A Survey paper on Vehicles Emitting Air Quality and Prevention of Air Pollution by using IoT Along with Machine Learning Approaches

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Abstract

We denoted a new method and Technology for automatic recognition of air quality, air Pollution and fog from a vehicles. Our system consists of sensors to acquire main data from emitting gases by vehicles using IoT - MQ135 and Arduino tools .It is used to Display the air quality and air pollution with the help of the instruments. When there are sufficient amount of harmful gases are present in the air like CO2, smoke, alcohol, benzene and NH3 .We discuss how this data can be collected, analyzed and merged to determine the degree of air pollution or fog. Such data is essential for control systems of moving vehicles in making autonomous decisions for avoidance. Backend systems need such data for forecasting and strategic traffic planning and control. Laboratory based experimental results are presented for weather conditions like air pollution and fog, showing that the recognition scenario works with better than adequate results. This paper demonstrates IoT - MQ135 and Arduino tools technology, already onboard for the purpose of autonomous driving, can be used to improve weather condition recognition when compared with a camera only system. We are going to make an IOT Based Vehicles Air Quality Sensors and support vector regression (SVR), to forecast pollutant and particulate levels and to predict the air quality index (AQI). Among the various tested alternatives, radial basis function (RBF) was the type of kernel that allowed SVR to obtain the most accurate predictions. Advance Technologies like Artificial Intelligence or Machine Learning based Prevention of Air Pollution system will activate an alarm when the air quality goes down beyond a certain level, means when there is sufficient amount of harmful gases are present in the air like CO2, smoke, alcohol, benzene and NH3. It will show the air elements in PPM on the LCD and as well as on webpage so that we can monitor it very easily. This paper covers the revision of the studies related to air quality and prevention of air pollution using machine learning algorithms based on sensor data in the context of vehicles.

Keywords: Air pollution, Artificial Intelligence, Machine Learning, MQ135, Arduino Tools, Support vector regression, Air Quality Index.

I. Introduction

The influence of machine learning technologies is rapidly increasing and penetrating almost in every field and air pollution prediction is not being excluded from those fields. This paper covers the revision of the studies related to air pollution prediction using machine learning algorithms based on IoT sensor. Air quality Monitoring provides raw measurements of gases and pollutants concentrations, which can then be analyzed and interpreted. To control Air pollution is a concern in many urban areas and is the major reason for respiratory problems among many people, monitoring the air quality may help many suffering from respiratory problems and diseases, and thereafter informing engineering and policy decision makers to improve the quality of air. Major contributor's air causing respiratory problems are Fine particles produced by the burning of fossil fuels (i.e. the coal, petroleum) noxious gases (sulfur dioxide, nitrogen oxides, carbon monoxide-CO, chemical vapors.)Ground-level ozone (Volatile Organic Compounds (have a high vapor pressure at ordinary room temperature, formaldehyde- HCHO gas being major component).

A prototype for a low cost indoor air monitoring device has been developed to measure the concentration of CO and HCHO gases, monitoring at a specified rate and communicating over cloud to notify to any wireless device when the threshold of these gases is reached. Initial plans included monitoring of additional CO2 and other noxious gases. But, this could not be achieved due to restrictions on traffic. Though the prototype can be extended and deployed across regions for high-fidelity emissions monitoring to explore the effects of anthropogenic and environmental factors on intra-hour air quality. This paper aims to review the articles related monitor the vehicles Emitting air quality and prevention of air pollution by using sensor with machine learning technologies.

II Related Work

The traffic model using VISSIM and emission model using VERSIT.The next expensive model that uses at helometer for Black carbon, CO analyzer for CO and these instruments are highly expensive. These approaches are not suitable for the real- time monitoring, hence the Internet of things approach was chosen to monitor the environment and update the user to regarding pollution level in their route and act accordingly. Internet of things is an emerging technology that will be used in real time approach efficiently. IOT was described as one paradigm and many vision in IOT. They were Things oriented vision based on smart objects, Internet-oriented vision based on communication, semantically oriented vision based on knowledge. The enabling technologies are identification, sensing, communication. The challenging area in IOT system is mainly sensing, identification, communication, interoperability, middleware, energy efficiency, cloud storage, scalability, reliability, robustness, security. The proposed system mainly focused on sensing, energy efficiency, and communication.

