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Predicting Health Conditions by monitoring Air Pollution

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ABSTRACT: The intensity of pollution has increased with era by set of dynamic issues like the increase in residents, increased automobile use, industrialization and urbanization resulting in destructive effects on human welfare by directly affecting health of people exposed to it. In order to scrutinize the quality of air, a IOT based Predictive Analytical Model is proposed. The factors of the environment to be examined are temperature, humidity, volume of CO, volume of CO2, detection of methane gas and oxygen level in air. The values of these parameters are transmitted to Cloud, a base station where they are being monitored and apply the analytical model. This model will be trained with a set of different combinations of parameter index values. The WSN monitors the real time data periodically and tests these values by applying to the above said model. This model results in prediction of health level index. Every person in the range of the system can check it over their smart phones. In this paper, a network enabled architecture system supporting sensors and WSNs is proposed as a platform to monitor the health level index to estimate his or her health related issues.

KEYWORDS: WSN, Air Pollution, Sensors, IoT, Microcontroller

I. Introduction

Pollution, in its many forms, can have abrupt and long-terms effects on human body and overall health. Exposure to pollution also affects the quality of human life, and can increase the risk of certain chronic diseases. The physical effects of pollution on the health depend on the type of pollution to which the people are most frequently exposed, including air, water or noise pollution.

Air Pollution

According to the Lawrence Berkeley National Laboratory (LBL), the degree to which you're harmed by air pollution depends on level of our exposure to injurious chemicals. Short term physical health effects of air pollution include eye, nose and throat irritation, upper respiratory infections--including bronchitis and pneumonia--headaches, nausea, allergic reactions and exacerbation of medical conditions, such as emphysema and asthma. Long-term physical health effects of air pollution may include chronic respiratory disease, lung cancer and heart disease. Long-term exposure to air pollution may even cause damage to your brain, nerves, liver or kidneys. Thus, pollution-related diseases range from mild to severe, and can significantly affect a person's quality of life. [1]

Air Pollution Index is necessary to measure the quality of air. Pollutants considered are PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, O_3, NH_3, and Pb. Based on the measurement, associated likely health impacts for different API categories and pollutants can be suggested using IOT and data science technologies.

Persistent healthcare applications employing sensor networks produce an enormous quantity of data that need to be sensed and analyzed for processing and future practice. Cloud computing along with the Internet of Things (IoT) concept is a new trend for efficient managing and processing of sensor data online. This paper presents an application based on Cloud Computing for management of mobile and wireless sensors, representing the health factors based on the combination of gases that affect the human health factors.

II. Problem Statement

The personal health monitoring of each individual is considered very important because of rise in health problems in today's world. Every health human being requires to breathe in a clear air but due to the increase in air pollution it is necessary to track the level of pollution in urban or sub urban areas. Polluted air consists of 97% of CO and 75% of NO. Hence it is essential to take appropriate measure to mitigate the negative impact of air pollution on health wherever necessary.

III. Proposed Work

It is proposed to create a tool to monitor the quality of air. The main mission is to record a density of gases present in air due to pollution and other related parameters to inform the people and to notify against the associated health issues.

A) System Architecture

The following architecture presents three tier model. Tier1 encompasses a no of wireless sensor nodes prearranged in different areas. These sensor nodes are integrated to form a wireless sensor network. Each sensor node consists of 4 different semiconductor sensors: 1) MQ2- Gas sensor for leakage detection , 2) MQ3 -Alcohol sensor for detecting concentration of alcohol 3) MQ7- Sensor for sensing CO Concentration in the air, and 4) MQ135 - Sensor for air quality control. These different sensors are set to periodically sense, sample and process signals.

Tier 2 encompasses cloud storage, a cloud computing model in which data is stored on remote servers accessed from the Internet, or "cloud." It is maintained, operated and managed by a cloud storage service provider on storage servers that are built on virtualization techniques.

