IoT BASED AIR POLLUTION FORECASTING AND MONITORING

AN INTERNAL FUNDED PROJECT REPORT

Submitted By

SRINITHYEE SK 185500166 - III Year

VENKATARAMAN N 185001192 - III Year

VISHAKAN S 185001192 - III Year

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KALAVAKKAM 603110

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SSN COLLEGE OF ENGINEERING : CHENNAI 603110

BONAFIDE CERTIFICATE

Certified that this project report titled **IoT BASED AIR POLLUTION FORECASTING AND MONITORING** is the *bonafide* work of **Srinithyee SK (185001166 - III Year)**, **Venkataraman N(185001192 - III Year)**, and **Vishakan S (185001196 - III Year)**, who carried out the project work under our supervision as an internal funded project in department of CSE during the Academic year 2019-2020.

Dr. R Priyadharshini
Supervisor
Associate Professor,
Department of CSE,
SSNCE

Ms. S Manisha
Supervisor
Assistant Professor,
Department of CSE,
SSNCE

Dr. Chitra Babu
Head of the Department
Professor,
Department of CSE,
SSN College of Engineering,
Kalavakkam - 603 110

Place:
Date:

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Srinithyee SK **Venkataraman N** **Vishakan S**

ABSTRACT

Air pollution is the single largest environmental and public health challenge in our current world. It leads to adverse effects in human health, climate and ecosystem. Air gets polluted due to the release of toxic greenhouse gases emitted from industries and vehicular exhaust. Particulate matter concentration in the air has reached record levels in recent years, and has contributed significantly to the decrease in air quality levels worldwide.

All this creates a need for real-time air quality monitoring so that appropriate decisions can be taken in a timely period.

Internet of Things is an enabling technology in this area, and can be used to perform this task of monitoring the air pollution levels in an environment. For our purposes, we use the very popular **Raspberry Pi**, which is a key component in many IoT applications currently.

On combining this technology with **cloud computing** technology, we get a novel technique for better data management. Besides greatly streamlining the conventional air quality monitoring system, it is also used in our project as a tool to forecast future values of these different gases/particulate matter in the

atmosphere, by analyzing the current trend in data and utilizing powerful machine learning algorithms like **XGBoost** to give reliable forecasts.

The aftermath of applying all these different technologies is that in the end we get a portable, low-cost, reliable, robust and easily manufacturable machine that can be used in any type of environment for efficient air quality sensing and prediction.

A by-product of the project is that research people and enthusiasts have access to a high-quality and reliable dataset for air quality levels in different areas, which can be used.

Thus, one can take targeted emergency disposal measures to minimize losses in environmental hot-spots, industries and factories. An individual can better assess and understand the air quality around himself/herself and can take steps necessary to maintain a safe and healthy living environment.

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CHAPTER 1

INTRODUCTION

Air pollution has become one of the major existential threats on Earth. Its seriousness has captured the attention of scientists, climate experts and politicians all over the world, and many novel ideas are being developed to curb air pollution.

This project is our small and humble contribution towards creating awareness amongst people about air pollution.

Air pollution monitoring largely till now has been entirely undertaken by government weather agencies and certain private agencies abroad as well. They study the air pollution levels of a city as a whole and provide metrics that reflect the average air quality in broad areas. These metrics are detected and analysed using high-cost, resource-intensive systems that are installed permanently in a place for the purpose of monitoring.

Our system was developed with the aim of making it low-cost, portable, personalized and comparably accurate to the sophisticated systems in use today. The three main enablers of our vision are Internet of Things (IoT), Cloud Computing & Machine Learning.

There are low-cost electrochemical gas sensors that detect different constituents of the air, like nitrous oxides, carbon dioxide, carbon monoxide, greenhouse gases like methane, dust sensors and many more. These sensors can be integrated onto a portable computer system like Raspberry Pi which can poll these sensors periodically to obtain readings. Since these sensors provide readings that are more relevant to the immediate environment around them, the monitoring aspect is much more personalized and reflective of the true air quality around the user. The whole arrangement can be fitted onto a relatively small breadboard, thus being very portable. It requires only a power supply and a working WiFi internet connection to work as expected.

The system once powered on, takes readings periodically, at every 2 minutes and stores them locally as well as upload it to the cloud, in our case, a simple Google Sheet which accumulates the periodical readings for further analysis and future use. Since readings are taken for every couple of minutes, the system is much more real-time compared to conventional systems. We have leveraged this property of our system and integrated it with a simple buzzer alarm to intimate the user if the pollution level around him/her is high, and thus acts as an indicator for possible gas leakage, smoke or fire situation. More details are provided in the Hardware Implementation section below.