The Air quality was measured using Air quality index standard. The GUI interface was created for regular monitoring .In another experiment; a portable sensor unit was developed. the sensor unit was connected to the Smartphone of the vehicle driver through Bluetooth where the monitoring application runs, this mobile app gets sensor data and tags it with GPS information, and send that data to cloud server using mobile packet data. The data was visualized through the application. The sensor Node has been deployed on the top of the vehicle in their experiment they have used Metal-oxide Semiconductor (MOS) sensor to measure CO, NO2, Ozone and an electrochemical sensor for CO. In other paper they were developed and conducted the experiment in Bangkok a portable device which has solid state gas sensors integrated with Personal digital assistant like mobile phones was communicated via Bluetooth along with GPS information, The pollution data was updated via internet GIS for real-time access of data. Another approach, The air quality monitoring system with an array of sensors which are the electrochemical and infrared sensor used to detect CO, NO, SO2, CO2 concentration level then this data successfully transmitted to server database .and data interact through a graphical user interface. Sensor technology used is less power consumption and accurate. The base station comprises a sink node serially connected to a computer which runs the GUI software. The sink or receiving node captures the data transmitted by the remote sensor node and serially forwards it to the computer. The environmental data are collected by a set of individual external sensors integrated into a board and working like one single sensor device with multi-sensing features. These sensors, integrated through the cell phone via Bluetooth, the Bluetooth interface communicates with the acquisition board to receive the air quality measurements. A connection is opened with the Arduino Module through which the environmental data are constantly received. And the data can be transferred to the server through UDP. The sensors that measure different gases namely, CO, NO2, and SO2 are connected with GPS through ARM circuit and the data is transferred. In another system, the calibration of the sensor considered as major problem calibration based on sensor type and quality the frequency of calibration of the sensor may vary. In this paper, introduced a Air Quality and Prevention of Air Pollution method to achieve the maintenance-free operation of the sensor network.

