TOWARDS CLOUD BASED APPROACH FOR AIR QUALITY ANALYSIS AND PREDICTION USING MACHINE LEARNING TECHNIQUES AND IOT IN SMART CITY

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Abstract

A number of pressing issues, including increasing waste generation pollution, high health care costs and rising energy consumption have given rise to smart cities as solutions to stop the overwhelming urbanization process. For an effective and sustainable smart city environment, this study suggests effective and superior cloud based machine learning solutions. Several issues that directly affect garbage increase and inappropriate waste disposal have been examined in this study. In the recent studies, an Internet of Things-based technology used to monitor a waste collection system in real-time, but it can't stop overspill and foul-smelling release gases from spreading. This study introduces an Internet of Things (IoT) smart bin that uses a machine learning and deep learning model to forecast the air pollutants existing in the bin environment and control garbage disposal. In order to forecast air quality based on real-time data and predict the bin's status, the smart bin is connected to a cloud server. We tested a non-traditional (long short term memory (LSTM) network-based deep learning) and traditional (k-nearest neighbors algorithm (k-NN) and logistic reg) model for generating alert messages about bin status and predicting the concentration of air pollutant carbon monoxide(CO) in the air at a given time. The system monitored garbage levels in real time and sent messages via the alert mechanism. The proposed works improve accuracy by applying machine learning over existing methods based on simple methodologies.

Keywords - *Smart City, AQI, Machine Learning, Regression, LSTM, Deep Leaning, IOT, Waste Management.*

1. INTRODUCTION

Over the last two decades, we have seen a remarkable increase in urbanization, with rural areas gradually being abandoned in favor of cities, which can provide several options in terms of education, employment, social life and overall quality of life. According to previous research, urbanization is a continuously rising phenomena that is anticipated to accelerate, with 70% of the people living in cities. This phenomenon has two main effects: on the one hand, it raises the city's cultural level and improves its economic circumstances; on the other hand, the city's population density leads to a number of organizational, social, technical, and economic issues that threaten the city's ability to remain economically and environmentally sustainable. Urbanization leads to increased traffic, pollution, gas emissions, waste and social inequality, all of which have detrimental effects on people and the environment. As a result, energy consumption and pollution levels rise, urban waste volume rises, inadequate infrastructure is reduced, social cohesion declines, and more[01].

Air Pollution in many cities, particularly smart cities, air pollution is a serious issue. Even while smart cities employ technology to efficiently manage resources and infrastructure, controlling air pollution remains a challenge. There are several methods that smart cities can address air pollution[1].One approach is to measure the quality of the air and identify the sources of pollution by processing the data from sensors. This information can be used to create programs and regulations that will reduce pollution. Controlling air pollution in smart urban areas requires a mix of innovations in technology, regulations and public awareness.[2].The technical solutions that can be used to measure air quality in smart cities are the main topic of this study. The model should be built with a reduced processing time because the data is time-based. We are therefore making use of a cloud platform.

2. MOTIVATION AND BACK GROUND

The main root cause of air pollution is the combustion of waste which produces poisonous and dangerous pollutants such as carbon monoxide (CO), particulates of matter (PM), sulfur dioxide (SO2), nitrogen dioxide (NO2), and ozone (O3)[38].One of the main air pollutants produced by burning waste and plastic is PM2.5 or airborne particulate matter with a diameter of less than 2.5 micrometers[39].Global warming, the greenhouse system and the environment are all severely impacted by air pollutants. They may cause psychological and health issues with breathing [**9**].When the concentration of PM in the air changes, researchers also looked at the long-term impacts on human health; the study came to the conclusion that PM has an impact on both time and quantity dependent results[37].

The various complex metallic and nonmetallic components that make up garbage cause to environmental instability and inappropriate collection of waste can endanger the health of living things. Waste policies are necessary in developing and underdeveloped nations, according to a new study. Rapid population growth has led to an increase in waste which has had detrimental consequences on the ecosystem. Developed countries can handle and manage waste, but less developed countries are unable to do. Unsystematic waste management and disposal are major contributors to the deteriorating of the environment's aesthetics. The main source of pollution in the environment is the excessive gathering of waste[40].Smart cities under development frequently exhibit irregularities in the disposal of garbage in dustbins placed in various regions, requiring extra human labor, financial resources and time[41].

Existing research suggests that the old waste management system should be replaced by an IoT-based solution. IoT-based technologies use RFID tags, sensors, and Long Range (LoRa) technology to collect waste in real time with minimal human intervention[43,44].The data gathered using IoT-based technologies provide real-time tracking of waste management authorities and air pollutants using integrated systems which include radio-frequency identification (RFID),global positioning system(GPS),general packet radio services (GPRS), geographic information system (GIS), and web cameras. The majority of traditional systems focus on waste monitoring and tracking as well as air quality monitoring[45,46].The comprehensive research is carried out for a suitable system for tracking and also predicting the presence of harmful air pollutants in waste is essential for maintaining the cleanliness of the environment. In order to prevent adverse impacts on the health of residents of smart cities like Bhubaneswar, our designed system incorporates both waste management and monitoring as well as air pollution predictions and monitoring.

In order to manage smart waste management systems, we carried out an innovative initiative using machine learning and an Internet of Things-based system. Our method demonstrated better accuracy than conventional waste management systems. The approach suggested also provides adequate details to monitor environmental air quality analysis. The proposed system can provide precise, real-time waste level monitoring, as well as notifications to the city's waste management via an alarm mechanism. It addresses the management of polluted waste in smart cities with under optimized waste disposal systems. It offers real time environmental monitoring of various harmful gas concentrations. Mechanisms for monitoring air quality enable users to predict the next concentration in the air and take prompt corrective action.

Research Questionnaires:
This study addresses the following research questions:

RQ-1: What are the methods and approaches made use of to monitor and manage waste in smart cities?
RQ-2: How can the percentage of air pollutants surrounding a smart-bin predicted and monitored?

A. Air Quality Index Calculation:
In some countries, the air pollution index (API) is used interchangeably with the air quality index (AQI).The number of pollutants depends on the area or location for which the air quality index is calculated. Nitric oxide, particulate matter, ammonia, benzene, nitrogen dioxide, toluene, sulfur dioxide, xylene, hydrogen, and carbon monoxide are some of the most frequent pollutants found in our atmosphere[3].The air quality index is calculated using the method below based on the concentration of contaminants. The final AQI is calculated using the highest AQI value among all contaminants[4].Our regression model uses this generated value as its target feature. The AQI has no specific upper limit; nevertheless, it can be classified, which differs by country.Table:1 shows the AQI category for India, along with an AQI range column[5].

$$I = \frac{I_{high} - I_{low}}{C_{high} - C_{low}}(C - I_{low}) + I_{low}$$

Where,

I = Air Quality Index

C = Concentration of Pollutant

C_{low} = the concentration break-point < C

C_{high} = the concentration break-point > = C

I_{low} = the index break-point corresponding to C_{low}

I_{high} = the index break-point corresponding to C_{high}

The AQI range is the target variable of the classification model, represented in our datasets by the AQI bucket.