The application manages the network taking care of .time synchronization, data retrieval and processing and fusion of data. The PDA with WLAN interface transmits the data to server connected to internet and establishes a secure channel to server and send periodic updates. Based on the information from sensors, the mobile client application on Tier 3 with the help of database should determine the user's health status and provide the alert through the User interface.

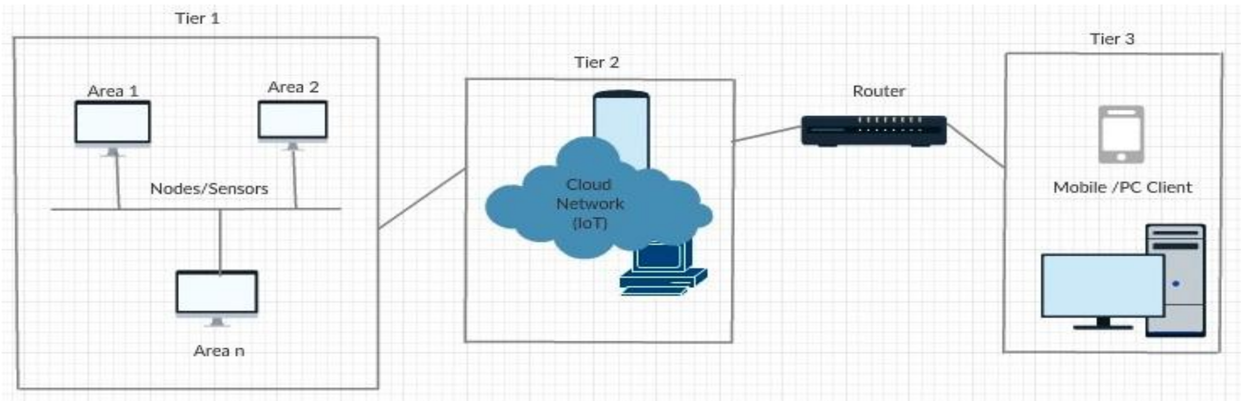
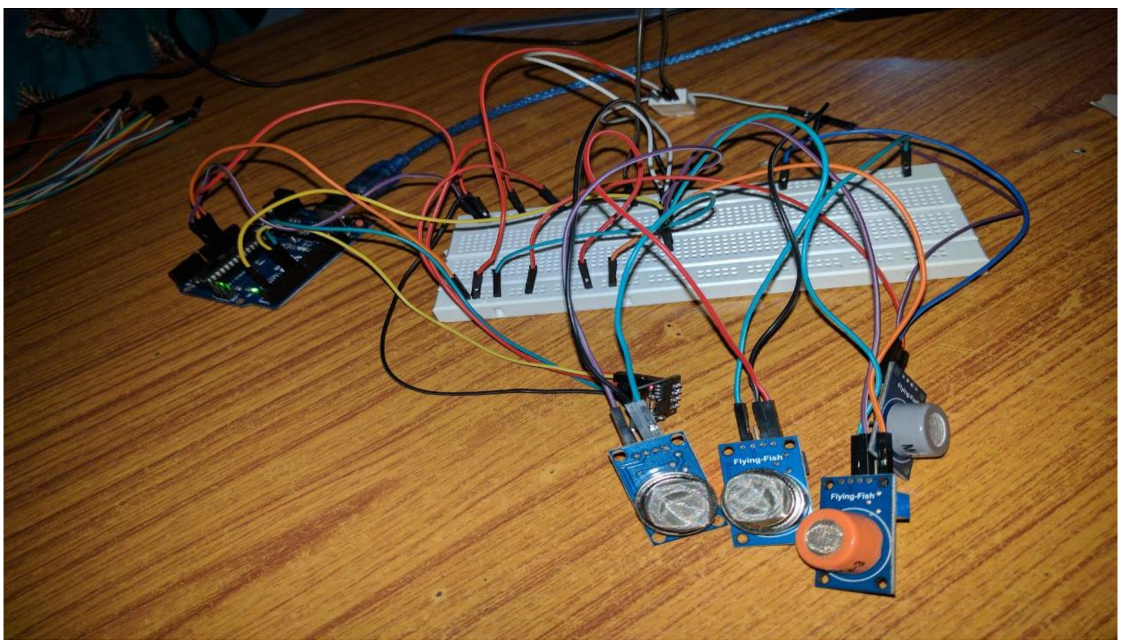


