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Real-Time Cloud Based Framework For Monitoring And Prediction Analysis Of Acetone In An Ambient Air Using Deep Learning

Shishir A. Bagal[1], Nitin K. Choudhari[2], A. R. Chaudhari[3]

[1]Research Scholar at Dept. of Electronics & Computer Science
Rashtrasant Tukadoji Maharaj Nagpur University, Nagpur (Maharashtra), India
shishirabagal@gmail.com1
[2]Principal, Priyadarshini Bhagwati College of Engineering, Nagpur (Maharashtra), India
drnitinchoudhari@gmail.com2
[3]Principal, Nutan Adarsh Arts, commerce and M.H. Wegad Science College, Umrer (Maharashtra), India
arcbce@gmail.com3

ABSTRACT

Objective: Acetone is one of the hazardous compounds available in an ambient air causing impact on human health and environmental safety, making its monitoring and analysis more vital. An IoT based, real time framework presented deals with the development of portable and low-cost system for acetone monitoring and analysis via deep learning (DL). Since its a cost-effective, compact system, it can be installed in any industry as compared with the traditional monitoring systems that are highly expensive and difficult to install anywhere. Methodology: This cloud integrated System developed using an ESP-32 IoT Controller and a Multi Sensor Module (ZPHS01B) and deployed in an industry and the real time data samples of the acetone were collected. The data samples were analysed using XGBooster algorithm (XGBOOST) – A deep learning model for the system performance evaluation.

Findings: The system performance evaluated based on the XGBOOST algorithm clearly indicates that the developed system is highly capable of monitoring acetone concentration in an ambient air. The analysis revealed that VOC grade and acetone concentration (0.96) has a very strong correlation. Moreover, Strong Positive correlations Among VOCs i. e. Acetone vs Benzene: 0.95, Acetone vs Toluene: 0.94, Acetone vs Methane: 0.94. Acetone shows that the developed device is highly capable of detecting the Acetone concentration. The weak relations between Acetone Vs Temperature (-0.06) and Acetone Vs Humidity (0.11) indicates that environmental variables do not strongly influence acetone concentration directly.

Novelty: The IoT based real time device developed for monitoring hazardous exhaust compounds is cost-effective, compact and easily deployable at a fraction of the cost of traditional systems. The dataset generated by the system can be useful to the regulating / external agencies for the pollution audit, framing the future policies, ensuring increased workplace safety and regulatory compliance in industrial settings. This device can be employed in industrial settings that can ensure increased workplace safety and regulatory compliance by providing an affordable and scalable environmental monitoring solution.

KEYWORDS: Volatile Organic Compounds (VOCs), Multi-Sensor Array (MSA), Internet of Things (IoT), ESP-32, Machine Learning (ML).

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INTRODUCTION

Deteriorating Air quality is one of the greatest threats to humanity; according to WHO research, almost 99% of the world's population is residing in the areas where WHO guidelines are not met. The air pollution is endangering the health of millions of people globally not only at the standard WHO prescribed level but also at lower concentration level [1]. According to a World Health Organization (WHO) assessment, about 92% of the world's population lives in locations where ambient air quality is greater than recommended. According to the research, worsening air quality kills one in every nine people each year, making it the most serious environmental health concern. Furthermore, new studies reveal that outdoor air pollution is the most dominant component, directly leading to 3 million fatalities per year [2].

A wide range of carbon-based substances that easily evaporate at ambient temperature are known as volatile organic compounds, or VOCs. Because of its extensive use in industrial processes and its status as a biomarker in human breath, acetone stands out among them. Acetone exposure can happen by ingesting, inhalation, or skin contact. It can cause a number of health problems, depending on the exposure duration. Irritation of the eyes, nose, throat, and lungs, as well as headaches, nausea, dizziness, and potentially unconsciousness are caused due to Short-term, high-level exposure acetone. Similarly, continuous exposure to acetone for Long-term may cause more serious effects like kidney, liver, and nerve damage, and reproductive problems [3]. The Occupational Safety and Health Administration (OSHA) establishes a permissible exposure limit (PEL) of 1000 ppm for acetone, whereas the National Institute for Occupational Safety and Health (NIOSH) suggests a time-weighted average (TWA) exposure limit of 250 ppm [4].