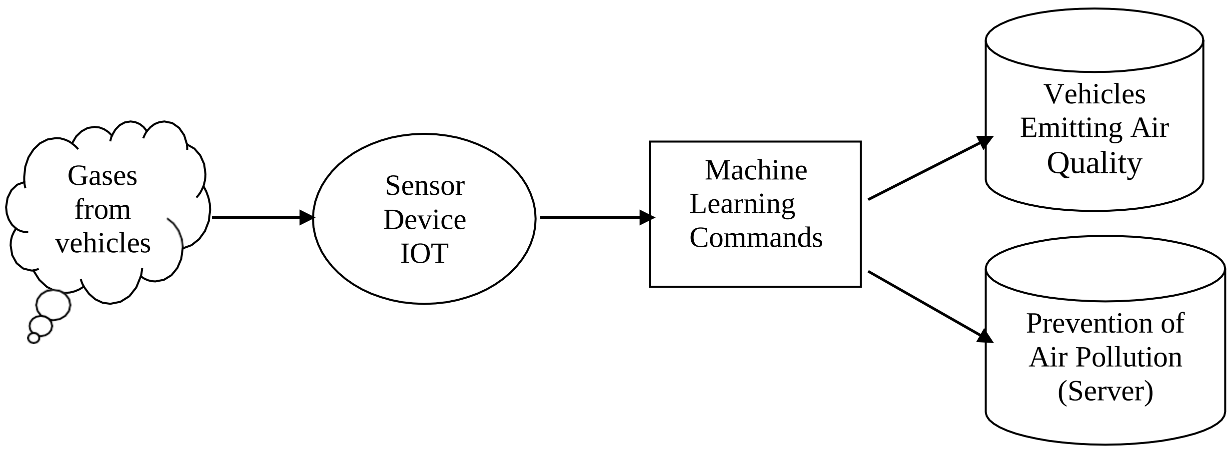

Figure 1 over View of the System Air Quality and Prevention of Air Pollution

III Smart Air Quality Monitoring

The SAQM methods present a summary of different SAQM approaches used in recent literature on air quality monitoring systems. Air quality characterization has been implemented using heterogeneous sensors and machine learning methods. The monitoring as well as characterization of water quality was achieved but interoperability issues were reported in this work due to use of heterogeneous sensors. Air quality evaluation using fixed as well as mobile nodes of sensors was implemented, capable to check the air quality in stationary as well as mobile ways. In this latter case, the compatible sensors were deployed as mobile nodes which can work satisfactorily in a moving environment. Data captured through smart sensor nodes were processed and analyzed with the help of machine learning techniques. Another air quality control process was studied using IoT and machine learning techniques in, with a focus on assessment of air pollution, deploying gas sensors which help in capturing air particles and analyzing the pollutants mixed in the air. Sensor networks have been established in moving vehicles for monitoring air quality with the help of machine learning; in, mobile sensor nodes and WSN were deployed. Infrared sensors were deployed to evaluate the air quality, especially analyzing volatile organic compounds (VOCs) in, with the help of machine learning methods. The elements of VOCs were detected and analyzed using spectroscopic observations. There are a few components present in the air that help assessing the quality of the air; one such component, called PM2.5, was predicted in, using extreme machine learning techniques tested upon spatio-temporal data collected in a certain duration of time over a range of distances covered by the sensors. Different forecasting models were suggested in for quality evaluation of urban air and the components like O3, SO2 and NO2 were determined and a comparison was made for the models used in the work. RFID and a gas sensor based air quality control mechanism were implemented in, to determine the level of pollution in the air by predicting the pollution value; IoT was employed to analyze sensory data captured through gas sensors.

RFID was primarily used in this work for detection of pollutants and communicating to WSNs with the help of IoT devices connected across WSN architecture. An SAQM system has been studied in, using a LoRaWAN (long range WAN)], and this work has been very useful for detecting temperature, dust, humidity and carbon dioxide components in the air. An intelligent air quality system was presented for detection of CO2, NOx, temperature and humidity in using AI and machine learning techniques for developing expert systems for air quality assessment. Furthermore, PM10, PM2.5, SO2, oxides of nitrogen (NOx), O3, lead, CO and benzene components were detected, on the basis of machine learning methods trained by spatio-temporal data, this was extended using deep learning for detection and detailed analysis of O3 components only. Another work employing heterogeneous sensors was studied in. UV light, AI and sensors and SVM was used for analyzing the sensor data, captured through heterogeneous sensors, and air quality was estimated. Machine learning algorithm, including SVM, M5P, and ANN with univariate and multivariate models to forecast O_3, NO_2, and SO_2 . the machine learning techniques in order to predict air pollution with better accuracy. As an input variables were taken air quality ($PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, O_3), meteorological wind speed, direction, pressure, humidity, temperature), chemical components organic carbon, black carbon, dust.