TABLE 1. AQI category for India

AQI Range	PM10	PM2.5	NO2	O3	CO	SO2	NH3	Color
Good(0-50)	0-50	0-30	0-40	0-50	0-1.0	0-40	0-200	deep green
Satisfactory(51-100)	51-100	31-60	41-80	51-100	1.1-2.0	41-80	201-400	light green
Moderate(101-200)	101-250	61-90	81-180	101-168	2.1-10	81-380	401-800	yellow
Poor(201-300)	251-350	91-120	181-280	169-208	10-17	381-800	801-1200	orange
Severe(301-400)	351-430	121-250	281-400	209-748	17-34	801-1600	1200-1800	red
Hazardous(401-500)	430+	250+	400+	748+	34+	1600+	1800+	maroon

B. Machine Learning:

In machine learning, approaches are used to train machines to detect patterns and relationships in datasets. Machines generate predictions based on these patterns. We use both supervised and unsupervised machine learning models[6].If there are no labels for the data, unsupervised machine learning is used to process raw data. For labeled data, supervised models are preferable. There are two main subcategories of supervised machine learning: classification and regression[7].

While classification generates an output with defined labels, a value that belongs to a preset category regression generates a continuous numerical result. A general machine learning model is shown in Figure: 1.The model describes the operation of general machine learning models. We can observe what steps are involved to make predictions from the input data[8].The figure also includes a list of alternative algorithms, as well as the evaluation criteria required to test these models. The diagram also shows the best division of the data frame into testing and training sets[8].In our research, we employ all of these procedures to produce predictions which has been described in detail.

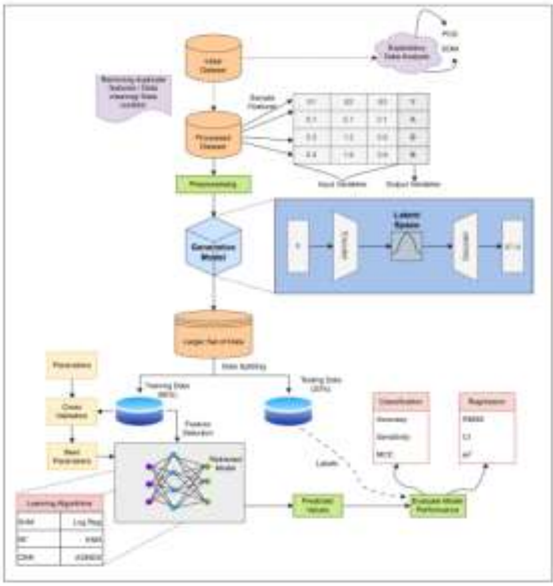

Fig.1: Machine Learning Model

- **Regression**: "Regression" is the process of determining the relationship between a specific dependent parameter and a large number of independent parameters. To put it merely, this implies fitting a function from a given set of tasks to the input data that was collected under an error function[9].The most widely used regression methods include random forest, lasso regression, decision tree regressor, support vector regressor and linear regression. Since the target variable (Air Quality Index) is a continuous numeric value, regression would be appropriate for this research [10].Apparently linear regression and lasso regression are being used here.
- **Lasso Regression:** Least Absolute Selection Shrinkage Operator is referred to as LASSO. Generally speaking, shrinkage is defined as a restriction on characteristics or variables. In order for the regression coefficients for specific characteristics to decrease until they equal zero, this technique determines and implements a constraint on the model parameters. Features like a regression coefficient of zero are not included in the model. Because of this, lasso regression modeling is basically a feature-choosing and shrinking technique that helps determine the key predictors. It will only select one characteristic from a set of linked features, and that attribute may be highly biased, even while it avoids over-fitting.
- **Linear Regression:** Using a variety of independent factors, this regression technique predicts a dependent variable as part of supervised machine learning[11].Compared to alternative regression techniques, it is easier to implement. The sub-indices of the pollutants nitric oxide, particulate matter, ammonia, nitrogen dioxide, toluene, xylene, sulfur dioxide, nitric oxide, benzene, and carbon monoxide are the independent characteristics used to predict air quality. The dependent attribute in this case is the

air quality index (AQI).This regression model offers a linear relationship between the dependent parameter, denoted as y and several independent parameters, denoted as series of x, as shown in figure.2.

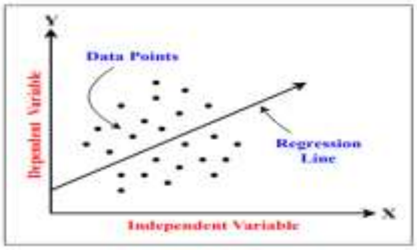

Fig. 2. Linear Regression

C. Classification:

Based on training data, the classification approach is a supervised machine learning technique used to identify the class of novel findings. Before classifying fresh findings into a variety of clusters or categories, such zero or one and yes or no, a software program first learns from the original datasets or observations[12].

Labels, objectives, and groups are other names for categories. Unlike regression, classification uses the name of a category as the target parameter instead of a value. Since the classification method is a supervised learning process, it requires labeled input data, which suggests that it incorporates input with acceptable output[13].These methods are mostly used to forecast the result for categorical variables, and the main goal of the classification algorithm is to determine the class of the original data. The following figure.3 provides a clear explanation of classification strategies. Class- A and Class- B are the two groups shown in the diagram. These groups share characteristics with each other, but not with other groups. Classification can be further divided into two: binary and multi-class [14].Unlike binary classification, which only predicts yes or no,0 or 1,multi-class classification involves the algorithm predicting several different categories. We are using random forest methods and a support vector machine in this study.

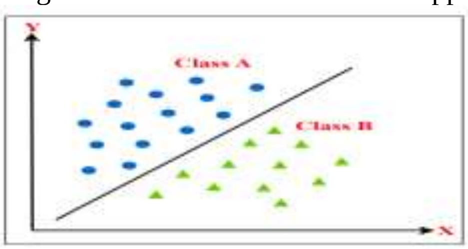

Fig. 3: Classification Model

- **Support vector machine**: The main goal of this method is to find a hyper-plane with n dimensions that clearly labels the data items (where n is the entire range of parameters).To separate the two sets of data elements, many feasible planes could be used. Our goal is the plane with the largest margin, or the greatest distance between the points in both classes[14].The margin distance should be maximized to improve the classification accuracy of future data points. Hyper planes act as decision boundaries for the data point classification process. Different categories can be applied to data points on either end of the plane. Furthermore, the number of features determines the hyper-plane's size. The hyper-plane is reduced to a line when the number of input parameters is two. The hyper-plane transforms into a two-dimensional plane when the number of input parameters is raised to three. It is challenging to envision a hyper-plane when there are more than three features. Support vectors are data points that are either near or immediately distant from the hyper plane. The classifier's margin is increased by employing these support vectors, which have an effect on the plane's position and orientation. The plane will reorient when the support vectors are removed[14].