Figure 1: Architecture of Health Monitoring System

B) Hardware Architecture



C) Working of Proposed System

Data mining acts as a solution for detecting the possible and associated health related issues due to pollution level. Data mining acts as a solution for many healthcare problems. Naïve Bayes is a data mining algorithm which serves in diagnosis of health conditions. This paper analyzes few parameters and predicts the related heath issue to be diagnosed.

Naive Bayes classifiers is a probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features. A Naive Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful in the field of medical science.

Bayes theorem provides a way of calculating the posterior probability, P(c|x), from P(c), P(x), and P(x|c). Naïve Bayes classifier assumes that the effect of the value of a predictor (x) on a given class (c) is independent of the values of other predictors. This assumption is called class conditional independence

Equations:

- P(c|x) is the posterior probability of class (target) given predictor (attribute).
- P(c) is the prior probability of class.
- P(x|c) is the likelihood which is the probability of predictor given class.
- P(x) is the prior probability of predictor

Where C and X are two events. Such Naïve Bayes classifiers use the probability theory to find the most likely classification of an unseen instance. The algorithm works well with categorized data in the training set.

Datasets are collected by using real time sensors. The data sets used in this work are the real time data collected by nodes set up in different areas periodically. The data set is developed to ensure people with health issues to have awareness on the environment they are moving around, to help them monitor their risk related health factors. People with asthma may find that the polluted air makes their asthma worse.

For those who are sensitive to air pollution, it's important that they are provided with accurate notification about their upcoming health issue due to air quality, so that they can plan their activities to reduce exposure, perhaps by taking different routes to work or school or avoiding strenuous exercise on those days.

The attributes used in our system are four different sensors called MQ2, MQ3, MQ135, MQ7. Their descriptions are shown and the associated disease in the Table.

MQ2 **(**Methane, Butane)	**MQ3(**ethanol)	**MQ135** **(**Co2, Ammonia, Benzene)	**Mq7** **(**Carbon Monoxide)	**Associated DISEASE**
(300-10000)ppm	(0.04-4)Mg/L	(1-1000)ppm	(0.1-100)ppm	No disease
-	-	-	150ppm	Slight Headache, Fatigue.
-	-	1500ppm	-	Headache and Sleepiness.
-	5Mg/L	-	-	Liver disease
(4-20)ppm	-	-	-	Diabetes mellitus
-	-	(2500-3000)ppm	(2500-3000)ppm	Asthama and Cysticfibrosis
-	(1-11)ppb	(2500-3000)ppm	-	Inflammation and Oxidative Stress.
11000 ppm	-	1500 ppm	-	Pulmonary edema(difficulty in breathing)
14000	-	-	More than 12000	Unconsciousness after 2–3 breaths. Death in less than three minutes and Lung Cancer

-	5mg/l	-	800ppm	Heart damage, Mania
		-	-	Loss of consciousness, liver diseases, low Blood Pressure
12000	4.5mg/l	-	200ppm	If methane is more, it is dangerous to human health causing mental behavioral disasters and headache.
11000	-	1800	12000	If Co_2 is more than 10%, it causes death, Headache, temporary Memory loss
		-		Nausea, Fatigue, less Oxygen available to breathe

*ppm – parts per million is the ratio of one gas to another.

Based on the training set that is classified based on the classes present, the naïve bayes model will be able to classify the input instances and predicts the associated disease based on the exposure to the environment.

IV. Experimental Results/Analysis

This system is implemented by using programming language C#, .NET framework, MongoDB database and IoT Technology.