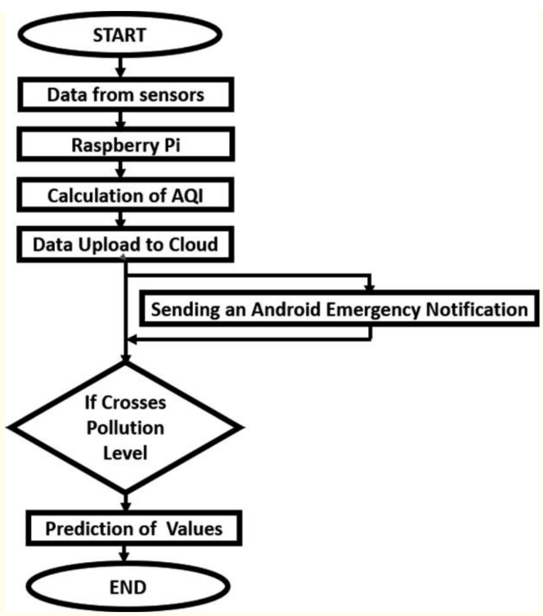

Figure 2 Smart Air Quality Monitoring

IV Vehicle Emissions Simulation Model

In this section, the vehicle pollutant simulation models are briefly described. These models have been developed in machine learning and automated code generation has been used to embed them i n IoT and which provides services accessible from sensors. They estimate instantaneous pollutant emissions: (NO_X), exhaust Particulate Matter in mass (PM) and number (PN), non-exhaust Particulate Matter CO and CO_2. Physical phenomena involved in pollutants formation are modeled according to elated literature. Vehicle technical features are taken into account by the way of a data bank of 0D/1D sub-system models automatically selected and tuned based on technical parameters retrieved from the license plate number. A tradeoff between precision, number of input parameters, and computation complexity had to be made to get the most suitable modeling accuracy. The impact of real-world driving conditions and situations where pollutant emissions are particularly high or low have to be caught by the designed vehicle simulation models.

More in details, as a first step, sensor provides inputs for a longitudinal dynamic vehicle model: vehicle velocity and altitude allow computing the power needed at the wheel to move the vehicle. A second sub-model is used to estimate, at each time-step, the reduction ratio between the wheel and the engine crankshaft, and so allows the conversion of velocity and power from wheel to engine speed and torque at the crankshaft. Estimation of engine-out emissions is based on engine physical modeling using mostly equations.

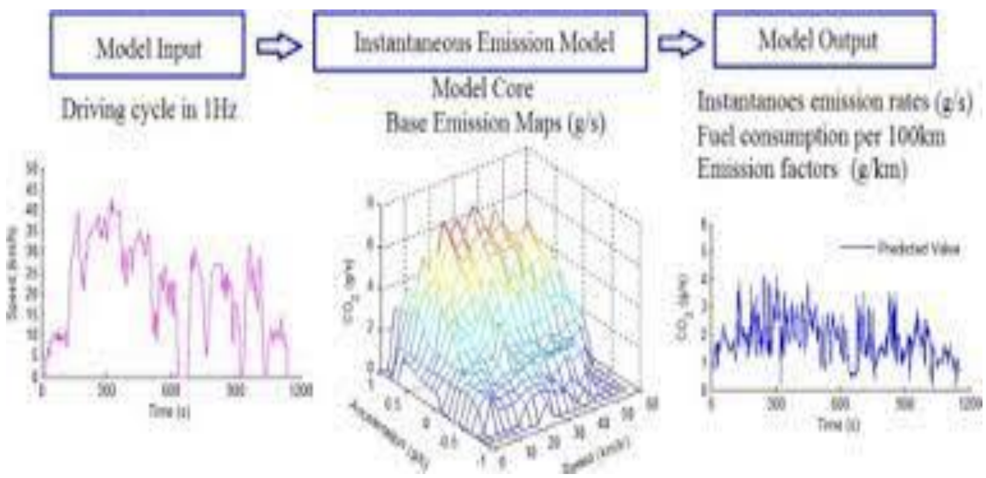

Figure 3 vehicles Emissions Simulation Model

To estimate tail-pipe emissions, an after-treatment model library was developed covering several sub-models, each of which representing a widely used physical after-treatment element of the exhaust line : Diesel Oxidation Catalyst (DOC),Diesel Particulate Filter (DPF), Selective Catalyst Reduction (SCR), Lean NO_X Trap (LNT), Three-Way-Catalyst (TWC). These models allow to describe precisely the evolution of the temperature and composition through the different elements, and to estimate the tail- pipe pollutants. Going further into details, each element is in fact spatially discredited into several slices to account for the non-uniform axial distribution of the properties inside the element itself.