- **Random Forest**: A "random forest" is a collection of various smaller decision trees that cooperate to accomplish tasks. One of this algorithm's most important characteristics is its ability to handle input data that contains either continuous variables for regression or categorical variables for classification [15].Classification problem yield useful results. Before attempting to discover how the random forest method works, it is vital to comprehend the ensemble technique. An ensemble is a collection of different models. We have boosting and bagging in ensemble. Random forest operates on the bagging principle, as illustrated in Figure.4.According to this principle, the final output is determined by voting and various subsets are created from the original training set as the replacement [15].As a result, a collection of models is utilized to generate predictions rather than just one.

Fig. 4: Bagging Principle

In the random forest, each tree offers a category prediction. The model's real forecast is the category that receives the most votes. The models' poor correlation is the key component. In the same way that assets with weak correlations might combine to form a collection that is larger than the sum of its parts, uncorrelated models can produce ensemble forecasts that are more accurate than any one of the individual projections. This striking appearance is the result of the trees shielding one another from their individual errors[15].

D. Cloud Computing

"Cloud computing" refers to the idea of providing ubiquitous, easily accessible, on-demand system access to a dispersed pool of adaptable computer resources. With significantly less engagement from service operators or organizational operations, it enables the quick deployment and release of these resources

[17].When technology migrates from personal desktop computers, single server applications, or personal data centers to a cloud of computers, a shift in the computing architecture takes place. Clients are only concerned with the computing function they are requesting because the basic workings of how computing is done in the cloud are hidden.Figure.5 provides a description of cloud computing including the computational functions that the cloud provides.

Serverless, infrastructure as a service (IaaS), software as a service (SaaS), and platform as a service (PaaS) comprise the four main categories into which the majority of cloud-based computing services fall. Because they are piled on top of one another, they are commonly referred to as the cloud computing stack. Knowing what these categories are and how they vary from one another makes it easier to accomplish the goals of the business[17].

Fig. 5: Cloud Computing Services

E. Machine Learning and Smart City Applications

In most recent studies, air pollution in smart cities was predicted using machine learning. The most widely used machine learning techniques are regression and deep learning models, while some research additionally use the support vector machine approach because these models outperform the others[18].IOT when used with artificial intelligence and machine learning can enhance a city's operations[32]. The primary focus is on improving the urban infrastructure in order to raise living standards. As seen in Figure.6, it highlights the importance of machine learning in domains in the context of smart cities utility services and technological solutions.

The importance of machine learning (ML) in a number of essential enabling technologies, including intelligent transportation, smart metering, logistics management, and healthcare, smart waste-management, smart-tracking, monitoring and forecasting systems and many more applications. Furthermore, this study assesses various data incursions for smart cities and lists the main factors influencing the evolution of smart city concepts[21].

Deep learning is a more general family of machine learning techniques based on artificial neural networks and representation learning [22].Deep learning combines several layers to gradually extract extremely complex features from the raw input data. Each level in deep learning acquires the ability to transform its input data into a little more abstract composite form [23].The learning process itself might decide how best to arrange the elements at various stages. By applying machine learning approaches to solve significant problems, DL has been making significant strides in the field of artificial intelligence for many years [24].

Neural systems utilized in machine learning are called artificial neural networks (ANNs).Neurons in artificial neural networks (ANNs) are activated by connections that are weighted according to previous activation [25].DL uses the Deep Neural Network (DNN) architecture to process signals and data more efficiently. It uses hidden layers positioned between the input and output layers to determine weighted layers from the input layer to the output layer.

Fig. 6: Machine learning based solutions for Smart City

- **Regression model:** Regression is one of the most well-known machine learning methods for forecasting air pollution. This is due to the continuous nature of the variable that needs to be anticipated. Four different advanced regression techniques Gradient Boosting, Random Forest, Decision[26].The four-layer architecture of data gathering, transmission, administration, and application has been proposed for pollution level prediction.

The results showed that the calculation time was significantly less than that of multi-layer feed-forward neural networks and gradient boosting approaches. Even while other machine learning algorithms are also more effective in predicting air quality, this study is restricted to regression techniques. By contrasting multi-layer convolution and random forest techniques on air pollution dataset, the study in[27] overcomes constraint. The hourly AQI values of pollution levels of different gas elements may be predicted by researchers with a reasonable degree of accuracy. The methodology is not succinctly explained in this study, despite the good findings obtained. In the future, the authors intend to improve their work by fine-tuning the SVR settings. Other methods for parameter optimization including particle swarm optimization or genetic algorithms would be interesting to investigate because the performance of the SVR model is greatly influenced by the selection of the kernel function and penalty parameter C[27].

- **Classification Model:** The use of categorization techniques to forecast air quality in smart cities has received relatively little attention. A popular method in research involving classification models is support vector machines. The authors of the study used support vector machines and neural networks to predict the air quality index. Different kernel functions may be used for different decision functions, and more complex plane types can be produced by mixing many kernel functions. The kernel function can be used to apply two vectors, and each point can be mapped into a high-dimensional space via a transformation[29].The F1 score, accuracy, recall, and precision are the main metrics used to evaluate a classification model. Accuracy is defined as the proportion of correct predictions for the test data. By dividing the number of accurate forecasts by the total number of forecasts, it is easy to compute. There is no information on false positives or false negatives in the accuracy measure. Consequently, a substantial amount of data is lost, some of which may be used to assess and enhance our model. space in dimensions[29].

- **Confusion Matrix:-** Essentially a N x N matrix, where N is the number of labels, this matrix assesses how well a categorization model works. Whereas each column in a confusion matrix represents an expected category, each row represents a genuine category. We may quickly generate this matrix using the SkLearn library's confusion matrix() method. The following figure.7 shows a confusion matrix[29].

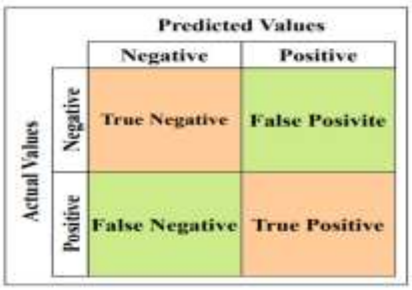

Fig. 7: Confusion Matrix

According to the confusion matrix above:

- A true positive (TP) indicates that the predicted and actual numbers are accurate.
- A false positive (FP) indicates an error because the true value must be false while the anticipated value is true.
- The term "true negative" (TN) indicates that both the predicted and true values are false
- When the projected value is false, a false negative (FN) indicates that the real value must be true.
- **Precision-** The ratio between the real positive value of the technique and its total true positive value is known as precision. Using the precision score() function from the SkLearn package, precision may be easily calculated. The fact that a model can only produce one true positive prediction while reporting the others as negative means that precision is insufficient. Therefore, 1/(1 + 0) = 1 would be the precision. Precision must be used in conjunction with another metric called "recall."

$$Precision\ (P) = \frac{TP}{(TP + FP)}$$

- **Recall-**We can use this metric the ratio of the number of true positives to the total number of positives. Recall is sometimes known as "true positive rate" or "sensitivity." The SkLearn library's recall score() function makes recall computation easy.

$$Recall\ (R) = \frac{TP}{(TP + FN)}$$

- **F1 Score-** The recall precision meter, also referred to as the F1 score, is another classification metric that integrates recall and accuracy. It is the recall and precision harmonic average. Only when precision and recall are both strong can the F1 score be excellent because the harmonic average is far more susceptible to low values. The F1 score can be easily calculated using the SkLearn library's F1 score() function.

$$F_1\ Score\ (R) = \frac{PR}{P + R}$$

Where, P = Precision. R = Recall.

