Internet of Everything (ITL 702)

RAIN MONITORING BASED ON IOE

B. E. Information Technology

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DECLARATION

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources.

We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in this submission.

We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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CERTIFICATE

This Internet of Everything Lab Mini-project "Rain Monitoring Based on IOE" by Christina Mannakal, Aditi Pednekar, Anudnya Patil and Sherly Mathias is complete in all respects and was successfully demonstrated on {11th November 2022}.

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CONTENTS

Chapter No.	Chapter Name	Page Number
1	Introduction	1
2	Literature Review	2-3
3	Problem Statement	4
4	System Design and Requirements	5
5	Data Analytics Algorithm	6-9
6	Results	10-11
7	Conclusion and Future Scope	12
8	References	13

Chapter 1 Introduction

Water is an essential resource. Several studies have been conducted to understand rain. The passage of rainfall through a particular area is a dynamic process, it will change the intensity and shape of rain. The measurement and sensing of the amount and type of rain helps us develop a detailed description of rain physically and dynamically. So a better study of our environment and preparing for possible environmental disasters such as droughts or floods. The main aim of water management from rainfall is to reduce economic impact and risk of lives. Most of the developing countries depend on rainfall for their water needs. However if the management of rainfall water is poor, it is difficult to determine water losses to ground water recharge and how much is still available etc. Therefore rainfall measurement and monitoring is an important factor. A rainfall monitoring system will continuously measure rainfall and transmit the data to a platform where emergency services or weather experts can alert the residents of the locality, which is threatened by the impending rain related disaster. The primary objective of the project is to alert its occupants if the rainfall exceeds to a dangerous scale. Reliable rainfall monitoring system is a key for any water system analysis and for operational water system control. Rainfall is measured using gauges which are manually read or automatically send data to a network using a wireless communication system. The system consists of a Tipping Bucket Rain Gauge, an arduino board, Wi-Fi module and temperature as well as humidity sensors. The key hardware here is the Tipping Bucket Rain Gauge which collects and measures the rainfall. The acquired data is processed and transmitted with help of an arduino module where the intended recipient can view it. Tipping bucket rain gauges commonly used for measuring rainfall throughout the world.

Chapter 2 Literature Review

The authors in [1], have analyzed how high rainfall can cause floods in some communities because we need a tool and system which is designed by using Arduino Uno Microcontroller which is integrated with Rain sensor, Humidity, and Temperature sensor to monitor the weather. The authors proposed an application designed to provide warnings and reports on the size of the rainfall level that can minimize the potential for flooding from the beginning. The results of this study indicate that the design of the system with a fuzzy method is very effective, more responsive in providing information about the level of rainy weather.

The authors in [2], have analyzed the cricket match scenario, as it is a very popular game in the country. Due to rain, a major problem that the Cricket stadiums are facing nowadays is that the match gets either the matches are canceled or being delayed and played after the rain. So the authors have proposed a solution by introducing a Rain detector with Alarm and also an Automatic Roofing System for the Cricket Stadiums. This system includes an auto roof which covers the whole stadium. Whenever there is rainfall the rain sensor activates and gives intimation to the Arduino UNO, GSM and it will indicate the LED to glow, buzzer to make sound and the servo motor will automatically close the roof. At the same time a message is sent to the connected mobile device regarding the rain alert. When the rain stops, the roof opens automatically.

The authors in [3], have analyzed that rainwater can be harvested for agricultural purposes and household activities because as water is the main thing in human life we must try to save it and use it for future purposes. The authors proposed a solution in this project that will trigger the alarm when it rains so we can make some actions for rain water harvesting and also to save the rain water for using it later for agriculture in fields. The rain water detector-alarm system will be useful in both domestic and industrial applications. The rain sensor can be made so sensitive that it can detect even the smallest drop of water and triggers the buzzer which is proven to be quite reliable and consistent.

In Table 1 below, we provide the summarized survey results from the research paper studied.