Acetone detection and monitoring are essential in a number of fields, such as medical diagnostics, workplace safety, and environmental monitoring. Acetone levels in exhaled breath have been linked to diseases like diabetes in the medical industry, where they are used as a non-invasive biomarker for disease monitoring [5]. Although traditional acetone (VOC) detection techniques like mass spectrometry and gas chromatography are accurate but are quite costly, time-consuming, and unsuitable for real-time monitoring. Electronic noses (e-noses), which use sensor arrays and pattern recognition algorithms to simulate the human olfactory system, are the result of recent developments in sensor technology and machine learning. But these systems face issues like higher costs, and the instability of the used instruments [6]. Acetone is one of the many VOCs that needs to be monitored and distinguish in real time. For example, research has shown that acetone may be successfully separated from other volatile organic compounds (VOCs) like ethanol by utilizing metal oxide semiconductor (MOS) sensor arrays in combination with deep learning methods like convolutional neural networks (CNNs) [7]. The integration of Internet of Things (IoT) technologies with sensor systems has further enhanced the capabilities of real-time monitoring. Microcontrollers like the ESP32, known for their low power consumption and built-in Wi-Fi and Bluetooth modules, facilitate the development of portable, wireless sensor devices [8][9][10]. These devices can transmit data to cloud platforms for storage, analysis, and visualization, enabling remote monitoring and timely decision-making. Machine learning algorithms play a pivotal role in processing the complex data generated by sensor arrays. Techniques such as XGBoost Regression (XGBregressor) Long Short-Term Memory (LSTM), have been employed to enhance the selectivity and sensitivity of gas detection systems [11][12].

The present study focuses on the development of an IoT-integrated real-time system for acetone detection and its analysis using machine learning. The system employs a multi-sensor array comprising of ZP-07 sensors for VOC detection and environmental sensors for parameters like temperature and humidity. An ESP32 microcontroller serves as the central processing unit, facilitating data acquisition, preprocessing, and wireless communication. The collected data undergoes feature extraction and is fed into machine learning models for accurate prediction and analysis of acetone concentrations. The integration of these technologies aims to provide a cost-effective, portable, and efficient solution for real-time acetone monitoring in various applications, including environmental surveillance, industrial safety, and healthcare diagnostics.

LITERATURE REVIEW / GAP IDENTIFICATION

To develop a low cost and portable, IoT based monitoring system, exploration of similar existing literature is required to identify the gap, understanding the technological advancement that is required for developing the proposed system.
With sate of the art technological advancements, air quality monitoring systems have taken from simple manual processes to complex real-time systems that make use of satellite photography, state-of-the-art Internet of Things (IoT) sensors, and effective artificial intelligence (AI) algorithms. Continuous data feeds from these systems make it possible to identify the origins of pollution, evaluate regulatory compliance, and create efficient mitigation plans. Through the integration of sensors and technologies like Zigbee and IoT, the study delves into the present environment, challenges, and prospective solutions in the field of air pollution monitoring and analysis [13][14]. which gather and analyse data on common pollutants including CO, CO2, VOC, and PM using a variety of approaches. Regression problems are increasingly often solved by machine learning (ML), especially deep learning (DL)-based models, which have attracted a lot of interest for air pollution prediction [15]. Amazon Large-scale deployment scenarios may be handled with ease because to SageMaker's scalability. To manage ML algorithms and Big Data on a corporate level, SageMaker leverages an enhanced Machine Learning Operations (MLOps) architecture. We can expand resources at a low cost thanks to SageMaker. Conversely, Lambda works well for event-driven, low-cost processes. Additionally, Elastic Container Services (ECS) ensures that deployed services expand seamlessly in response to demand [16]. To reduce the effects of acetone exposure on workshop workers, a system was constructed using an ESP32 microcontroller, an HCHO sensor, and a DHT11 sensor. [17] Jungmo Ahn et al. presented a deployable Internet of Things (IoT) based system for identifying and classifying the various types of volatile organic compounds (VOCs) in the air that uses a paper-based fluorometric sensor in conjunction with integrated processing and camera modules to create our proposed solution, VOC kit [18].