F. Deep Learning Approaches

An Internet of Things (IoT)-based system for predicting and for assessing air quality. It uses a machine learning technique called a recurrent neural network (RNN) to monitor pollution. In order to anticipate pollution levels, a recurrent neural network is used to continuously monitor the components online. Each sensor data is sent to a cloud server.

This study uses a DHT11 sensor(as depicted in figure.10 and 11) to continuously gather digital temperature and humidity data. The system uses air detectors to gather this data, which is subsequently sent to a microcontroller. After gathering the data, the microcontroller uploads it to a web service. When it comes to estimating, the Long Short-Term Memory (LSTM) approach is unstable. Rapid convergence and high accuracy training time reduction are made possible by it[31].However, disappearing and shattering variations are prevalent in RNNs which leads to the training model either stabilizing or abruptly stopping. While Bi-LSTM can make the most of future knowledge, regular LSTM and RNN often ignore it when processing time. The effectiveness and comparability of the results form the basis of the main findings of this study: the model uses CNN and LSTM, which have high precision and stability, to efficiently identify the spatial and temporal aspects of the data[33].In smart cities, this technology could enhance the estimation of air pollution[29].

G. Cloud Enabled AI Approaches

This study detailed a cloud-enabled method for measuring vehicle flow-related pollutants, and the results were analyzed by summing the emissions from every single vehicle. By examining the raw CCTV footage of the location and the recurrent data collected by the sensor units positioned strategically across the region, the variations in the emission lines are found. This proposed work has taken into consideration the pollution issue in the Bhubaneswar Municipal Corporation (BMC) Smart City zone[35].

3. RELATED WORK

A. Data collection and Evaluation:

While creating this system, one of the main challenges we encountered was the need for a common database that contained garbage statistics. In order to target smart garbage collection and smart air monitoring, our application did not have access to any real-world datasets. There is currently only one dataset on air quality that shows the concentration of various pollutants in the air [51].The collection includes records for the concentrations of several gases found in a contaminated environment. Several different types of sensors were used to get this data in the contaminated environment.

We developed a smart bin with an air monitoring module, weight, odor and distance sensors. Several distinct smart bin locations were set up in various zones in the smart city. The garbage(waste) was weighed and its level was assessed using weight and distance sensors, respectively. Garbage odor was detected using odor sensors[51].Unlike other we used a TGS2600 sensor in order to detect hydrogen, ethanol, and CO levels in the air. The TGS 2600 has high sensitivity to low concentrations of gaseous air contaminants such as hydrogen and carbon monoxide which exist in cigarette smoke. The sensor can detect hydrogen at a level of several ppm. Due to miniaturization of the sensing chip, TGS 2600 requires a heater current of only 42mA [51].

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Fig. 8: TGS2600 Sensor

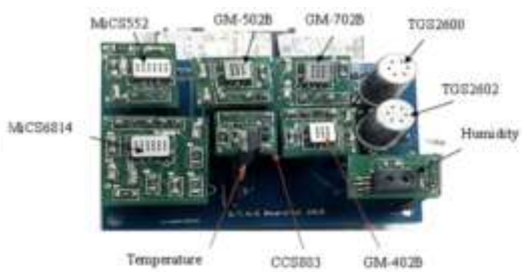

Fig. 9: Main PCB board fitted with all gas sensor modules.

At the side of the smart bin was a TGS2600 sensor.CO has a little lower density than air at room temperature. The air and CO concentrations differ slightly. The type of trash in the bin may contribute to the elevated CO concentration, but other external factors, such as incomplete burning of carbon-containing fuels like coal, oil, charcoal, wood, kerosene, natural gas, and propane, may also play a role. Installing a sensor inside the smart bin will only provide the CO level inside the bin, not the surroundings around the smart bin. After taking these issues into account, we positioned the TGS2600 sensor outside the bin in order for it to monitor the amount of CO in the surrounding air and identify any gas leaks that may occur inside the bin[51].

Fig. 10: DHT11 Sensor

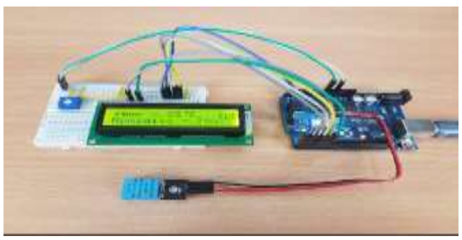

Fig. 11: DHT11 Sensor Measuring
Temperature and Humidity.

Incomplete combustion processes or other chemical wastes found in smart bin produce CO. [51].Either AWS cloud server or Google Cloud Server (GCP) can be preferred to use as data storage to store the sensor data depending upon the requirement and scalability of data fetched through the sensors. Air quality, odor sensor, waste level, and garbage weight data were kept individually for every waste bin. For every waste bin, the actual hourly averaged concentration measurements of the gas were stored separately. The dataset included the smart bins' readings during a six-month period.In order to do various analyses, this dataset was subsequently downloaded from the web server[17].

TABLE 2. Lists of the key features considered in the model, along with their descriptions.

FEATURES	DESCRIPTION
LOCATION AREA	BMC Zones
AQI	Air quality index
PM2.5	Particulate matter 2.5-micrometer in ug / m3
PM10	Particulate matter 10-micrometer in ug / m3
NO	Nitric oxide in ug / m3
Benzene	Benzene in ug / m3
CO	Carbon monoxide in mg / m3

Toluene	Toluene in ug / m3
NOx	Nitric x-oxide in ppb
Xylene	Xylene in ug / m3
SO2	Sulphur dioxide in ug / m3
NH3	Ammonia in ug / m3
Ethanol	Ethanol in ug / m3
Hydrogen	Hydrogen in ug / m3

B. Periodic monitoring of Air Pollutant in Waste:

One of the primary objectives of our proposed approach is to monitor and forecast air pollution. We employed deep learning techniques to accurately predict future concentrations of a certain gas in the atmosphere in order to accomplish this goal. The LSTM model was used to forecast, and a comparison with a invariant model which was regarded as the basis model was also conducted. The dataset included the various gases' hourly concentrations. A window of size 120 (24 × 5) was created using several days' worth of gas level observations in order to train the model[59].The dataset was standardized by calculating the means and standard deviation. We used a baseline model prior to training the model. The baseline approach took into account the entire history for a given input point and forecasted that the next point would be the average of the previous observations. The following figure.12 displays the system's forecast, with the actual data received at that specific time slot representing the true future, the green circle representing the model prediction, and the blue line representing the preceding instant[59].