Table 1 Summary of Literature Survey

Sr. no	Title	Methodology	Gaps/future scope
1.	Rain Detection System for Estimate Weather Level using the Mamdani Fuzzy Inference System.	This tool and system is designed by using Arduino Uno Microcontroller which is integrated with Rain sensor, Humidity, and Temperature sensor to monitor the weather. Analog and digital input data from Arduino are sent one by one to the	Implementation of weather forecasting requires accurate data from reliable sources to be used as material forecasting in the future. The use of forecasting in

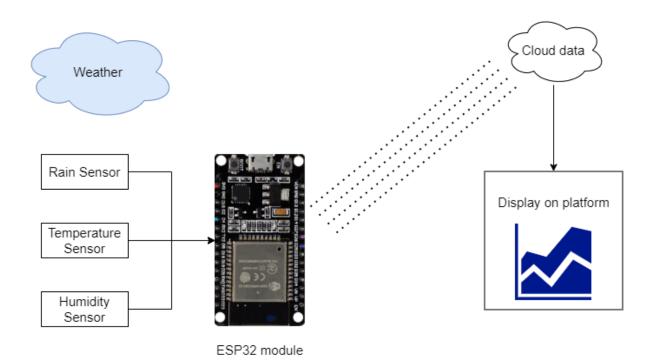
		Fuzzy Interface using serial protocols, the data processed using the Fuzzy Algorithm is used comparing the results of the Rain sensor, Humidity and Temperature sensor outputs.	the rainfall detection system may reduce the accuracy of the initial concept by using the Fuzzy Mamdani method to determine a precise and real time rainfall decision level.
2.	Rain Detector with Alarm	This paper is based on the project which is an embedded system consisting of a Rain drop sensor, Arduino Uno board and a SIM900 GSM module. Arduino Uno receives and processes the data from the sensors. The GSM unit acts as an interface between the Arduino and the user's mobile. The rain sensor will be placed at an open place. As soon as it senses the rain it will pass information to the Arduino which will in turn make the LED to glow, Buzzer to make sound and the alert message will be sent in turn the Servo Motor will automatically close the roof.	This Project does not indicate the rate at which rain falls on the roof. Until the detector is wet, a signal is issued or the LED lights up. The detector will not work until it is wet if something happens.
3.	Smart Rain Detector Using Arduino	The elements of this system includes Arduino Uno, Rain Sensor, Sensing Pad, Rain Module and Buzzer. This system works in such a way that, when there is rain, the rainwater acts as a trigger, which switches on the buzzer.	To use more appropriate rain sensor and make precise automatic rain sensing system with the help of a microcontroller based system to implement some security features for farmers

Chapter 3 Problem Statement

To build a rain sensing/monitoring smart device which will sense the environment parameters like humidity, temperature and provide probability of rain by conducting analysis..

System Design and Requirements

System Design



System requirements

Hardware Requirements:

- 1. ESP32 Module (NodeMCU)
- 2. FC-37 Rain sensor
- 3. DHT11 Humidity & Temperature Sensor
- 4. Jumper Wires
- 5. Breadboard

Software Requirements:

- 1. OS: Windows 7 or above
- 2. Browser: Chrome/Firefox/Edge/Brave
- 3. Application: Arduino IDE
- 4. MathWorks ThingSpeak