Filter

	created_at	Temprature	Humidity	MQ2	MQ3	MQ7	MQ135
1	2017-02-18 15:23:04 UTC	28.3	67	355	137	378	74
2	2017-02-18 15:23:19 UTC	28.3	67	355	137	378	74
3	2017-02-18 15:23:34 UTC	28.4	67	356	136	378	74
4	2017-02-18 15:23:49 UTC	28.3	67	350	135	374	73
5	2017-02-18 15:24:04 UTC	28.3	67	355	137	378	74
6	2017-02-18 15:24:19 UTC	28.3	67	351	135	374	74
7	2017-02-18 15:24:34 UTC	28.3	67	354	136	377	73
8	2017-02-18 15:24:49 UTC	28.3	67	349	135	372	73
9	2017-02-18 15:25:04 UTC	28.3	67	351	135	374	74
10	2017-02-18 15:25:19 UTC	28.4	67	356	137	378	74
11	2017-02-18 15:25:34 UTC	28.3	67	350	135	374	73
12	2017-02-18 15:25:49 UTC	28.3	67	353	136	376	73
13	2017-02-18 15:26:04 UTC	28.3	67	339	123	363	70
14	2017-02-18 15:26:19 UTC	28.2	67	337	122	361	70
15	2017-02-18 15:26:34 UTC	28.3	67	351	135	374	74
16	2017-02-18 15:26:49 UTC	28.3	67	356	137	378	73
17	2017-02-18 15:27:04 UTC	28.3	67	353	136	376	73
18	2017-02-18 15:27:19 UTC	28.3	67	340	124	364	70
19	2017-02-18 15:27:34 UTC	28.3	67	350	135	374	73
20	2017-02-18 15:27:49 UTC	28.3	67	350	135	374	73
21	2017-02-18 15:28:04 UTC	28.3	67	353	136	376	73
22	2017-02-18 15:28:19 UTC	28.5	68	347	129	373	71
23	2017-02-18 15:28:34 UTC	28.3	67	350	135	374	73
24	2017-02-18 15:28:49 UTC	28.3	67	353	136	376	73
25	2017-02-18 15:29:04 UTC	28.3	67	351	135	374	74
26	2017-02-18 15:29:19 UTC	28.5	68	349	130	376	70
27	2017-02-18 15:29:34 UTC	28.3	67	353	136	376	73
28	2017-02-18 15:29:49 UTC	28.3	67	353	136	376	73