METHODOLOGY

The presented work employs integration of Multi Sensor Array (MSA) Module ZPHS01B with ESP-32-an IoT Controller and AWS Cloud for the monitoring and analysis of Acetone, as shown in the figure-1.

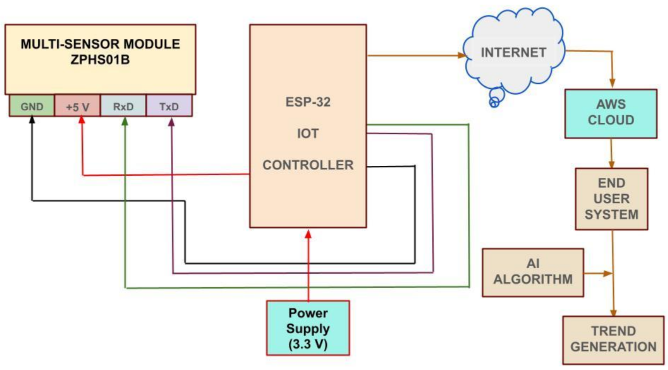


Figure. 1. Block Diagram - Acetone Monitoring and Analysis System

The ESP-32 is a low power IoT controller that has in-built Wi-Fi through which it transmits the sensor data (VOC) on the cloud. The MSA consists of multiple sensors that includes sensors for detection of Carbon Dioxide, Carbon Monoxide, Formaldehyde, Nitrogen Dioxide, Volatile Organic Compounds (VOC) sensor, Temperature and Humidity sensor as shown in the figure 2 [19]. It also has a UART port to initiate the communication between MSA and the ESP-32 Controller. The commands are given by the ESP-32 controller to the MSA to enquire about the sensor data and MSA generates the response providing the sensor data to ESP-32. It also has a UART port to initiate the communication between MSA and the ESP-32 Controller. The commands are given by the ESP-32 controller to the MSA to enquire about the sensor data and MSA generates the response providing the sensor data to ESP-32. ESP32 processor is employed to read the sample values of the VOC and transmit it over the cloud using the inbuilt Wi-Fi capability of ESP-32.

The data from the sensor are fetched by initiating the dialogue between ESP-32 and MSA in the form of Command - Response (question answer). The byte commands are issued from the ESP-32 to MSA and MSA responds to these commands by sending the appropriate data to the ESP-32. The data received by the ESP-32 is then transmitted to the cloud, which is configured with the help of Amazon Web Services (AWS) to create the data base. The samples are read with a baud rate of 9600 at an interval of 5 Sec. and transmitted to cloud with baud rate 115200 using serial transmission. The database created is analysed by deep learning model i. e. Long Short-Term Memory (XGBOOST) algorithm to evaluate the system performance with the help of relation between VOC Grade and Acetone, Acetone concentration prediction.

ZP-07 – A Multi Sensor Array

The MSA has a VOC sensor (ZP07 Module) that monitors the concentrations of acetone, toluene, benzene, methane, and alcohol vapours using a semiconductor gas sensor technique by altering the resistance in reaction to these volatile organic compounds.