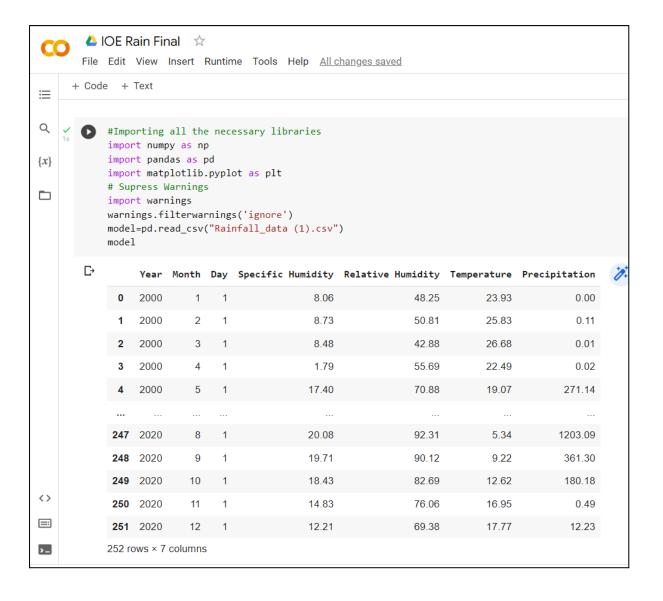
Chapter 5 Data Analytics

Regression analysis is a set of statistical methods used for the estimation of relationships between a dependent variable and one or more independent variables. It can be utilized to assess the strength of the relationship between variables and for modeling the future relationship between them.

In this project, linear regression is used and the dataset is divided in the ratio of 70:30.

The Dependent variable is precipitation and the independent variables are year, month, day, specific humidity, relative humidity and temperature. We can calculate probability of rain through precipitation.

Performance parameters are rmse and mean absolute error percentage.



0	model.head(5)							
C→		Year	Month	Day	Specific Humidity	Relative Humidity	Temperature	Precipitation
	0	2000	1	1	8.06	48.25	23.93	0.00
	1	2000	2	1	8.73	50.81	25.83	0.11
	2	2000	3	1	8.48	42.88	26.68	0.01
	3	2000	4	1	1.79	55.69	22.49	0.02
	4	2000	5	1	17.40	70.88	19.07	271.14

[93] model.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 252 entries, 0 to 251
Data columns (total 7 columns):

#	Column	Non-Null Count	Dtype
0	Year	252 non-null	int64
1	Month	252 non-null	int64
2	Day	252 non-null	int64
3	Specific Humidity	252 non-null	float64
4	Relative Humidity	252 non-null	float64
5	Temperature	252 non-null	float64
6	Precipitation	252 non-null	float64

dtypes: float64(4), int64(3)