fig: Data Set for Pollution Data Sensor Data

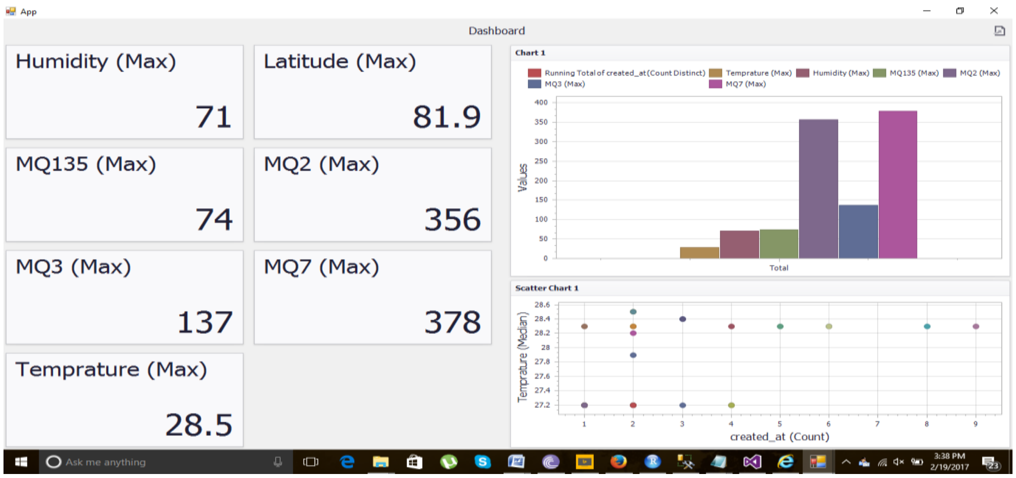


Fig: Dash Board for Pollution Control

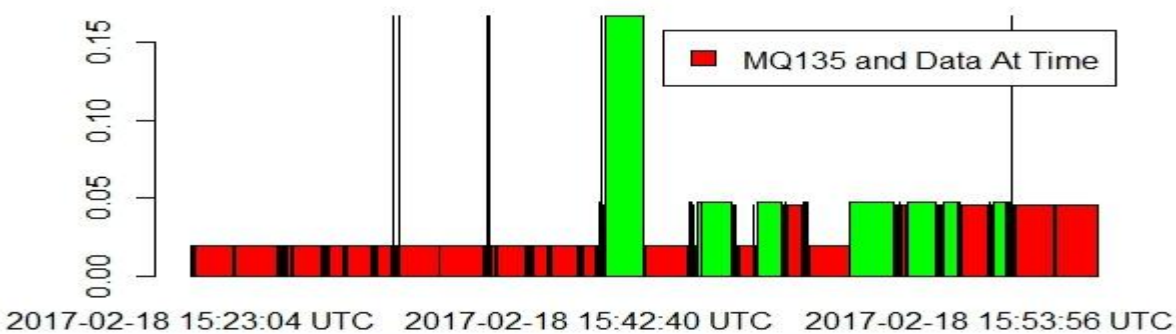


Fig:MQ3 Data at high values and mentoring through the Bar chart analysis

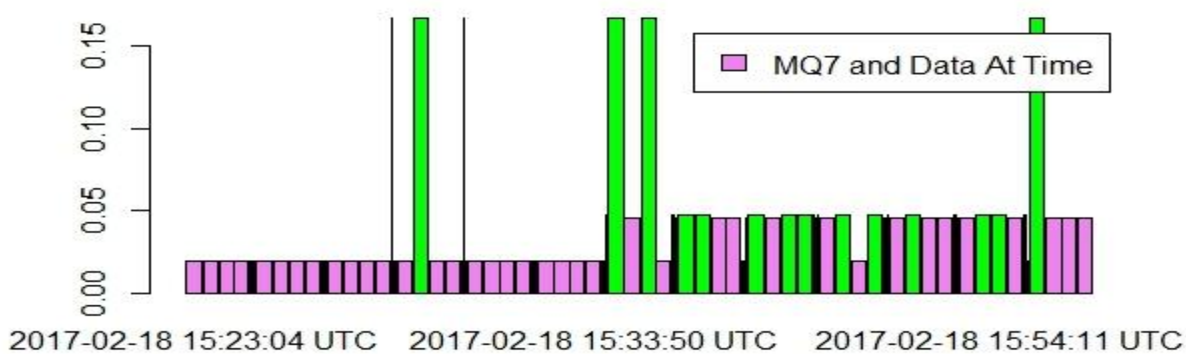