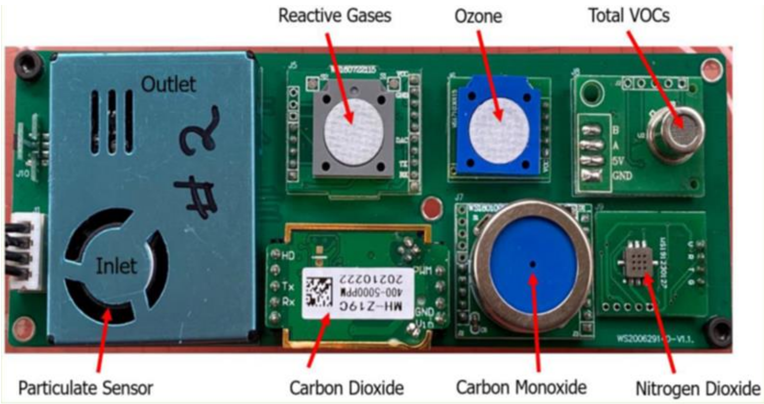


Figure. 2. ZPHS01B – Multi Sensor Array Module

The module's heating element helps to maintain the appropriate sensor temperature for efficient gas interaction, while the signal conditioning circuit and microprocessor process the sensor's resistance changes to provide usable output data. Figure-3 below shows the sensitive characteristics of the VOC sensor to various hazardous compounds [20], [21]. This sensor module is used for monitoring and detection of Acetone in an ambient air. This characteristic clearly indicates that the sensor is highly sensitive to the Acetone and other VOCs.

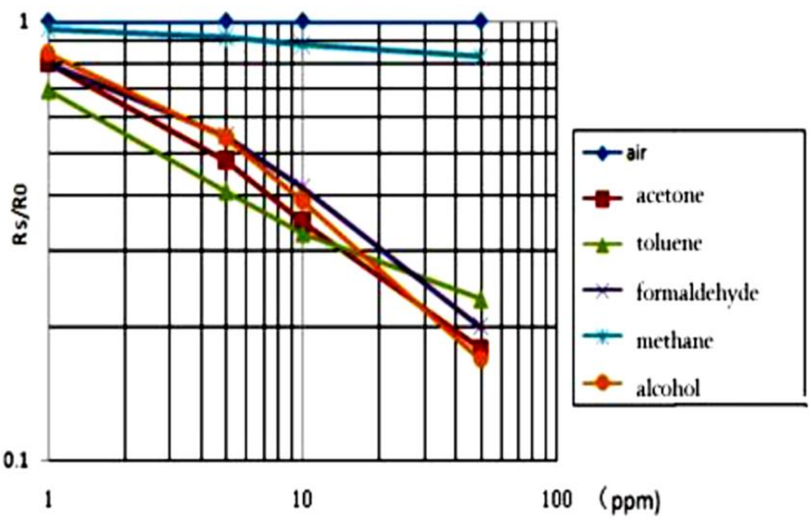


Figure. 3. Sensitivity Characteristics of VOC Sensor

Figure-4, below shows the experimental set up for monitoring and detection of Acetone using ZP-07 sensor. it consists VOC sensor that has four terminals: two terminals for power supply and two signal outputs i. e. Signal A & Signal B. The sensor's resistance changes based on gas concentration.

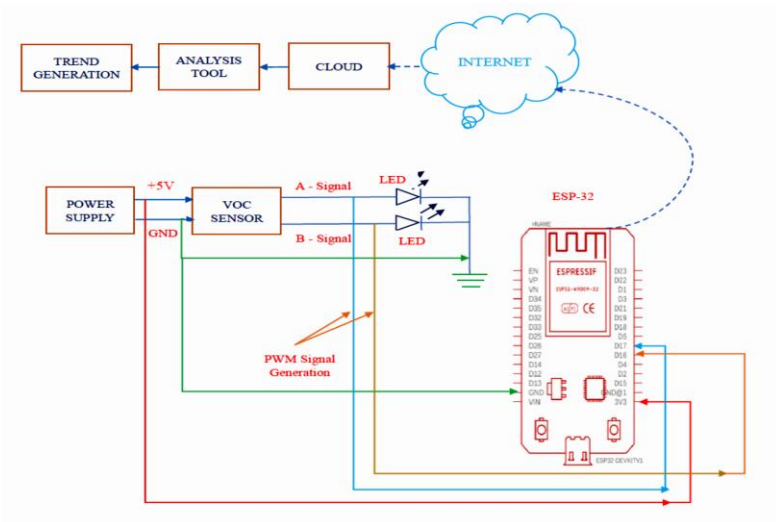


Figure. 4. Detailed Block Diagram of Acetone Detection

It detects pollutant gases by interacting with air molecules, causing a change in electrical resistance. This change is processed and converted into a PWM output signal. A higher concentration (lower Rs) leads to a higher duty cycle on Output A. This increases LED ON time, making it glow brighter for more pollution. A microcontroller measures the PWM duty cycle. It maps the duty cycle to pollution classes (Table 1) as prescribed in the ZP07 datasheet. Thus, the monitoring and detection of Acetone is carried out. The table consists of ten pollution class, with corresponding PWM signal durations on Signal A and Signal B along with the duty cycle. This pollution class table is aggregated in ZPHS01B MAS module in to four class / Grade i. e. Grade 0, Grade 1, Grade 2 and Grade 3 as shown in Table. 2