This approach is fully consistent with classical models of packed-bed catalysts developed since the 1970s Several benefits of this approach make it necessary for our application: it leads to realistic dynamics of pollutants conversion efficiency during heat-up phases (such as start-up and sudden accelerations) and during transient cool down phases as well pedal release, slow driving, which would not be captured by a simple map-based model.

V Air Quality Index

The green color corresponds toa very good to good air quality. The higher the index, the redder it is and the worse the air quality. A value greater than 90 corresponds to the exceeding of the information and recommendations threshold for one of the three pollutants concerned (NO_2, O_3, PM10) by the pollution episode management system. The air quality index is for now a daily estimate of the global pollution level updated every day around 14h. This is a multi- pollutant index which takes the value of the highest of the three sub-indexes. The hour-per-hour estimation of the air quality index is currently in progress.

$$AQI = \frac{(AQI_{Hi}) - (AQI_{Lo})}{(Conc_{Hi}) - (Conc_{Lo})} \times \left((\mathbf{Conc_i}) - (Conc_{Lo})\right) + (AQI_{Lo})$$

Where

$Conc_i$ = Input concentration for a given pollutant

$Conc_{Lo}$ = The concentration breakpoint that is less than or equal to $Conc_i$

$Conc_{Hi}$ = The concentration breakpoint that is greater than or equal to $Conc_i$

AQI_{Lo} = The AQI value/breakpoint corresponding to $Conc_{Lo}$

AQI_{Hi} = The AQI value/breakpoint corresponding to $Conc_{Hi}$.

AQI Category (Range)	PM_{10} 24-hr	$PM_{2.5}$ 24-hr	NO_2 24-hr	O_3 8-hr	CO 8-hr (mg/m^3)	SO_2 24-hr	NH_3 24-hr	Pb 24-hr
Good (0-50)	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	0-0.5
Satisfactory (51-100)	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	0.6 –1.0
Moderate (101-200)	101-250	61-90	81-180	101-168	2.1- 10	81-380	401-800	1.1-2.0
Poor (201-300)	251-350	91-120	181-280	169-208	10.1-17	381-800	801-1200	2.1-3.0
Very poor (301-400)	351-430	121-250	281-400	209-748*	17.1-34	801-1600	1201-1800	3.1-3.5
Severe (401-500)	430 +	250+	400+	748+*	34+	1600+	1800+	3.5+

Table 1 Air Quality Index computation table

The index calculated at a scale of 24 hours for the major urban areas and on a kilometer scale for the rest of the region. The data come from the fine scale air quality forecasting models called SIRANE developed by the University of Lyon Ecole Centrale de Lyon and implemented by the Auvergne-Rhone-Alpes region air quality observatory. These models are reachable through web services giving the air quality index for any location defined by its Sensor coordinates.

Research	Purpose	Data and Technique
Air quality characterization \	Air quality monitoring and Prevention of Air Pollution	Heterogeneous sensors and machine learning based predictive model Used
Air quality modelling	Air quality monitoring	vehicles
Air pollution	Air quality monitoring	Gas sensors from mobile vehicle data, IoT and machine learning
Air quality in vehicular sensor network	Air quality monitoring ,Prevention of Air Pollution	Sensors with mobile nodes
Detection of VOC in air	Organic compound detection	Infrared, spectroscopy and machine learning

Research	Purpose	Data and Technique
PM2.5 estimation	Air quality in terms of PM2.5 concentration levels	Spatio-temporal geographic data, Extreme machine learning technique
Urban air	Urban air pollution in terms of O3, NO2 and SO2 concentrations	Forecasting models
Air pollution prediction	Air pollution control	RFID, Gas sensors and IoT
Smart air quality	Air quality	Temperature, humidity, dust and carbon dioxide sensor; LoRaWAN

Research	Purpose	Data and Technique
Intelligent air quality system	Air quality for detection of CO2, NOx, temperature and humidity	UV light, AI and sensors
Ozone, PM10 and PM2.5	PM10, PM2.5, SO2, Oxides of nitrogen (NOx), O3, lead, CO and benzene	Machine learning and spatio-temporal data
Air quality	Air quality	Heterogeneous sensors and SVM
Abnormal O3	Ozone (O3)	Ozone data and deep learning
Wearable sensors	Temperature and humidity monitoring	Wireless and wearable senor technology

Table 2 Research on Air Quality systems using Advance Machine learning With IoT.