The final and most crucial process of our system is the data analysis and prediction part, which aims to provide the user with expected values in the near future for the different air pollution influencing agents such as methane, dust, carbon monoxide, humidity, temperature, pressure, residual smoke etc. This helps the user get a visual and mathematical picture on the air quality around him/her. Our system also provides the user with various statistical insights like mean,median, extreme values noted, quartile measures and also enables the user to understand the data visually through plots such as histograms, density plots and scatter plots. The machine learning models that we use in our system to capture the intricate tendencies and fluctuations of the air quality data (obtained from the sensors) is XGBoost. These are two very well-known and highly robust models used in various applications.

XGBoost is a prominent machine learning method that has gained in popularity recently, and it outperforms conventional random forests and other popular models. It basically implements a gradient boosting framework to existing machine learning methods, making it much more superior and efficient.

The model works effectively well for our purpose as well. Details regarding the working and implementation specifics can be found below in the Software Implementation section.

CHAPTER 2

LITERATURE SURVEY

Paper 1 – Urban air pollution monitoring system with forecasting models.

Authors - E. Rezk, A. Kadri, K. B. Shaban

Conference/journal – IEEE journal, 2016: Three machine learning (ML) algorithms - Support Vector machines, M5P model trees, and Artificial Neural Networks (ANN) are used to build accurate forecasting models for one-step and multi-step ahead of concentrations of ground-level ozone (O_3), nitrogen dioxide (NO_2), and sulphur dioxide (SO_2). Two types of modelling are pursued: univariate and multivariate. The results show that using different features in multivariate modelling with M5P algorithm yields the best forecasting performance.

Paper 2 – IOT- Based Air Pollution Monitoring and Forecasting System.

Authors - Liu Xianpeng, XuPeng, Chen Xiaojun

Conference/journal – IEEE conference, 2015 In this paper, a large number of field data provided by frontend sensor network makes big data analysis in background application layer more direct and effective, providing a real and effective decision-making. The algorithm can be further improved which can increase number of input layer.

Paper 3 – IoT for environmental variables in urban areas.

Authors - Jorge E. Gómez, Fabricio R. Marcillo, Freddy L. Triana, Victor T. Gallo,Byron W. Oviedo, Velssy L. Hernández

Conference/journal – ELSEVIER International Conference, 2017: The paper suggests the use o listener sensors to collect information and the management used as a mediator to the storage to retrieve and delivery information. Machine learning algorithm can be used to predict the future air condition to deliver accurate information to take quick measurements.

Paper 4 – A Comprehensive Evaluation of Air Pollution Prediction Improvement by a Machine Learning Method

Authors - Xia Xi, Zhao Wei, Rui Xiaoguang, Wang Yijie, Bai Xinxin, Yin Wenjun, Don Jin

Conference/journal – IEEE conference, 2015 In this paper the air pollution prediction works by air quality index using the machine learning algorithms. From experiments, for different city, the best result can be obtained by different group of feature selection and model selection. Usage of sensors can further enhance the usability of the model.

Paper 5 – Wireless Sensor Network Based Pollution Monitoring System in Metropolitan Cities.

Authors - Shwetal Raipure, Deepak Mehetre

Conference/journal – IEEE International Conference, 2015: In this paper AVR ATmega-32 Microcontroller and sensor grid are used to detect the sensor values from different sensor like parameters MQ5, MQ7, temperature and humidity dataset. The simulation results shows that performance of the quality of service increased in the network.

Paper 6 – Distributed System as Internet of Things for a new low-cost, air pollution Wireless Monitoring on Real Time.

Authors - Walter Fuertes, Diego Carrera, César Villacís, Theofilos Toulkeridis, Fernando Galárraga, Edgar Torres, and Hernán Aules

Conference/journal – IEEE International Conference, 2015: Paper proposes a low-cost wireless monitoring system, that enables air quality referential parameters measurements based on a multilayer distributed model. Agile methodologies such as Scrum and extreme programming was used.

Paper 7 – A smart environmental monitoring system using Internet of Things

Authors - Dr. A. Sumithra, J.Jane Ida, K. Karthika, Dr. S. Gavaskar

Conference/journal – IJSEAS Journal, 2016: IoT was used in monitoring air or water quality, atmospheric or soil conditions to monitor air pollution using sensors along with cloud storage and big data analytics. It is suggested to include future prediction.

