split the train images into three groups. After the model has been created using the other 80% of the photographs and validate using other 10% of photographs, it is tested using the remaining 10% of the images.

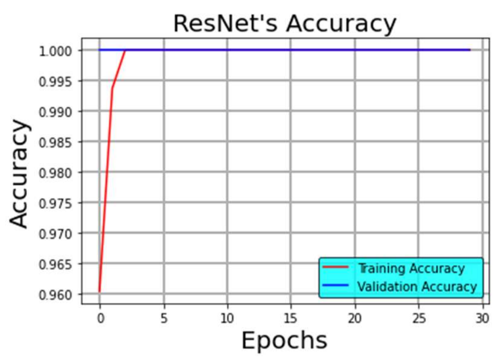
The bifurcations of various class kinds and the proportionate number of photos are displayed in Table 5.4.

- The Train Dataset has 480 samples.
- Sample count for Validation Dataset 60
- Sample count for Test Dataset 60

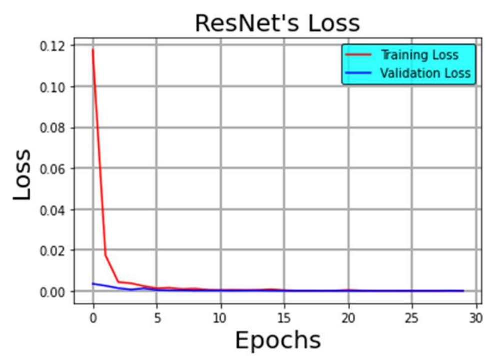
Class	No. of images for Training	No. of images for Validation	No. of images for Test
Healthy	160	20	20
Leaf Blight	160	20	20
Rust	160	20	20
Total No. of images	180	60	60

Table 5.4 No. Of Samples for Training, Validation and Test for Proposed System Generated Dataset

5.7.2 Outcomes of Model for Jasminum sambac



[A] Accuracy



[A] Loss

Figure. 5.8 Plots of [A] Accuracy and [B] Loss for Diseases identification in Jasminum sambac

		Healthy	Leaf Blight	Rusty
Actual Class	Healthy	20	0	0
	Leaf Blight	0	20	0
	Rusty	0	0	20

Table 5.5 Confusion Matrix for The Prediction of Resnet152v2 Model Trained with Transfer Learning for Mogra Crop

As shown in figure 5.8 the accuracy of proposed model for live Jasminum sambac images, is 100% with tends to zero loss. Table 5.5 shows the confusion matrix in which it is quite observable that all three types are identified correctly without any misjudge. This work once again proves the efficiency of deep learning technique with generalization ability.

The decision support system enlighten here, can forecast the moisture with minimum errors, at the same time it can monitor the health of a crop by identifying different stages of leaf.