Pollution Class	High (ms) Signal A	Low (ms) Signal B	Duty Cycle (%)
1	10	90	10%
2	20	80	20%
3	30	70	30%
4	40	60	40%
5	50	50	50%
6	60	40	60%
7	70	30	70%
8	80	20	80%
9	90	10	90%
10	100	0	100%

Table 1: Output Signal – Pollution Class Mapping

The VOC grades in ZPHS01B Multi Sensor Module (MSA) is classified in to four group. i.e. grade 0-3. Where grade 0 – indicates – Negligible / Small VOC concentration, grade 1 – indicates – Medium VOC concentration, grade 2 – indicates - High VOC concentration, and grade 3 – indicates – Very High VOC concentration.

Pollution Grade	VOC Concentration
0	Negligible / Small
1	Medium
2	High
3	Very High

Table 2: Pollution Grade – VOC Concentration

2.1.1– Interfacing multi–Sensor Module (MSA) with ESP 32

The ESP-32 is driven by the power supply (3.3 v) and in turn it drives the the multi–Sensor Module (MSA) is driven by the ESP 32 by supplying the working voltages of +5v at V_{CC} and GND as shown in the figure. 1 above. It also has a UART (TTL) port to initiate the serial communication between multi–Sensor Module (MSA) and the ESP-32 Controller using RxD and TxD pins. The data format followed for serial communication is 8- bit data, 1- stop bit and a baud rate of 9600. The RxD pin of ESP-32 is connected with TxD pin of ZPHS01B – a multi–Sensor Module (MSA) and Vice-Versa to facilitate the serial communication. The communication between ESP-32 and multi–Sensor Module (MSA) takes place in the form of command and response. The commands (8 bit) are given by the ESP-32 controller to the multi–Sensor Module (MSA) to enquire about the sensor data and

MSA generates the response providing the sensor data to ESP-32. ESP32 processor is employed to read the sample values of the VOC along with other environmental parameters and transmit it over the cloud using the inbuilt Wi-Fi capability of ESP-32. The data received by the ESP-32 is then transmitted to the cloud, which is configured with the help of Amazon Web Services (AWS) and ESP-32 IoT Controller to form the data base.

2.1.2– Interfacing multi–Sensor Module (MSA) with ESP 32

In order to interface an ESP32 microcontroller to AWS DynamoDB for VOC monitoring, the ESP32 hardware-software configuration and cloud environment must be configured. Create an AWS IAM user / Root Use ID first, then create a thing using IOT core and incorporate the MQTT test client by downloading the certificates as per the requirements of the services. Next is to provide it programmatic access and rights to utilize the API Gateway and DynamoDB services. For the ESP32 and AWS to communicate and transmit data securely, this is necessary. The sensor data will then be efficiently organized by creating a DynamoDB table, typically referred to as VOC_Data, with device_id serving as the partition key and timestamp as the sort key.

Once the table is created, it's time to configure an HTTP API with the help of AWS API Gateway to receive POST requests. This API can be directly integrated with DynamoDB using service integration for data processing. On the other hand, connect the VOC sensor (such as the ZPHS01B or MQ-135) to one of the UART pins (RxD to TxD & TxD to RxD) of ESP32. Use the Arduino IDE to develop the software module (sketch) that reads VOC data from the sensor, connects to a Wi-Fi network, and transmits the data into JSON (a file format) with a baud rate of 115200. This JSON payload is then sent via HTTP POST requests to the API Gateway endpoint with appropriate headers. The API Gateway sends the data to the DynamoDB database after the request has reached the cloud. There, it is stored and is made accessible for real-time monitoring or additional analysis. This configuration makes it possible to have an economical, scalable, and effective system for ongoing environmental monitoring. Users may remotely monitor VOC levels by integrating the ESP32's Wi-Fi capabilities with AWS's cloud infrastructure, which makes the system perfect for monitoring air quality in urban, industrial, and residential settings.