Paper 8 – Machine Learning Approach to Forecasting Urban Pollution

Authors - Yves Rybarczyk, Rasa Zalakeviciute

Conference/journal – IEEE 2016: This paper addresses the question of how to predict fine particulate matter given a combination of weather conditions by Predicting the air pollution with 2223 dataset using decision tree algorithm.

Paper 9 – IoT enabled Environmental Monitoring System for Smart Cities

Authors - Jalpa Shah, Biswajit Mishra

Conference/journal – IEEE 2016 IoT enabled environmental monitoring system for monitoring temperature, relative humidity and CO2.

Paper 10 – Predicting Trends in Air Pollution in Delhi using Data Mining

Authors - ShwetaTaneja, Dr. Nidhi Sharma, Kettun Oberoi, Yash Navoria

Conference/journal – IEEE 2016: In this paper they tried to utilize data mining tool WEKA to predict future along with algorithm like linear regression and multilayer perceptron.

CHAPTER 3

AIR POLLUTION PREDICTION AND MONITORING HARDWARE IMPLEMENTATION

The air pollution model localises the prediction pertaining to the user's area rather than using the one that generalizes for the whole region/ district.

The user is provided with the web-based user interface, which he/she could use to see predictions and the most recent value from the sensor, the user is even alerted of immediate pollution using a alarm.

The researchers can even use the statistical analysis - Mean, Median, Mode, Accuracy, Minimum, Maximum for each sensor i.e each pollutant individually.

3.1 Hardware Components

Raspberry Pi 3 model B+

Technical parameters and features:

- Quad Core 1.2GHz Broadcom BCM2837 64bit CPU
- 1GB RAM
- BCM43438 wireless LAN and Bluetooth Low Energy (BLE) on board

- 100 Base Ethernet
- 40-pin extended GPIO
- 4 USB 2 ports
- 4 Pole stereo output and composite video port
- Full size HDMI
- Micro SD port for loading your operating system and storing data
- Upgraded switched Micro USB power source up to 2.5A
- Power: 5V/2.5A DC power input
- Operating system support: Linux and Unix

MQ-135

MQ-135 is a Air quality sensor that is used to measure the air-quality index of the environment

Technical parameters and features:

- Wide detecting scope
- Fast response and High sensitivity
- Stable and long life
- Operating Voltage is $+5V$
- Detect/Measure $NH_3, NO_x, alcohol, Benzene, smoke, CO_2$, etc.

- Analog output voltage: 0V to 5V
- Digital output voltage: 0V or 5V (TTL Logic)
- Preheat duration 20 seconds
- Can be used as a Digital or analog sensor
- The Sensitivity of Digital pin can be varied using the potentiometer

MQ-9

MQ-9 is used to detect CO and combustible gases

Technical parameters and features:

- Wide detecting scope
- Fast response and High sensitivity
- Stable and long life
- Operating Voltage is +5V
- Concentration 10-1000ppm CO & 100-10000ppm combustible gas

- Loop Voltage Vc $\leq 10VDC$

MQ-2

MQ-2 sensor is used to detect Methane, Butane, smoke and LPG

Technical parameters and features:

- Wide detecting scope

- Operating Voltage is +5V
- Can be used to Measure or detect LPG, Alcohol, Propane, Hydrogen, CO and even methane
- Analog output voltage: 0V to 5V
- Digital Output Voltage: 0V or 5V (TTL Logic)
- Preheat duration 20 seconds
- Can be used as a Digital or analog sensor
- The Sensitivity of Digital pin can be varied using the potentiometer

BMP280

BMP28- is used to measure atmospheric pressure

Technical parameters and features:

- Model: GY-BMP280-3.3
- Chip: BMP280
- Power supply: 3V/3.3V DC
- Peak current: 1.12mA
- Air pressure range : 300-1100hPa (equi. to +9000 to -500m above sea level)
- Temperature range: -40 to +85 °C
- Digital interfaces: I²C (up to 3.4 MHz) and SPI (3 and 4 wire, up to 10 MHz)

- Current consumption of sensor BMP280: 2.7µA @ 1 Hz sampling rate

DHT11

DHT11 is used to measure temperature and humidity

Technical parameters and features:

- Operating Voltage: 3.5V to 5.5V
- Operating current: 0.3mA (measuring) 60uA (standby)
- Output: Serial data
- Temperature Range: 0°C to 50°C
- Humidity Range: 20% to 90%
- Resolution: Temperature and Humidity both are 16-bit
- Accuracy: ±1°C and ±1%

3.2 Hardware implementation / Model

The Air-Quality sensors MQ135, MQ9, MQ2, BMP280, DH11 are connected to the power distributor which is then connected to the Raspberry pi 3+, The GPIO pins are used are used to connect the alarm to sense any immediate pollution. The Raspberry Pi is powered using a type B cable. The Raspberry pi contains a 16GB SD card to store backup data.