The prediction of the baseline model was unreliable since it only used averaging techniques. An RNN is used to improve future instance value forecasting. One type of neural network that works well with time series data is an RNN. The intrinsic information in cells that are passed on to the following cells is maintained by processing a time series step by step. A unique kind of RNN-based LSTM model was trained to estimate the gas concentration throughout the course of the next hour. In the figure.13,the outcomes of the model's forecast are displayed. The expected value, which represents the gas concentration at the moment is shown for Time Slot 0[59].

The graph clearly shows that there was a small discrepancy between the projected and actual numbers. By merely using the averaging approaches, the baseline model was unable to manage any changes in subsequent cases. The input-output gate structure and memory cell were features of the LSTM model. Information was recorded in the memory cell and its ability to flow into or out of the memory cell was assessed by the input-output gate. It outperformed the baseline model in predicting future occurrences as a result of these features[59].

Future event forecasting can also be accomplished by adjusting the LSTM model's configuration to provide more accurate predictions in the future. In order to train it for the prediction of gas levels in the upcoming 12-hour time intervals, the LSTM model configurations were modified. In order to forecast the next gas concentration level in the upcoming 12 hours, the model was trained using several days' worth of hourly data[59].The model's output is displayed in Figure.14.Since the model prediction deviated more from instance zero, it predicted the gas level's future value. When the LSTM model was trained on a larger dataset, the anticipated future and true future overlapped on the graph, indicating an improvement in prediction accuracy[59].The baseline, simple LSTM and improved LSTM models were tested on offline and real-time datasets to determine their accuracy[59].The following figure.15 displays the accuracy of these three methods. When tested in real-time circumstances, it was shown that the Modified LSTM model could attain an accuracy of approximately 90%.The graph indicates that in real-time circumstances, a basic baseline model obtains an accuracy of about 80%.The concentration of gases and other outside variables affect the system's accuracy. The CO concentration using the baseline model is displayed in the following figure.12.The CO concentration forecast for the next 1 and 12 hours is displayed in figures 13.and 14 as follows.

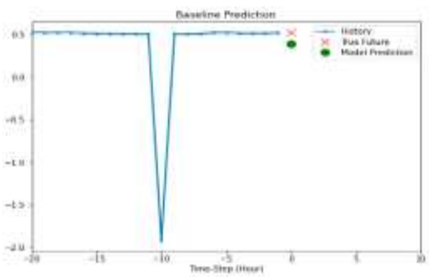

Fig.12: Prediction performed by univariant model

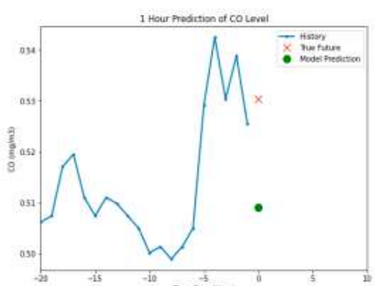

Fig.13: Prediction performed by univariant model

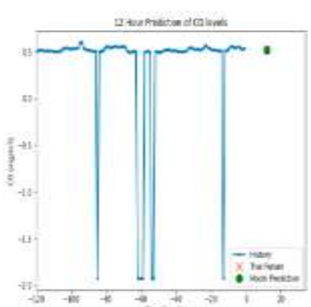

Fig.14: LSTM forecasting for 12 h.

Fig.15: Offline vs. online accuracy of forecasting.

C. Obtaining Results Using Cloud Platform:

Results show that the cloud platform helps reduce the execution time for all four models, and the time required for data pre-processing can also be reduced. The execution times using personal computer Jupyter Notebook and SageMaker's Jupyter Notebook are given in Table.3.The aforementioned models are deployed on the cloud platform using AmazonSage Maker service. The Amazon SageMaker provides a Jupyter Notebook where we can execute the same Python code[51].Because of its tremendous scalability, Amazon SageMaker can effectively handle big datasets and modeling approaches. Large volumes of data can be processed more effectively as a result, significantly cutting down on processing time. Amazon SageMaker provides high-performance computer instances for machine learning tasks. These examples have strong CPUs and GPUs that can significantly accelerate machine learning model implementation, leading to quick predictions[51].

TABLE 3. Execution Times.

Execution time in sec	Personal Computer	Amazon SageMaker
Linear Regression	0.0876	0.0300
Lasso Regression	0.0648	0.0227
Regression with EDA	15.9757	5.6913
Random Forest	2.0583	1.7559
Support Vector	22.3401	17.8312

Machine		
Classification with EDA	33.6758	21.3630

By utilizing Amazon SageMaker batch transform to execute inference on huge datasets in parallel, prediction time can be greatly reduced. When evaluating air quality in smart cities, where a vast amount of data needs to be evaluated, this approach is particularly helpful. All things considered, Amazon SageMaker offers several features and capabilities that can speed up the process of measuring air quality in smart cities. We can swiftly and affordably generate accurate air quality forecasts by employing these capabilities[51].

The following figure.16 displays a graph that plots each model's execution times in seconds. The machine learning models are shown on the x-axis, while the time in seconds is shown on the y-axis. The pink line indicates execution in Amazon SageMaker, whereas the blue line depicts execution on the desktop. The main conclusion of this paper is that adopting a cloud platform results in shorter execution times[51].Air quality data is a time series, meaning the values change hourly. A reduced runtime will be beneficial for this type of data. It is also challenging to manage the time series data collected from smart cities because smart cities generate numerous data that require processing time. Cloud computing plays a significant role in situations like this, as it shortens the run time and aids in storing the vast amounts of data acquired[51].When it comes to simultaneously monitoring and managing waste and air quality, the conventional waste disposal system is inefficient.

This study addressed the aforementioned issues by anticipating the concentration of harmful gases in the air and assessing a bin's condition using a machine learning technique[51].

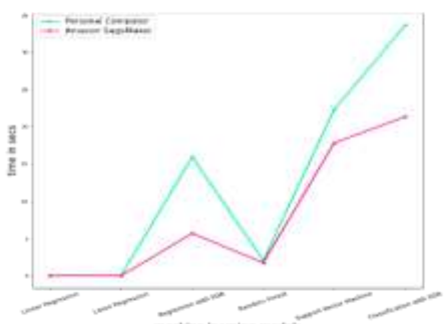

Fig.16: Execution Time in seconds.