Fig:MQ7 Data at high values and mentoring through the Bar chart analysis

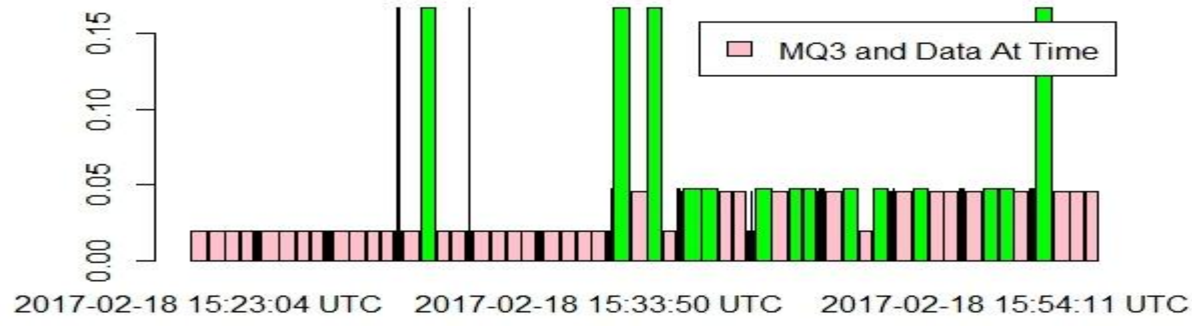


Fig:MQ3 Data at high values and mentoring through the Bar chart analysis

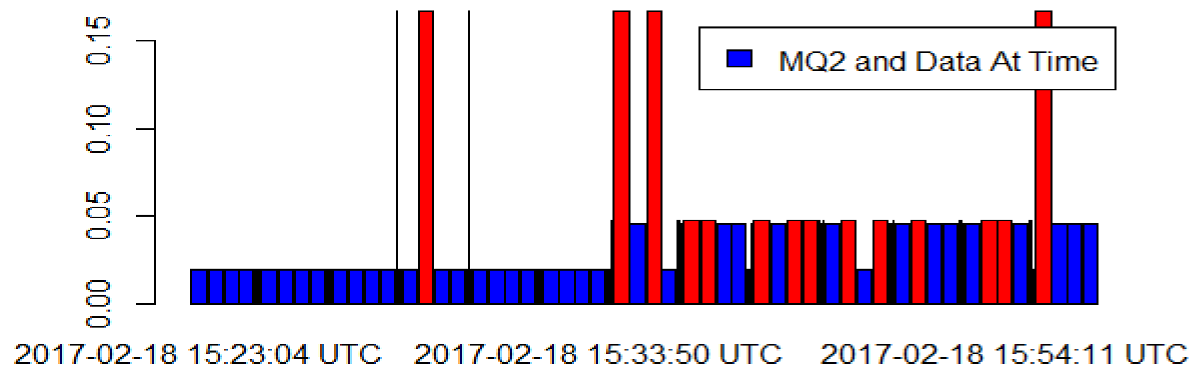


Fig:MQ2 Data at high values and mentoring through the Bar chart analysis