VI Machine Learning Approaches for Air Pollution Prevention

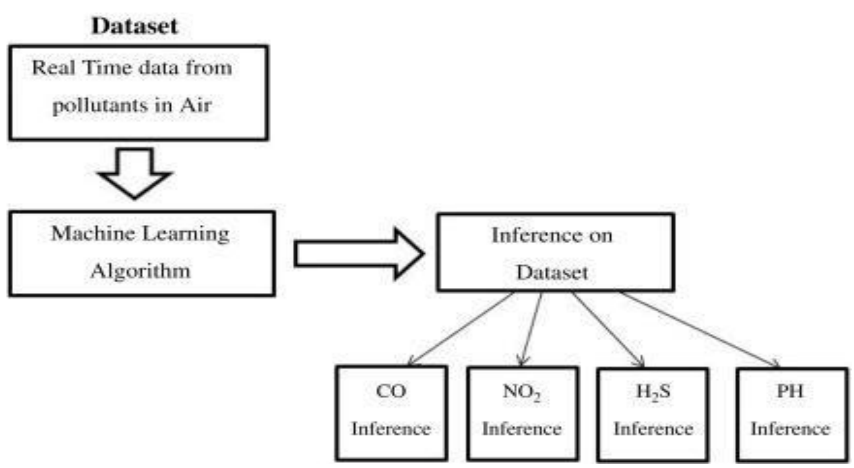

Figure 4 Dataset Analysis for Air Pollution

Our goal is to predict the concentration of air pollutants of the next day on the basis of the historical meteorological and air pollutant data. In this work, we have focused on using the former day's data to predict the next day's hourly pollutants. In particular, we let ($\mathbf{x}_i$; y_i) denote the ith training data, where $y_i \in \mathrm{R}^{24\times1}$ denotes the concentration of a certain air pollutant on a day, and $\mathbf{x}_i$ = ($\mathbf{u}_i$; $\mathbf{v}_i$) denotes the observed data on the previous day that include two components, where a semicolon ";" represents the column layout. The first component $\mathbf{u}_i = (\mathbf{u}_{i,1}; \ldots ; \mathbf{u}_{i,D}) \in \mathrm{R}^{24\cdot D\times1}$ includes all meteorological data over 24 h for the previous day, where $\mathbf{u}_{i,j} \in \mathrm{R}^{24\times1}$ denotes the jth meteorological feature of the 24 h and D is the number of meteorological features; the second component $\mathbf{v}_i \in \mathrm{R}^{24\times1}$ includes the hourly concentration of the same air pollutant on the previous day. The general formulation can be expressed as

$$f_k(W, \mathbf{x}_i) = \sum_{j=1} \mathbf{e}_k^T.\ \mathbf{u}_{i,j} \quad w_{k,j} + \mathbf{v}_i^T \mathbf{w}_{k,D+1} + w_{k,0}, \qquad k = 1,$$

Where W denotes the parameters of the model, $f\,(W, \mathbf{x}_i)$ denotes the prediction of the air pollutant concentration, and $\phi(\cdot)$ denotes a regularization function of the model parameters W.Next, we introduce two levels of model regularization. The first level is to explicitly control the number of model parameters. The second level is to explicitly impose a certain regularization on the model parameter. For the first level, we consider three models that are described below:

The first model is a baseline model that has been considered in existing studies and has the fewest number of parameters. In particular, the prediction of the air pollutant concentration is given by

$$f_k(W, \mathbf{x}_i) = \sum_{j=1}^{D} \mathbf{e}_k^T.\ \mathbf{u}_{i,j} \quad w_j + \mathbf{e}_k^T.\ \mathbf{v}_i \quad w_{D+1} + w_0, \qquad k = 1,$$