Finally, we have received the responses to the research questions as follows:

RQ-1: What are the methods and approaches made use of to monitor and manage waste in smart cities? Monitoring and managing waste and predicting the levels of air pollutants (CO) in in-surrounding environments were the goals of this study. In this study, we have examined the challenges with current systems as well as the drawbacks of conventional waste collecting methods. There have been very few attempts to suggest a way to manage waste and simultaneously monitor waste and harmful gases in real time within the current state-of-the-art methodologies[51].Various methods have been used to detect air pollution. Techniques based on images and sensors have been employed for monitoring the air quality. We determined our problem statement from the literature review: There isn't yet a system that manages waste and analyzes the impact of toxic air pollutants in the bin environment using machine learning techniques.
RQ-2: How can the percentage of air pollutants surrounding a smart-bin predicted and monitored?
In order to monitor the air pollutant in the bin-surrounding environment, an LSTM model that predicted the amount of CO in the air was used. A TGS2600 sensor that detected the CO levels at the current moment was used to collect the data[51].In order to estimate the next instance value, we first used a baseline model that took into account the previous occurrences. Then, we used averaging techniques. Although the baseline model's efficiency appeared to be good, it wasn't always dependable in real-time situations.[59].An LSTM model based on deep learning was employed to increase the system's accuracy. In order to forecast the CO concentration during the following 12 hours, the LSTM model was adjusted to be trained on the values from the previous days. Both the offline and online modes were used to assess the trained model's accuracy. The system's overall accuracy shows in forecasting the concentration over the following 12 hours observation was higher than in the offline mode.

4. CONCLUSION

The overall objective of smart cities is to enhance our quality of life and provide solutions for a variety of issues. For instance, traffic congestion, pollution, high health care costs, and rising energy consumption are just a few of the pressing problems that smart cities are attempting to address in order to stop the overwhelming urbanization process. Because of the population's rapid growth, we have witnessed a surge in waste piles over the past few decades[51].

A system that forecasts air pollutants and monitors and manages waste is required to raise people's standard of life and prevent future adverse incidents. In order to determine the benefits and drawbacks of current treatments, a thorough literature analysis was conducted. The proposed work recognized and resolved the limitations of the traditional system. In order to find the best model for categorizing bin status as filled, half-filled and un-filled, a thorough evaluation of machine learning classifiers on real-time garbage datasets was conducted. Recall values in a real-time testing environment have been 78% and 82% for the logistic regression and KNN models, respectively. The level of air pollutants at a specific time slot was predicted using an LSTM-based model that took into account the prior entries in sensor time-series data. Approximately 90% and 89% accuracy values respectively were demonstrated by the modified LSTM and simple LSTM models in forecasting the future concentration of gases in the atmosphere[59].The system offered notifications through an alert mechanism in addition to real-time waste level monitoring.

The cloud database received information from an odor sensor, weight sensor, distance sensor, and air monitor. The cloud server used the previously trained model to extract the different features and label a certain bin. The system's ambiguity was double checked using posterior and prior probability. Comparing the suggested work to existing solutions based on straightforward methods, it was discovered that the use of machine learning improved accuracy[59].

Deploying our system in more number of locations and then collecting data for an extended length of time duration is one of the next phases. Because of the bin's fixed size, the machine learning model can currently classify bin state with ease. Deep learning techniques may be applied in the future to bin status classification[59].At the moment, the technology is able to forecast a particular amount of CO concentration. Future research can examine the connections between various air pollutants and construct a mathematical model that takes into account how changes in a single element affect the various air pollutants present in the atmosphere. These results also demonstrate that run-time is decreased when models are run on Amazon SageMaker instead of a desktop computer.

Accuracy is also preserved while execution time is decreased. Large datasets can be processed more quickly than with personal computers thanks to AmazonSageMaker's distributed computing design, which consists of numerous compute instances working together in a distributed fashion. For instance, use Amazon SageMaker,a cloud-based solution that can dynamically scale the computing resources used according on the size of the dataset to increase performance and reduce execution times[51].

At the length, it can be concluded that, even though machine learning has pre-defined algorithms and built-in tools, it may offer an effective and adaptable way to quickly alter the framework to suit their unique needs. Additionally, choosing the type of instance and creating unique training algorithms are simple tasks. By adopting dispersed cloud-based infrastructure for a secure and sustainable smart city environment, we can reduce execution time and enhance quality.

References

1. M. Y. Thu,W.Htun, Y.L.Aung, P. E. E. Shwe, and N. M. Tun, "Smart air quality monitoring system with lorawan," in 2018 IEEE International Conference on Internet of Things and Intelligence System (IOTAIS), 2018, pp. 10–15.
2. N. M. Kumar, S. Goel, and P. K. Mallick, "Smart cities in india: Features, policies, current status, and challenges," in 2018 Technologies for Smart-City Energy Security and Power (ICSESP), 2018, pp. 1–4.
3. S. Duangsuwan, A. Takarn, R. Nujankaew, and P. Jamjareegulgarn, "A study of air pollution smart sensors lpwan via nb-iot for thailand smart cities 4.0," in 2018 10th International Conference on Knowledge and Smart Technology (KST), 2018, pp. 206–209.
4. L. Bai, J. Wang, X. Ma, and H. Lu, "Air pollution forecasts: An overview," International Journal of Environmental Research and Public Health, vol. 15, no. 4, 2018. [Online]. Available: https://www.mdpi.com/1660-4601/15/4/780.