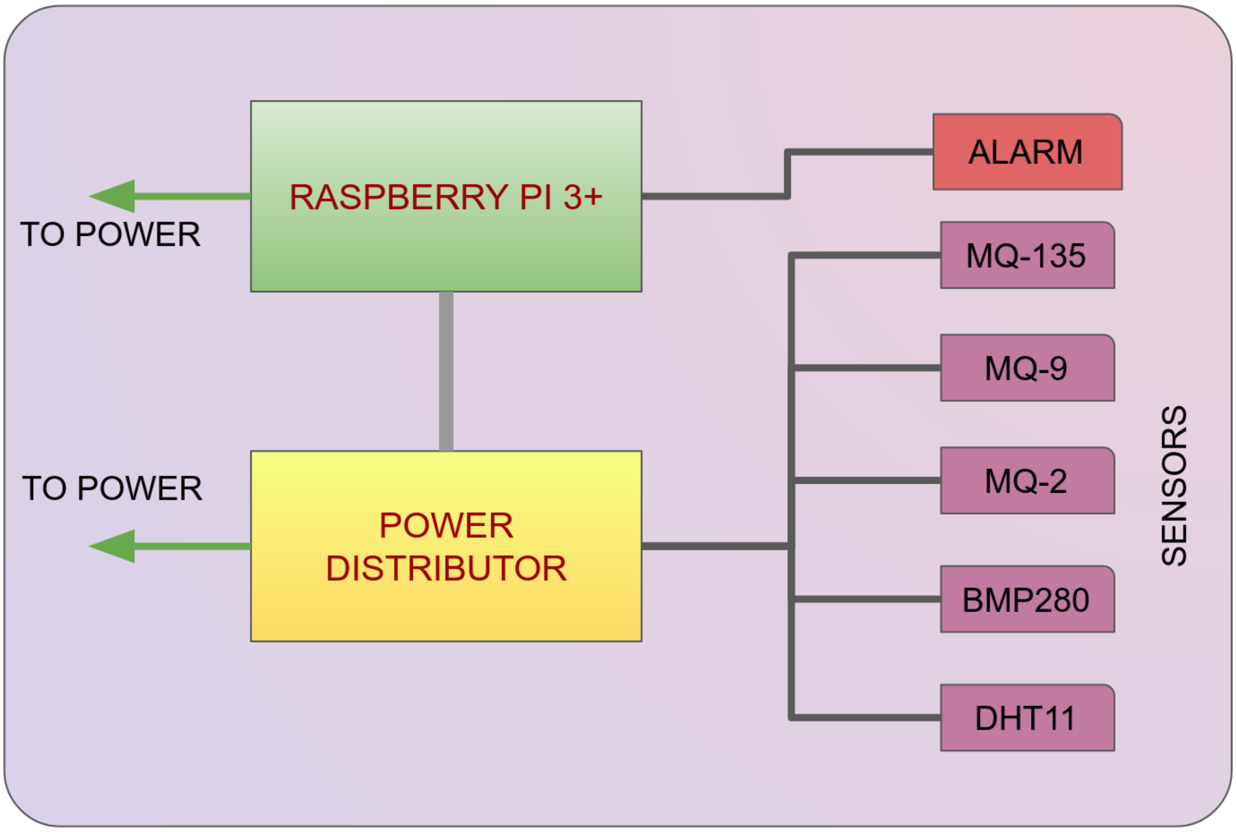


FIGURE 3.1: Block diagram of Hardware implementation Layer

3.3 Architecture model

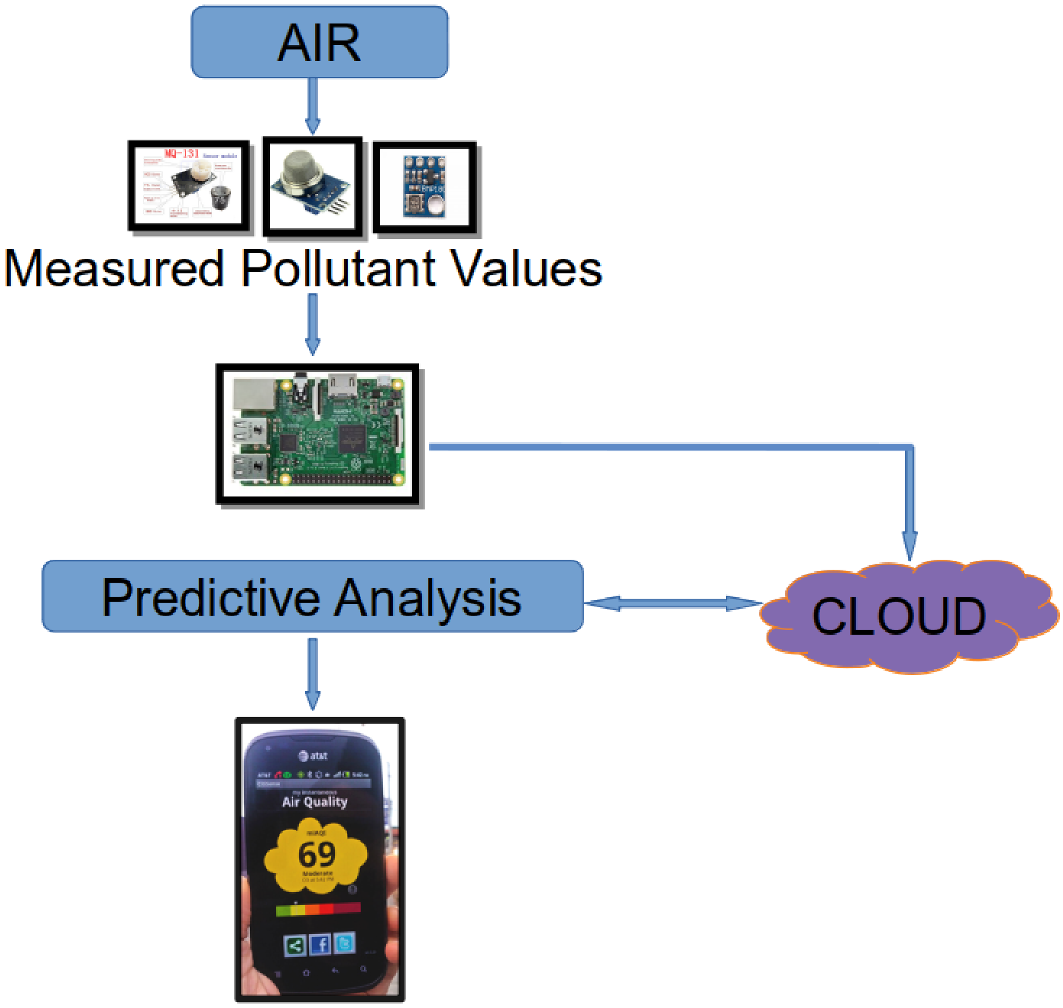


FIGURE 3.2: Architecture diagram

CHAPTER 4

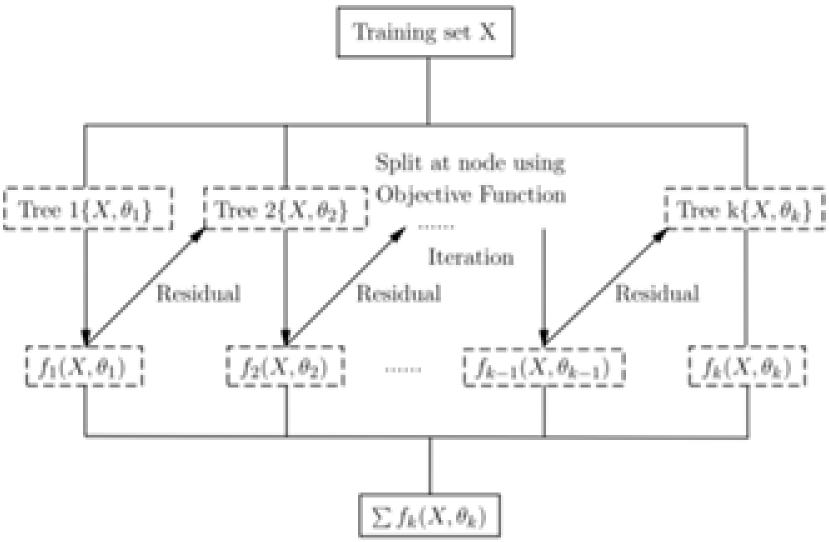
AIR POLLUTION PREDICTION AND MONITORING SOFTWARE IMPLEMENTATION

The data collected from the sensors are recorded real time in google sheets. This data is synchronized with the software and is used to train the Machine Learning model. Before feeding the data to train the model, it is cleaned, removing fallacious data and empty data cells. The analytics and modelling approach for the prediction engine for dynamic, low velocity settings is presented. The algorithmic model used for these settings is based on supervised machine learning technique called XGBoost for predicting air pollution, and is briefly discussed below.