Experimentation

The device developed for the detection and monitoring of Acetone was installed and the experimentation was carried out at Ameya Paper Mills situated at MIDC, Hingna, Distt, Nagpur (India). The samples of Acetone were read from the device and collected on the cloud using AWS for over a span of seven days

Figure. 5. Device installation at Experimentation Site
(Ameya Paper Mills situated at MIDC, Hingna, Distt, Nagpur (India))

The frequency of the data collection was 12 data samples per minute. Figure-5 below shows the experimentation site, where the experimentation was carried out.

The samples from the device were read using the UART protocol (serial communication pins RxD and TxD of ZPHZ01B) and these samples were collected on the Amazon Web Services (AWS) cloud to form the data set using IoT Controller i. e. ESP-32 with a baud rate of 115200 as shown in the Figure-5 below. The analysis of the data set is carried out to develop the relation between Toluene and VOC. Also, the effect of temperature and humidity on the toluene is studied. The following section deals with the analysis of the toluene.

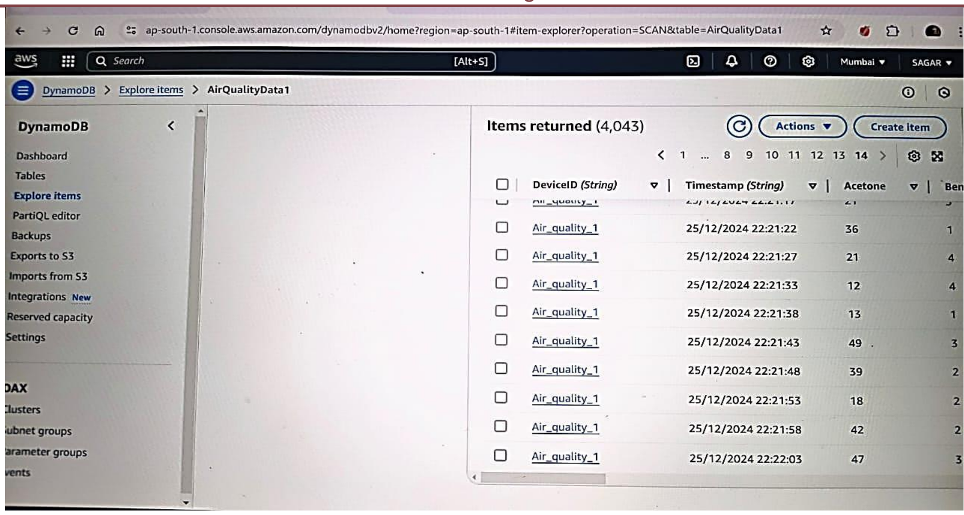
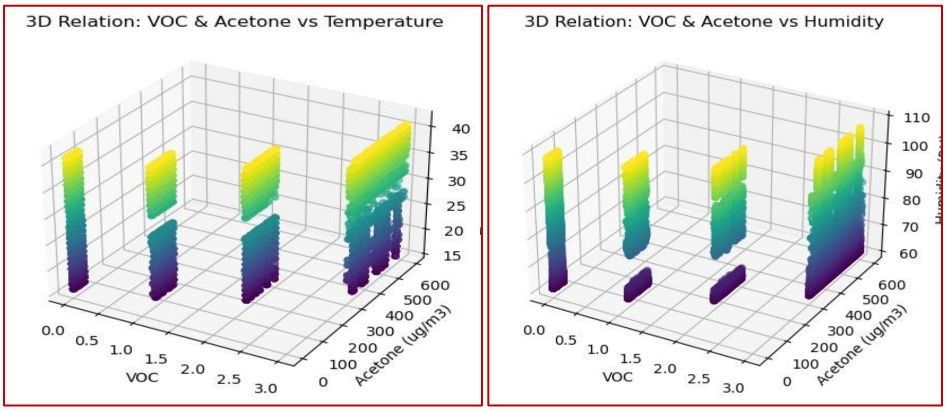


Figure. 6. Data Sample collection on AWS Cloud

RESULTS & DISCUSSION

The 3D plot of VOC & Acetone vs Temperature, Humidity is shown in the Figure.7 (a) and (b) that provides a visualization of how VOC (Volatile Organic Compounds) levels and Acetone concentrations vary with Temperature and humidity. Figure (a) shows the weak correlation between VOC & acetone versus temperature and Figure (b) shows strong correlation between VOC & acetone versus humidity. This indicates that acetone concentration decreases as the temperature rises and vice versa and indicating acetone concentration increases as the humidity rises.