5. M. Bisht and K. R. Seeja, "Air pollution prediction using extreme learning machine: A case study on delhi (india)," in Proceedings of First International Conference on Smart System, Innovations and Computing. Singapore: Springer Singapore, 2018, pp. 181–189.
6. T. E. Karakasidis, F. Sofos, and C. Tsonos, "The electrical conductivity of ionic liquids: Numerical and analytical machine learning approaches," Fluids, vol. 7, no. 10, 2022. [Online]. Available: https://www.mdpi.com/2311-5521/7/10/321
7. Y. Rybarczyk and R. Zalakeviciute, "Machine learning approaches for outdoor air quality modelling: A systematic review," Applied Sciences, vol. 8, no. 12, 2018. [Online]. Available: https://www.mdpi.com/2076-3417/8/12/2570.
8. Z. Qi, T. Wang, G. Song, W. Hu, X. Li, and Z. Zhang, "Deep air learning: Interpolation, prediction, and feature analysis of fine-grained air quality," IEEE Transactions on Knowledge and Data Engineering, vol. 30, no. 12, pp. 2285–2297, 2018.
9. E. Gambhir, R. Jain, A. Gupta, and U. Tomer, "Regression analysis of covid-19 using machine learning algorithms," in 2020 International Conference on Smart Electronics and Communication (ICOSEC), 2020, pp. 65–71.
10. G. E. Kulkarni, A. A. Muley, N. K. Deshmukh, and P. U. Bhalchandra, "Autoregressive integrated moving average time series model for forecasting air pollution in nanded city, maharashtra, india," 2018, pp. 1435–1444. [Online]. Available: https://doi.org/10.1007/s40808-018-0493-2.
11. S. Kavitha, S. Varuna, and R. Ramya, "A comparative analysis on linear regression and support vector regression," in 2016 Online International Conference on Green Engineering and Technologies (IC-GET), 2016, pp. 1–5.
12. M. Carney, B. Webster, I. Alvarado, K. Phillips, N. Howell, J. Griffith, J. Jongejan, A. Pitaru, and A. Chen, "Teachable machine: Approachable web-based tool for exploring machine learning classification," in Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, ser. CHI EA '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 1–8. [Online]. Available: https://doi.org/10.1145/3334480.3382839.
13. P. C. Sen, M. Hajra, and M. Ghosh, "Supervised classification algorithms in machine learning: A survey and review," in Emerging Technology in Modelling and Graphics, J. K. Mandal and D. Bhattacharya, Eds. Singapore: Springer Singapore, 2020, pp. 99–111.
14. J.Wiley and L. Sons, Introduction to Machine Learning, 2019, ch. 1, pp. 1–25. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1002/ 9781119556749.ch1
15. Rubal and D. Kumar, "Evolving differential evolution method with random forest for prediction of air pollution," Procedia Computer Science, vol. 132, pp. 824–833, 2018, international Conference on Computational Intelligence and Data Science. [Online]. Available: https://www.sciencedirect.com/science/ article/pii/S1877050918308263.
16. N. U. Khan, M. A. Shah, C. Maple, E. Ahmed, and N. Asghar, "Traffic flow prediction: An intelligent scheme for forecasting traffic flow using air pollution data in smart cities with agging ensemble," Sustainability, vol. 14, no. 7, 2022. [Online]/https://www.mdpi.com/2071-1050/14/7/4164 .
17. Q. Liu, J. Gu, J. Yang, Y. Li, D. Sha, M. Xu, I. Shams, M. Yu, and C. Yang, Cloud, Edge, and Mobile Computing for Smart Cities. Springer Singapore, 2021, pp. 757–795. [Online]. Available: https://doi.org/10.1007/ 978-981-15-8983-6\ 41.
18. Y.-S. Chang, H.-T. Chiao, S. Abimannan, Y.-P. Huang, Y.-T. Tsai, and K.-M. Lin, "An lstm-based aggregated model for air pollution forecasting," Atmospheric Pollution Research, vol. 11, no. 8, pp.

1451–1463, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1309104220301215.

19. D. Sch¨urholz, S. Kubler, and A. Zaslavsky, "Artificial intelligence-enabled context-aware air quality prediction for smart cities," Journal of Cleaner Production, vol. 271, p. 121941, 2020. [Online]. Available: https://www. sciencedirect.com/science/article/pii/S0959652620319880
20. Y. Qian, D. Wu, W. Bao, and P. Lorenz, "The internet of things for smart cities: Technologies and applications," IEEE Network, vol. 33, no. 2, pp. 4–5, 2019.
21. S. Mehta, B. Bhushan, and R. Kumar, Machine Learning Approaches for Smart City Applications: Emergence, Challenges and Opportunities. Springer International Publishing, 2022, pp. 147–163. [Online]. Available: https://doi.org/10.1007/978-3-030-90119-6\ 12.
22. W. contributors, "Deep learning — Wikipedia, the free encyclopedia," 2023, [Online; accessed 22-March-2023]. [Online]. Available: https://en.wikipedia. rg/w/index.php?title=Deep\ learning&oldid=1145954968.
23. B. S. Freeman, G. Taylor, B. Gharabaghi, and J. Th´e, "Forecasting air quality time series using deep learning," Journal of the Air & Waste Management Association, vol. 68, no. 8, pp. 866–886, 2018. [Online]. Available: https://doi.org/10.1080/10962247.2018.1459956.
24. S. Du, T. Li, Y. Yang, and S.-J. Horng, "Deep air quality forecasting using hybrid deep learning framework," IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 6, pp. 2412–2424, 2021.
25. S. M. Cabaneros, J. K. Calautit, and B. R. Hughes, "A review of artificial neural network models for ambient air pollution prediction," Environmental Modelling Software, vol. 119, pp. 285–304, 2019./https://www.sciencedirect.com/science/article/pii/S1364815218306352
26. S. Ameer, M. A. Shah, A. Khan, H. Song, C. Maple, S. U. Islam, and M. N. Asghar, "Comparative analysis of machine learning techniques for predicting air quality in smart cities," IEEE Access, vol. 7, pp. 128 325–128 338, 2019.
27 R. Murugan and N. Palanichamy, "Smart city air quality prediction using machine learning," in 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), 2021, pp. 1048–1054.
28. M. Castelli, F. M. Clemente, A. Popoviˇc, S. Silva, and L. Vanneschi, "A machine learning approach to predict air quality in california," p. 8049504, 2020. [Online]. Available: https://doi.org/10.1155/2020/8049504.
29. U. Mahalingam, K. Elangovan, H. Dobhal, C. Valliappa, S. Shrestha, and G. Kedam, "A machine learning model for air quality prediction for smart cities," in 2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET), 2019, pp. 452–457.
30 .T. W. Ayele and R. Mehta, "Air pollution monitoring and prediction using iot," pp. 1741–1745, 2018.
31. B. Ghose and Z. Rehena, "A deep learning approach for predicting air pollution in smart cities," in Computational Intelligence and Machine Learning. Singapore: Springer Singapore, 2021, pp. 29–38.
32. A. Bekkar, B. Hssina, S. Douzi, and K. Douzi, "Air-pollution prediction in smart city, deep learning approach," Journal of Big Data, vol. 8, p. 161, 2021. [Online]. Available: https://doi.org/10.1186/s40537-021-00548-1.