4.1 Boosting

Boosting refers to a class of learning algorithms that fit models by combining many simpler models (Schapire and Freund, 2012). The beauty of this powerful algorithm lies in its scalability, which drives fast learning through parallel and distributed computing and offers efficient memory usage. XGBoost uses the craft of penalization of the individual trees. The trees are consequently allowed to have varying number of terminal nodes. XGBoost can shrink leaf using penalization. The benefit of this is that the leaf weights are not all shrunk by the same factor, but leaf weights estimated using less evidence in the data will be shrunk more heavily. Again, we see the bias-variance trade-off being taken into account during model fitting. The superior performance of XGBoost in supervised machine learning is the reason why it is chosen to train the classifier in this work. Gradient boosting is the original model of XGBoost, combining weak base learning models into a stronger learner in an iterative fashion. As shown in Fig. below, at each iteration of gradient boosting, the residual will be used to correct the previous predictor that the specified loss function can be improved. As an enhancement, regularization is added to the loss function to establish the objective function in XGBoost measuring the model performance, which is given as

$$J(\theta) = L(\theta) + \Omega(\theta) \tag{4.1}$$



Flow chart of extreme gradient boosting.

FIGURE 4.1: Gradient Boosting

The parameters trained from given data are denoted as θ. L is the training loss function, such as square loss or logistic loss, which measures how well the model fits on training data. Ω is the regularization term, such as L_1 norm or L_2 norm, which measures the complexity of the model. Simpler models tend to have better performance against over-fitting.

4.2 Data Specification

Air quality dataset: It contains the air quality data of a place in Chennai. Each data item of the dataset contains the timestamp, Smoke concentration, Carbon Monoxide concentration (MQ-9 sensor), Air Quality Index (MQ-135 sensor), Humidity, Temperature, Pressure (in hPa) and Dust (in µg/m3) respectively measured by the air quality monitoring system. Table drawn below provides the statistical description of the leading indicators in the air quality dataset, including the maximum, minimum, and average values of the contained data.

Features	**Minimum**	1^{st} **Quartile**	**Median**	**Mean**	3^{rd} **Quartile**	**Maximum**
Smoke	114.0	122.6	126.1	126.6	129.0	162.5
CO	59.12	85.88	96.70	99.02	109.39	270.55
Air Quality	63.70	82.38	100.78	102.97	121.77	167.30
Humidity	56.00	66.00	73.00	73.23	79.00	172.00
Temperature	13.00	28.00	28.00	28.05	29.00	29.00
Pressure	982.0	985.0	986.0	986.6	988.0	990.0
Dust	1.370	2.440	3.250	5.931	8.630	32.920

4.3 Data Feature contribution

In order to evaluate the validity of the basic features and statistical features, we enumerate the 7 features in Figure by their feature importance. Each of these features contain six statistical features, and predictive features, which verifies the feasibility and effectiveness of using statistical features and the predictive correlation features in this project.