(a) **(b)**

Figure. 7. 3D plot of VOC & Acetone vs (a) Temperature (b)Humidity

At higher temperatures (30°C to 40°C), there's a less dense clustering of high Acetone concentrations, indicating decreased emission rates of Acetone at higher temperatures whereas there is much denser concentration of acetone at higher humidity levels.

The Correlation Heat-Map

This correlation heatmap as shown in figure. 8 represents the pearson correlation coefficients between the different gas concentrations (Methane, Acetone, Benzene, Acetone) and environmental variables (Temperature and Humidity). It provides a clear view of interdependencies among features that are crucial for feature selection, model design, and sensor calibration in a real-time detection system. The analysis revealed that VOC grade and acetone concentration (0.96) has a very strong correlation. Moreover, Strong Positive correlations Among VOCs i. e. Acetone vs Benzene: 0.95, Acetone vs Toluene: 0.94, Acetone vs Methane: 0.94. Acetone Vs Temperature (-0.07) and Acetone Vs Humidity (0.11) These correlations are weak, indicating that environmental variables do not strongly influence Acetone concentration directly.

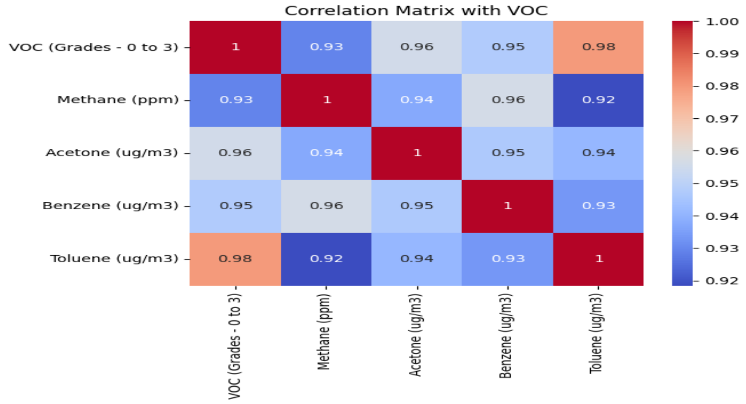


Figure. 8. Correlation Heatmap

Predictive Analysis

XGBoost is advanced version of gradient boosting machine learning algorithm that has the ability to handle a wide variety of problems including text recognition, natural language processing, time series forecasting, image and video captioning, sentiment analysis and computer vision [22]. The XGBOOST algorithm is applied for analysing the dataset created over the cloud using AWS. The details of application of the XGBOOST is discussed in the section below.

The dataset accessed from the AWS cloud is first cleaned and the it is given as an input to the XGBOOST algorithm. The process with reading an Excel file, excluding the first five rows, which are either header data or metadata that not required for analysis. After that, it eliminates any leading or following whitespace from the column names to standardize them. To allow time-series operations, the Timestamp column is changed to datetime format. To maintain data integrity for the toluene values, any rows with missing values are eliminated. After that, the Timestamp column is assigned as the index and the dataset is arranged chronologically. The Device_ID column is removed as it is not pertinent to the analytical activities. The normalization of toluene data takes place that scales each feature to have a mean of 0 and a standard deviation of 1, ensuring compatibility with machine learning algorithms sensitive to feature scaling. This updated output of toluene is then mapped in a new Data_Frame with the original column names and preserving timestamp index. The input-output pairs are generated using a sliding window approach from the scaled data, where the last 24-time steps act as features and the current values of the target columns act as labels.