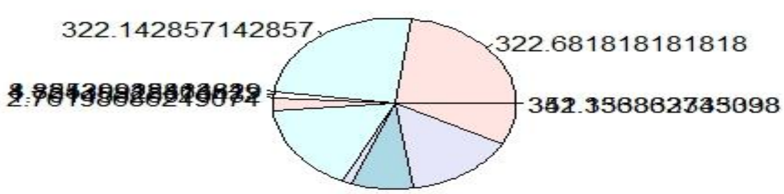


Fig: Pollution At the Date and time in the AIR

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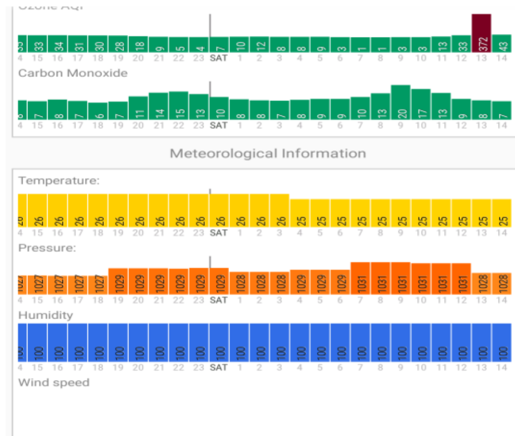
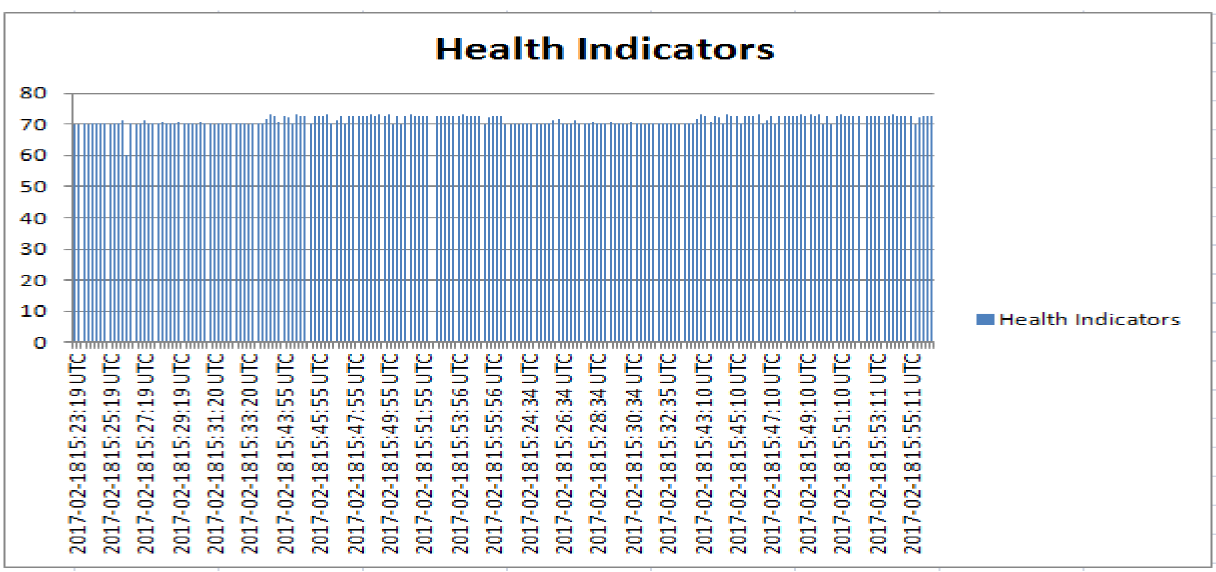
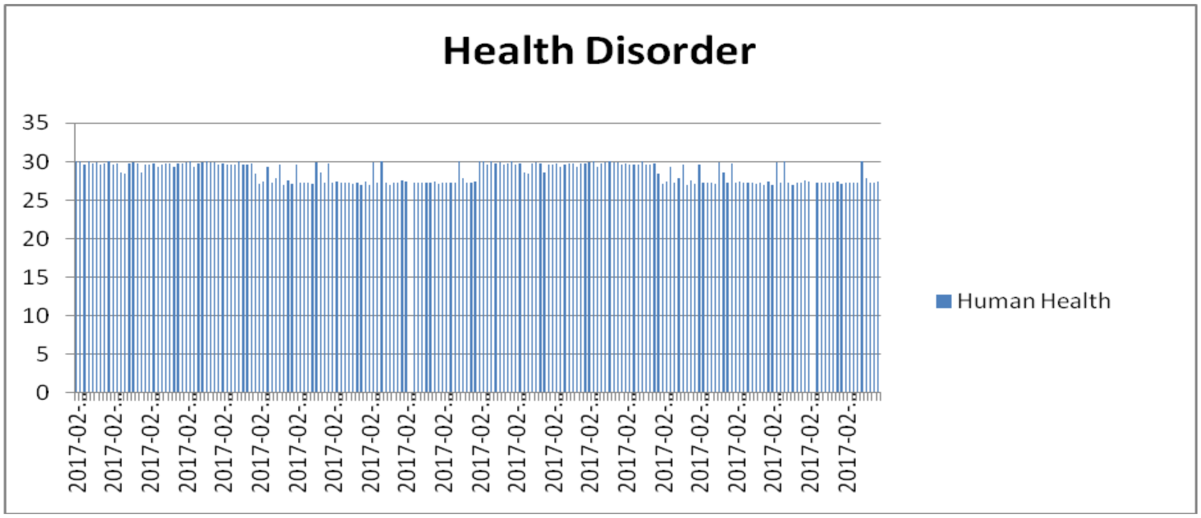
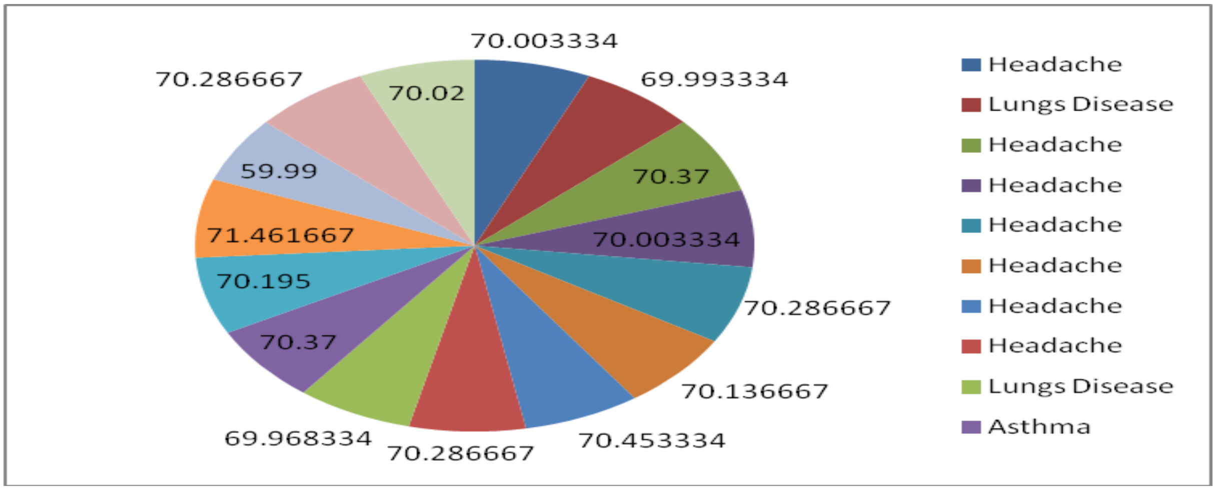