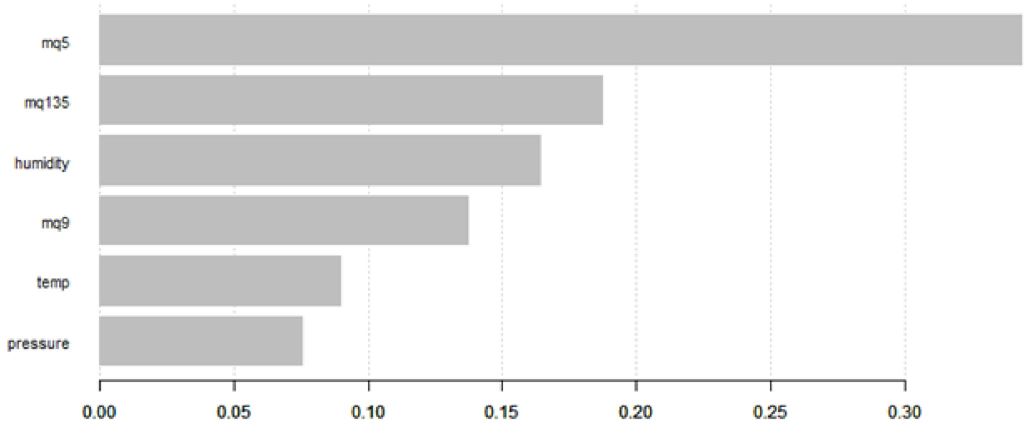


FIGURE 4.2: Feature Importance graph

4.4 Algorithm

1. Initialization: $\hat{y}_i^{(0)} = 0$

2. Add a new tree at each iteration t:

(a) At the beginning of each step t, compute G_i and H_i

$G_i = \Sigma_{i \in I_j}\, g_i$ and $H = \Sigma_{i \in I_j}\, h_i$ Where,

$$g_i = \frac{d}{d\hat{y}_i^{(t-1)}} d(y_i, \hat{y}_i^{(t-1)})$$

and

$$h_i = \frac{d^2}{d^2\hat{y}_i^{(t-1)}} d(y_i, \hat{y}_i^{(t-1)})$$

(b) Build the tree $f_t(x)$:

(A) Start with an empty tree.

(B) For each node, find the best splitting for each feature and select the one maximising gain.

(c) Add the tree $f_t(x)$ to the model:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \eta f_t(x_i)$$

where η is the learning rate.

The **Gain** implies the relative contribution of the corresponding feature to the model calculated by taking each feature's contribution for each tree in the model. A higher value of this metric when compared to another feature implies it is more important for generating a prediction.

The **Coverage** metric means the relative number of observations related to this feature.

The **Frequency (R)/Weight (python)** is the percentage representing the relative number of times a particular feature occurs in the trees of the model.

	Feature	Gain	Cover	Frequency
1:	mq5	0.34405159	0.31002350	0.43884359
2:	mq135	0.18773240	0.19247892	0.19792439
3:	humidity	0.16472043	0.10606940	0.08747220
4:	mq9	0.13741459	0.34702060	0.24314307
5:	temp	0.09021129	0.02010231	0.01111935
6:	pressure	0.07586970	0.02430527	0.02149741

FIGURE 4.3: Sample statistical data from the dataset

4.5 Linear Booster Specific Parameters

- lambda and alpha: These are regularization term on weights. Lambda default value assumed is 1 and alpha is 0.
- lambda_bias: L2 regularization term on bias and has a default value of 0.

4.6 Learning Task Parameters

- base_score: The default value is set to 0.5. It is essential to specify the initial prediction score of all instances, global bias.

- Objective: The default value is set to reg: linear. It is essential to specify the type of learner which includes linear regression, logistic regression, Poisson regression etc.

- Eval_metric: It is essential to specify the evaluation metrics for validation data, a default metric will be assigned according to objective

- Seed: It is essential to specify the seed to reproduce the same set of outputs.