The next step is to train and test the data sample for prediction. The ratio of training and testing data samples are 80:20 i. e. 80% samples are used for training and 20% samples are used for testing. The multi-output time series prediction model is composed of a Dense layer with 32 ReLU-activated neurons, an XGBOOST layer with 64 units that analyzes sequential input, and a final Dense layer that generates predictions for Toluene. The Adam optimizer and mean squared error loss are used to assemble the model, and if validation performance does not improve after 10 epochs, an early stopping mechanism is configured to end training and restore the optimal model weights. 10% of the training data is set aside for validation, while the remaining 90% is used to train the model. It has a batch size of 32 and operates for up to 100 epochs. To aid avoid overfitting, it has an early stopping function that stops training if performance stops getting better.

Figure. 9 below shows Prediction Graph of Acetone with respect to VOC grade. The toluene concentration (Actula and Predicted) is available along the X-axis and the VOC grade is available on the Y-axis. The graph has two different coloured signals, one with blue colour represents the actual toluene concentration and orange colour represents concentration of the predicted toluene with respect to VOC grade. The prediction analysis has revealed the RMSE :0.281274, MAE: 0.153073 and R^2 Score: 0.849821 indicating that the device performance using XGBOOST for prediction of toluene is highly recommendable.

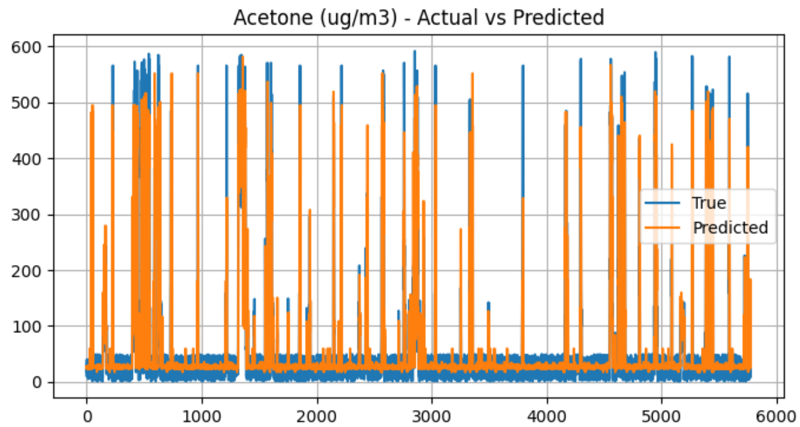


Figure. 9. Actual Vs Predicted Acetone Concentration

CONCLUSION

The real time, IoT based system developed for the monitoring and Prediction Analysis of Acetone was installed in the paper mill industry in MIDC Hingna, Distt, Nagpur (India) and an experimentation was carried out. The samples of the Acetone were collected over the cloud from the sensor module with the help of an IoT controller. The data set was analysed using XGBoost algorithm and the system performance is evaluated using parameters like MAE and R^2. The analysis revealed that VOC grade and acetone concentration (0.96) has a very strong correlation. Moreover, Strong Positive correlations Among VOCs i. e. Acetone vs Benzene: 0.95, Acetone vs Toluene: 0.94, Acetone vs Methane: 0.94. Acetone shows that the developed device is highly capable of detecting the Acetone concentration. The weak relations between Acetone Vs Temperature (-0.06) and Acetone Vs Humidity (0.11) indicates that environmental variables do not strongly influence acetone concentration directly. Strong Positive Correlations Among VOCs: Acetone vs Benzene: 0.94, Acetone vs Acetone: 0.94, Acetone vs Methane: 0.92. The prediction analysis has revealed the RMSE :0.281274, MAE: 0.153073 and R^2 Score: 0.849821 indicating that the device performance using XGBOOST for prediction of toluene is highly recommendable.

Finally, it can be concluded that the IoT based real time device developed for monitoring hazardous exhaust compounds is cost-effective, compact and easily deployable at a fraction of the cost of traditional systems. The dataset generated by the system can be useful to the regulating / external agencies for the pollution audit, framing the future policies, ensuring increased workplace safety and regulatory compliance in industrial settings. This device can be employed in industrial settings that can ensure increased workplace safety and regulatory compliance by providing an affordable and scalable environmental monitoring solution.

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