memory usage: 13.9 KB

model.describe() ₽ Year Month Day Specific Humidity Relative Humidity Temperature Precipitation 252.000000 252.000000 252.0 2.520000e+02 2.520000e+02 2.520000e+02 252.000000 count mean 2010.000000 6.500000 1.0 6.145007e+14 2.116867e+12 8.130833e+08 206.798929 6.067351 3.458922 0.0 9.636212e+15 2.843746e+13 1.290730e+10 318.093091 2000.000000 1.000000 1.0 8.600000e-01 1.940000e+00 4.730000e+00 0.000000 min 25% 2005.000000 3.750000 1.0 9.685000e+00 5.119000e+01 1.063000e+01 0.402500 2010.000000 6.500000 1.0 1.458500e+01 6.659000e+01 1.687500e+01 11.495000 2015.000000 9.250000 1.0 1.887500e+01 8.551750e+01 2.220250e+01 353.200000 2020.000000 12.000000 1.529660e+17 4.425470e+14 2.048970e+11 1307.430000 [95] model.shape (252, 7) [96] model.columns

```
from sklearn.preprocessing import MinMaxScaler
    # Creating an instance of the sklearn.preprocessing.MinMaxScaler()
    scaler = MinMaxScaler()
    # Scaling the Price column of the created dataFrame and storing
    # the result in Scaled Column
   model[["ScaledPreci"]] = scaler.fit_transform(model[["Precipitation"]])
    print(model)
        Year Month Day Specific Humidity Relative Humidity Temperature
C→
   0
        2000
                 1
                      1
                                      8.06
                                                       48.25
                                                                   23.93
   1
        2000
                  2
                     1
                                      8.73
                                                       50.81
                                                                   25.83
        2000
                                                       42.88
   2
                  3
                      1
                                     8.48
                                                                   26.68
        2000
                  4
                                     1.79
                                                       55.69
   3
                      1
                                                                   22.49
    4
        2000
                  5
                      1
                                     17.40
                                                       70.88
                                                                   19.07
         . . .
                                     . . .
   247 2020
                                    20.08
                                                      92.31
                                                                   5.34
                8
                     1
                                                      90.12
   248 2020
                9
                     1
                                    19.71
                                                                   9.22
   249 2020
                10 1
                                    18.43
                                                      82.69
                                                                   12.62
                                                      76.06
   250 2020
                                    14.83
                                                                   16.95
                11
                    1
   251 2020
                12
                                    12.21
                                                      69.38
                                                                   17.77
                      1
        Precipitation ScaledPreci
                        0.000000
   0
                0.00
                0.11
                         0.000084
   1
                0.01
   2
                         0.000008
   3
                0.02
                         0.000015
   4
               271.14
                         0.207384
   . .
                 . . .
              1203.09
                         0.920195
   247
   248
               361.30
                         0.276344
               180.18
   249
                         0.137812
   250
               0.49
                         0.000375
   251
               12.23
                         0.009354
    [252 rows x 8 columns]
```

```
[98] #define X=features and Y=target variables
       Y=model['ScaledPreci']
       # X=model[['Year', 'Month', 'Day', 'Specific Humidity', 'Relative Humidity', 'Temperature']]
       X=model[['Year', 'Month','Day','Relative Humidity','Temperature']]
✓ [109] Y.shape, X.shape
       ((252,), (252, 5))
/ [101] from sklearn.model_selection import train_test_split
       X_train,X_test,y_train,y_test=train_test_split(X,Y,train_size=0.7,random_state=5)
  X_train.shape,X_test.shape,Y_train.shape,Y_test.shape
       ((176, 5), (76, 5), (176,), (76,))
  import statsmodels.api as sm
       # Add a constant to get an intercept
       X train sm = sm.add constant(X train)
       # Fit the resgression line using 'OLS'
       lr = sm.OLS(y_train, X_train_sm).fit()
       # Print the parameters,i.e. intercept and slope of the regression line obtained
       lr.params
   [→ Year
                           3.888127e-04
       Month
                           -1.827015e-02
       Day
                           -7.889811e-07
       Relative Humidity -1.835272e-15
                           -3.143700e-02
       Temperature
       dtype: float64
```

```
#Performing a summary operation lists out all different parameters of the regression line fitted
print(lr.summary())
                                OLS Regression Results
Dep. Variable: ScaledPreci
                                                R-squared:
                                 OLS Adj. R-squared:
                                                                                    0.613
                          Least Squares
Method:
                                               F-statistic:
                                                                                       93.42
Method: Least Squares F-statistic:
Date: Tue, 01 Nov 2022 Prob (F-statistic):
Time: 06:10:13 Log-Likelihood:
No. Observations: 176 AIC:
Df Paciduals: 177 RIC:
                                                                                 6.47e-36
Df Residuals:
                                       172 BIC:
Df Model:
Covariance Type: nonrobust
_____
                           coef std err t P>|t| [0.025 0.975]
                                      -----

        Year
        0.0004
        2.45e-05
        15.843
        0.000
        0.000
        0.000

        Month
        -0.0183
        0.004
        -4.919
        0.000
        -0.026
        -0.011

        Day
        -7.89e-07
        2.29e-07
        -3.442
        0.001
        -1.24e-06
        -3.37e-07

        Relative Humidity
        -1.835e-15
        1.63e-15
        -1.124
        0.263
        -5.06e-15
        1.39e-15

        Temperature
        -0.0314
        0.002
        -16.344
        0.000
        -0.035
        -0.028

 _____

        Omnibus:
        32.069
        Durbin-Watson:
        2.134

        Prob(Omnibus):
        0.000
        Jarque-Bera (JB):
        67.824

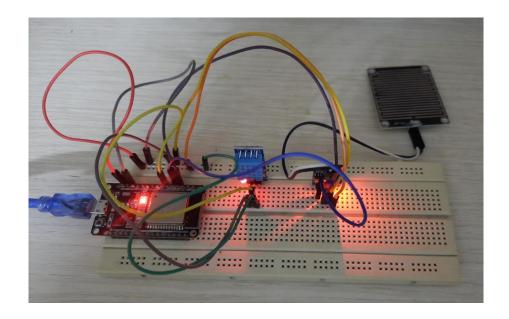
        Skew:
        0.826
        Prob(JB):
        1.87e-15

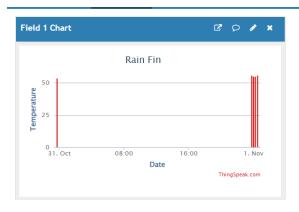
        Kurtosis:
        5.553
        Cond. No.
        2.28e+15

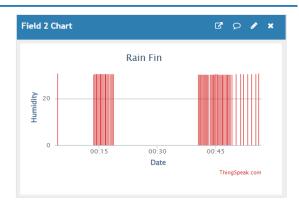
_____
 [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
 [2] The condition number is large, 2.28e+15. This might indicate that there are
 strong multicollinearity or other numerical problems.
[105] # Add a constant to X_test
      X_test_sm = sm.add_constant(X_test)
       # Predict the y values corresponding to X_test_sm
       y_pred = lr.predict(X_test_sm)
      y_pred.head()
      247
               0.471366
              0.056836
       168
      127
              0.444529
               0.008367
       83
       216
                0.103347
       dtype: float64
[106] #Imporitng libraries
       from sklearn.metrics import mean_squared_error
       from sklearn.metrics import r2_score
 ] from sklearn.metrics import mean_absolute_error,mean_absolute_percentage_error
       mean_absolute_error(y_test,y_predict)
       mean_absolute_percentage_error(y_test,y_predict)
 → 3.8221283334379476e+23
 pickle.dump(Lr, open('model.pkl','wb'))
       model = pickle.load(open('model.pkl','rb'))
       #Y,M,D,H,T
       pop = model.predict([[2020,1,1,48.25,23.93]])
       array([0.04235236])
```