Fig: Mobile App Pollution Control

Created_at	Longitude	Latitude	Human Health	Disease	Health Indicators
2017-02-18 15:23:19 UTC	16.81	81.52	29.996666	Headache	70.003334
2017-02-18 15:23:34 UTC	16.81	81.52	30.006666	Lungs Disease	69.993334
2017-02-18 15:23:49 UTC	16.81	81.52	29.63	Headache	70.37
2017-02-18 15:24:04 UTC	16.81	81.52	29.996666	Headache	70.003334
2017-02-18 15:24:19 UTC	16.81	81.52	29.713333	Headache	70.286667
2017-02-18 15:24:34 UTC	16.81	81.52	29.863333	Headache	70.136667
2017-02-18 15:24:49 UTC	16.81	81.52	29.546666	Headache	70.453334
2017-02-18 15:25:04 UTC	16.81	81.52	29.713333	Headache	70.286667
2017-02-18 15:25:19 UTC	16.81	81.52	30.031666	Lungs Disease	69.968334
2017-02-18 15:25:34 UTC	16.81	81.52	29.63	Asthma	70.37
2017-02-18 15:25:49 UTC	16.81	81.52	29.805	Asthma	70.195
2017-02-18 15:26:04 UTC	16.81	81.52	28.538333	Asthma	71.461667
2017-02-18 15:26:19 UTC	16.81	81.52	28.395	Lungs Disease	59.99
2017-02-18 15:26:34 UTC	16.81	81.52	29.713333	Asthma	70.286667
2017-02-18 15:26:49 UTC	16.81	81.52	29.98	Asthma	70.02
2017-02-18 15:27:04 UTC	16.81	81.52	29.805	Asthma	70.195
2017-02-18 15:27:19 UTC	16.81	81.52	28.621666	Asthma	71.378334







V. Conclusion

Data mining applications are used vastly in the medical and agricultural field to detect diseases affecting human beings and to the crop fields based on the data set and the attributes provided. Researchers have been investigating and applying different data mining techniques to predict the degree of air pollution in advance thus improving the quality of life. In the proposed work naïve bayes algorithm is used to classify the data set because naive bayes provides accurate results, and helps the people to be aware of the diseases with which they might get affected due to their exposure to the polluted environment as soon as they reach the polluted area.

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