$w_0, w_1, \ldots, w_D, w_{D+1} \in \mathrm{R}$ are the model parameters, where w_0 is the bias term. We denote this where $\mathbf{e}_k \in \mathrm{R}^{24\times1}$ is a basis vector with 1 at only the kth position and 0 at other positions; model by $W = (w_0, w_1, \ldots, w_{D+1})^T$. It is notable that this model predicts the hourly concentration on the basis of the same hourly historical data of the previous day and that it has D +2 parameters.

Algorithm : Supervised Machine Learning Algorithm.

Input: X, Y, W0, *h*0, S, and T

for s = 1, . . . , S **do**

*h*s = *h*s1/2

for t = 1, . . . , T **do**

Sample i 2 f1, ..., ng

Update W0

t using Equation

Update Wt using Equation

end

W0 = åT

t=1W1/WT

end

Output: W0

Table 3 Supervised Machine Learning Algorithm

VII Experimental System

A) Arduino CCS811 Air Quality Sensor

Arduino CCS811 Air Quality Sensor is a microcontroller board based on the ATmega328P which has 14 digital input/output pins, 6 analog inputs, a 16 MHz quartz crystal, a USB connection, 2 power sources with 3.3V and 5.0V respectively, an ICSP header and reset button. Programs can be loaded on to it through the easy-to-use Arduino software. It contains everything needed to support the microcontroller and simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter or battery to get started.

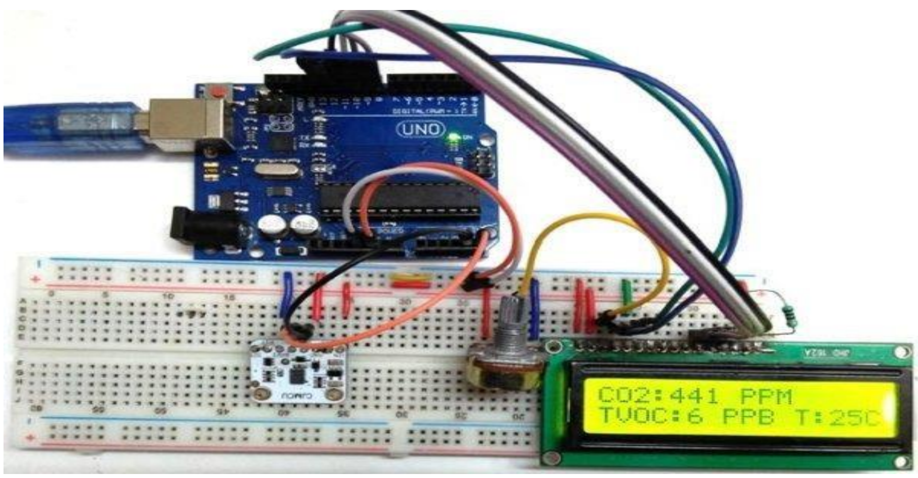

Figure 5 CCS811 Air Quality Sensor

B) MQ135Gas Sensor

MQ135 sensor for detecting a wide range of gases, including NH3, NOx, alcohol, benzene, smoke and CO2. MQ135 gas sensor has high sensitivity to Ammonia, Sulfide and Benze steam, also sensitive to smoke and other harmful gases which is used as smoke sensor.

Figure 6 Gas Sensors for Air Quality

C) Ultrasonic Sensor HC-SR04 With Arduino

Ultrasonic sensors measure distance by using ultrasonic waves which is used for obstacle detection. It measures the distance by measuring the time between the emission and reception. The sensor has 2 openings on its front from that one opening transmits ultrasonic waves and the other receives them reflected back from the target.