Chapter 6 Results

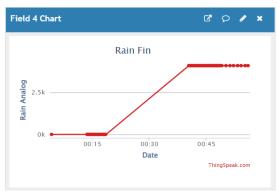
Setup:

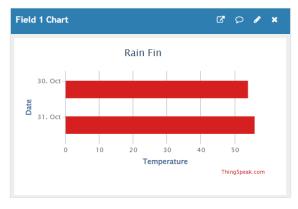


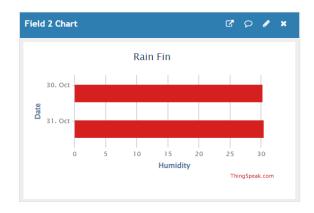


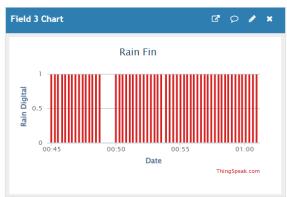






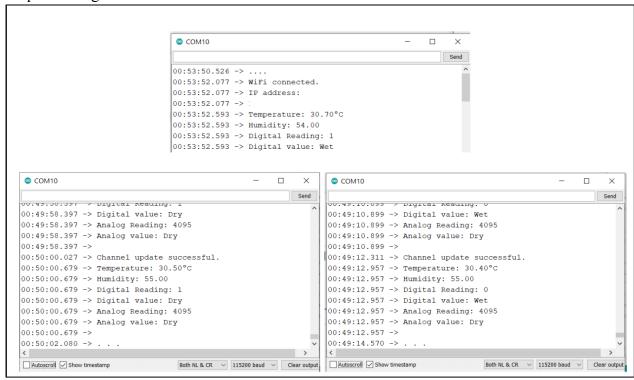








Output reading on Arduino IDE Serial Monitor with baudrate 115200:



Chapter 7 Conclusion and Future Scope

In this project we built a Rain Sensing/Monitoring smart device which senses the environment and alerts the user about rain and conducts analysis. This project introduces an intelligent rain sensing/ monitoring system in the IoT platform which would help users by alerting them about rain so they can take appropriate actions. This rain monitoring system will display the data collected from the sensor using thingspeak as an analysis platform. The result is displayed in the form of a graph.

This system can be improved by adding additional mechanisms like a shutter that automatically closes when the sensor detects rain. We can add LEDs that can indicate the probability of rain i.e green LED will glow if it is not going to rain anytime soon and red LED will glow if there is high probability of rain.

References

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