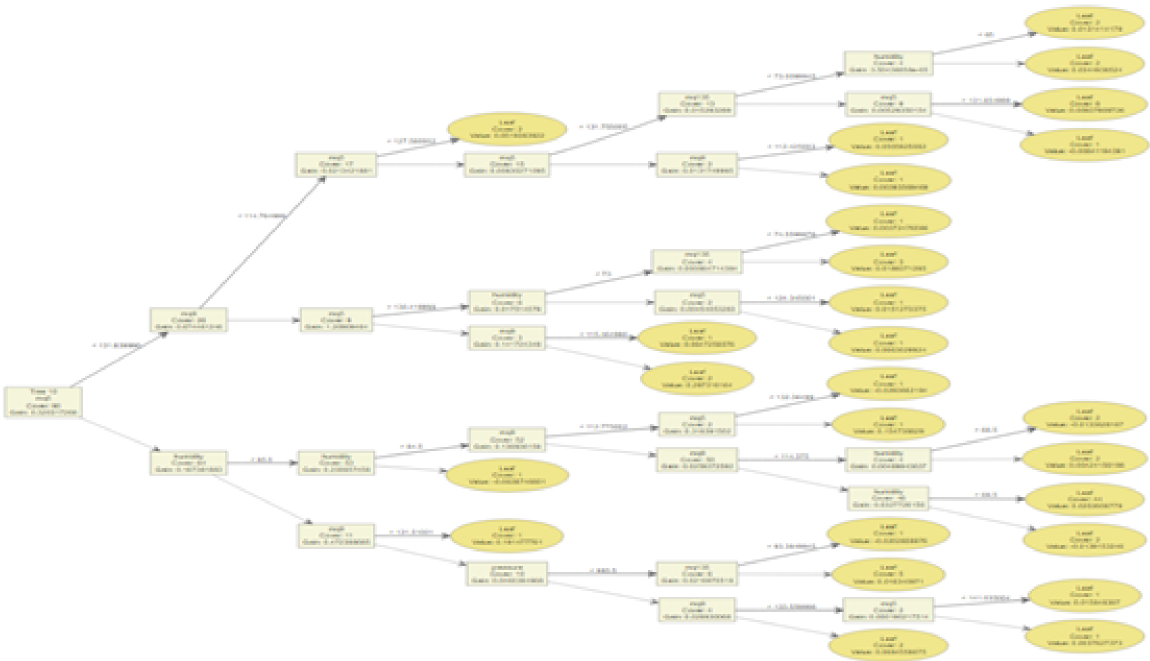


FIGURE 4.4: XGBoost training

4.7 Evaluation Function

To validate the model effectiveness, we evaluate the prediction model using two evaluation functions, i.e., Root Mean Square Error (RMSE), and Mean Absolute Error (MAE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{r} (n_i - 1) s_i^2}{N - r}}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |(f_i - y_i)|$$

CHAPTER 5

CONCLUSION AND FUTURE WORK

Conclusion

Thus, we have proposed an IoT-based air pollution monitoring and prediction system which overcomes the major pitfalls of conventional air pollution monitoring systems. The new system is much more real-time and localized with respect to the sensed metrics and is also cost-effective. The system is robust and can be deployed in various environments, and can also be used in remote places as well. Alerting the user on increased pollution levels will help the user make informed choices and might even help prevent disasters in case of gas leakage or sudden fire.

The system operates under low power requirements, and does not impose a burden to the user in terms of data consumption as well. The user is provided with a sleek and easily navigable user interface that can be accessed via the Internet, to view the air quality metrics around his immediate locality, and to visualise these metrics in the form of graphs. The user can also make note of the latest future predicted air quality metrics from the interface.

The underlying storage mechanism is also simplified and easily accessible with Google Sheets, and other weather researchers and statisticians can make use of our publicly available, clean dataset for their own purposes.

The XGBoost machine learning model also performs upto expectations, and provides good predictions of future values with a measured accuracy of **79.76%**.

This indicates the power of our system, and to the user it means that our predictions are trustworthy and reliable.

Since the model works based on the values obtained from a particular locality only, the predictions are not general, but rather personalized for each user. It is expected that the growth of IoT will be massive in the upcoming years, and the adoption of such systems will be commonplace very soon, as each user understands the criticality of air pollution in our world.

Future Work & Enhancements

1. More sensors can be incorporated to provide additional insights to the user.
2. The entire hardware setup can be built into an end-product with the help of integrated circuit designing and printed circuit boards, with a single power outlet.
3. Other IoT oriented wireless transmission mechanisms such as ZigBee, Bluetooth and 6LoWPAN could be incorporated to seamlessly transmit sensed data in the absence of WiFi.
4. A fully-fledged cloud-based database management system powered with various front-end analytical tools could be built to maintain and scale the application for the masses.
5. More sophisticated deep learning based forecasting models can be utilized for prediction purposes.

Appendix A

Account Statement

Amount Received from College : **Rs.21000**

S.No.	Description		Quantity	Unit price	Amount
1.	Raspberry Pi 3+		1	5000	5000
2.	MQ-135 sensor		2	243	486
3.	MQ-9 sensor		1	210	210
4.	MQ-2 sensor		1	212	212
5.	Air Dust sensor		1	2300	2300
6.	BMP-280 sensor		1	510	510
7.	DHT-11 sensor		1	550	550
8.	Electric Alarm		1	50	50
9.	ADC Chip		1	455	455
10.	Power Board Chip		1	550	550
11.	Bread Board		1	200	200
12.	Sensor power adapter		1	1000	1000
13.	Pi power adaptor		1	500	500
14.	SD Card & card reader		1	800	800
15.	Cables		2	175	350
	Sub Total				13173
	GST & Shipping Costs				1418
	Miscellaneous Costs	Hosting Fees			2650
		Jump wires			300
		Electric Components			300
		Assembling charges			1700
		Repair Charges			1200
	Total amount Spent				**20741**

TABLE A.1: Account Settlement

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