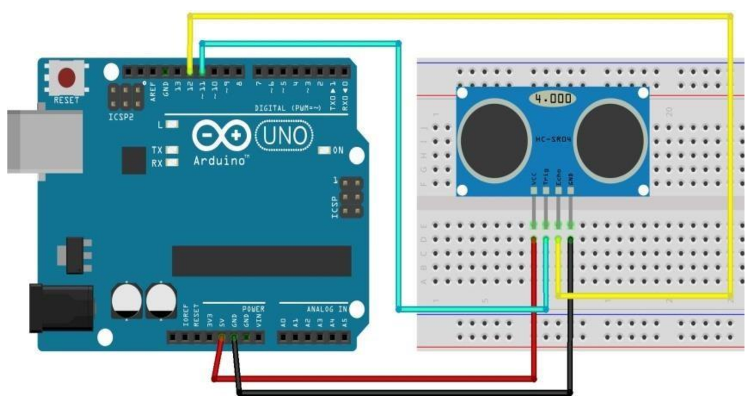

Figure 7 Ultrasonic Sensor HC-SR04 With Arduino

D) Air Pollution Monitoring Node

The Arduino IDE to write the code our code has to connect the local area network by using the credentials provided in the code. After that, our code has to work on getting the input from the sensor, and then it must display the data on the webpage, which is created using nodeMCU. Please note that we are not dealing directly with the ppm. We are calculating the voltage variations with respect to the pollution content in the air. If the output voltage of the MQ sensor is less than 20% of the max voltage value, we considered it a normal amount of pollution content present in the air. If the output voltage is increased and stabilizes in the range of more than 20% to less than 70%, then it is considered as a medium amount of pollution content present in the surrounding air. If the output voltage increases more than 70% of the maximum value, then it is considered as dangerous level.

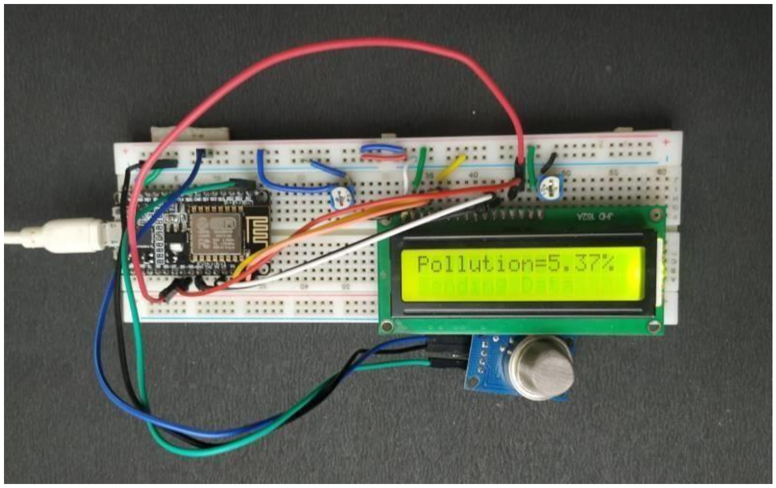

Figure 8 Pollution Monitoring Node

VIII CONCLUSION AND FUTURE WORK

This paper discusses an innovative Survey on Vehicles Emitting Air Quality and Prevention of Air Pollution by using IoT Along with Machine Learning Approaches . Even we have developed efficient machine learning methods for air pollutant prediction also. Supervised Machine Learning Algorithm for solving different formulations. We have described a method for forecasting the air quality index outside a vehicles. with sensor enabled by an atmospheric dispersion forecast model. The Sensor will be a component of an Open Innovation Platform for rapid innovation of HVAC control methods and mechanisms. The advancement in the sensing technology and covering all the aspects of monitoring of vehicular pollution will make the 'Automobile Air Pollution Monitoring' model more efficient. The model is designed in such a way that if anyone wants to add new features can easily do so. The model happily accepts and supports the new technology and also helps in preserving the natural resources. As we all know that global warming is taking place due to environmental pollution. Vehicular pollution is the main cause for the environmental pollution. By using the proposed system, the global warming can be reduced to some extent

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