33. C.-J. Huang and P.-H. Kuo, “A deep cnn-lstm model for particulate matter (pm2.5) forecasting in smart cities,” Sensors, vol. 18, no. 7, 2018. [Online]. Available: https://www.mdpi.com/1424-8220/18/7/2220.
34. I. K¨ok, M. U. S¸im¸sek, and S. Ozdemir, “A deep learning model for air quality ¨ prediction in smart cities,” in 2017 IEEE International Conference on Big Data (Big Data), 2017, pp. 1983–1990.
35. Y. Mehta, M. Manohara Pai, S. Mallissery, and S. Singh, “Cloud enabled air quality detection, analysis and prediction - a smart city application for smart health,” in 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), 2016, pp. 1–7.
36. S. Al-Janabi, M. Mohammad, and A. Al-Sultan, “A new method for prediction of air pollution based on intelligent computation,” Soft Computing, vol. 24, pp. 661–680, 2020. [Online]. Available: https://doi.org/10.1007/s00500-019-04495-1.
37. Lionetto, M.G.; Guascito, M.R.; Caricato, R.; Giordano, M.E.; Bartolomeo, A.R.D.; Romano, M.P.; Conte, M.; Dinoi, A.; Contini, D. Correlation of Oxidative Potential with Ecotoxicological and Cytotoxicological Potential of PM10 at an Urban Background Site in Italy. Atmosphere 2019, 10, 733. [CrossRef].
38. Wiedinmyer, C.; Yokelson, R.J.; Gullett, B.K. Global emissions of trace gases, particulate matter, and hazardous air pollutants from open burning of domestic waste. Environ. Sci. Technol. 2014, 48, 9523–9530. [CrossRef] [PubMed].
39. Yan, F.; Zhu, F.; Wang, Q.; Xiong, Y. Preliminary study of PM2. 5 formation during municipal solid waste incineration. Procedia Environ. Sci. 2016, 31, 475–481. [CrossRef]
40. Gollakota, A.R.; Gautam, S.; Shu, C.-M. Inconsistencies of e-waste management in developing nations–Facts and plausible solutions. J. Environ. Manag. 2020, 261, 110234. [CrossRef] [PubMed].
41. Lu, J.; Dong, C. Research of shortest path algorithm based on the data structure. In Proceedings of the 2012 IEEE International Conference on Computer Science and Automation Engineering, Beijing, China, 22–24 June 2012; IEEE: Piscataway, NJ, USA, 2012.
42. Nayak, S.; Narvekar, M. Real-time vehicle navigation using modified A∗ algorithm. In Proceedings of the 2017 International Conference on Emerging Trends & Innovation in ICT (ICEI), Maharashtra, India, 3–5 February 2017; IEEE: Piscataway, NJ, USA, 2017.
43. Dev, A.; Jasrotia, M.; Nadaf, M.; Shah, R. IoT based smart garbage detection system. Int. Res. J. Eng. Technol. 2016.
44. Anitha, A. Garbage monitoring system using IoT. in 14th ICSET-2017, IOP Conf. Series: Materials Science and Engineering. Semant. Sch. 2017. [CrossRef].
45. Shariff, M.; Shelyna, S.-S. Real Time Air Quality Reporting System; Universiti Tun Hussein Onn Malaysia: Parit Raja, Malaysia, 2015.
46. Sirsikar, S.; Karemore, P. Review paper on air pollution monitoring system. Int. J. Adv. Res. Comput. Commun. Eng. 2015, 4, 218–220. [CrossRef].
47. Wijaya, A.S.; Zainuddin, Z.; Niswar, M. Design a smart waste bin for smart waste management. In Proceedings of the 2017 5th International Conference on Instrumentation, Control, and Automation (ICA), Yogyakarta, Indonesia, 9–11 August 2017; IEEE: Piscataway, NJ, USA, 2017.
48. Shyam, G.K.; Manvi, S.S.; Bharti, P. Smart waste management using Internet-of-Things (IoT). In Proceedings of the 2017 2nd International Conference on Computing and Communications Technologies (ICCCT 2017), Chennai, India, 23–24 February 2017; IEEE: Piscataway, NJ, USA, 2017.

49. Anguraj,K.,Thiyaneswaran,B., Megashree, G., Shri, J. P., Navya, S., & Jayanthi, J. (2021). Crop recommendation on analyzing soil using machine learning. Turkish Journal of Computer and Mathematics Education, 12(6), 1784-1791.
50. Siddique, M.J.; Islam, M.A.; Nur, F.N.; Moon, N.N.; Saifuzzaman, M. BREATHE SAFE: A Smart Garbage Collection System for Dhaka City. In Proceedings of the 2018 10th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, Bangladesh, 20–22 December 2018; IEEE: Piscataway, NJ, USA, 2018.
51. Nitin Kumar," Development Of A Smart Waste Management System Using IOT Technology", nternational Journal of Electrical Engineering and Technology (IJEET) Volume 11, Issue 3, May 2020, pp.515-521, Article ID: IJEET_11_03_057, ISSN Print: 0976-6545 and ISSN Online: 0976-6553,DOI: https://doi.org/10.17605/OSF.IO/F4EX6
52. Chalke, S.S.; Bhalerao, M.; Bangar, S.; Gaikwad, D. A Survey on IOT Based Smart Garbage Monitoring System. Int. J. Adv. Res. Ideas Innov. Technol. 2018, 4.
53. .Pan, P.; Lai, J.; Chen, G.; Li, J.; Zhao, M.; Ren, H. An Intelligent Garbage Bin Based on NB-IOT Research Mode. In Proceedings of the 2018 IEEE International Conference of Safety Produce Informatization (IICSPI), Chongqing, China, 10–12 December 2018; IEEE: Piscataway, NJ, USA, 2018.
54. Draz, U.; Ali, T.; Khan, J.A.; Majid, M.; Yasin, S. A real-time smart dumpsters monitoring and garbage collection system. In Proceedings of the 2017 Fifth International Conference on Aerospace Science & Engineering (ICASE), Islamabad, Pakistan, 14–16 November 2017; IEEE: Piscataway, NJ, USA, 2017.
55. Ng, K.M.; Suhaimi, M.A.H.N.; Ahmad, A.; Razak, N.A. Remote air quality monitoring system by using MyRIO-LabVIEW. In Proceedings of the 2018 9th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, Malaysia, 3–4 August 2018; IEEE: Piscataway, NJ, USA, 2018.
56. Bharadwaj, B.; Kumudha, M.; Gowri Chandra, N.; Chaithra, G. Automation of Smart waste management using IoT to support "Swachh Bharat Abhiyan"—A practical approach. In Proceedings of the 2017 2nd International Conference on Computing and Communications Technologies (ICCCT), Chennai, India, 23–24 February 2017; IEEE: Picataway, NJ, USA, 2017.
57. Gutierrez, J.M.; Jensen, M.; Henis, M.; Raiz, T. Smart waste collection system based on location intelligence. Procedia Comput. Sci. 2015, 61, 120–127. [CrossRef].
58. Surapaneni, P.; Maguluri, L.; Symala, M. Solid Waste Management in Smart Cities using IoT. Int. J. Pure Appl. Math. 2018, 118, 635–640.
59. Shamin, N.; Fathimal, P.M.; Raghavendran, R.; Kamalesh, P. Smart Garbage Segregation & Management System Using Internet of Things (IoT) & Machine Learning (ML). In Proceedings of the 2019 1st International Conference on Innovations in Information and Communication Technology (ICIICT), Chennai, India, 25–26 April 2019; IEEE: Piscataway, NJ, USA, 2019.
60. Wohlfart, R. Carbon Monoxide Dangers in the Boiler Room. 2015. Available online: www.pmmag.com/ articles/97528-carbonmonoxide-danger-in-the-boiler-room (accessed on 10 July 2020).
61. Li, Y.; Huang, J.; Luo, J. Using user generated online photos to estimate and monitor air pollution in major cities. In Proceedings of the 7th International Conference on Internet Multimedia Computing and Service, Zhangjiajie, China, 19–21 August 2015.

62. Chakma, A.; Vizena, B.; Cao, T.; Lin, J.; Zhang, J. Image-based air quality analysis using deep convolutional neural network. In Proceedings of the 2017 IEEE International Conference on Image Processing (ICIP), Beijing, China, 17–20 September 2017; IEEE: Piscataway, NJ, USA, 2017.
63. De Vito, S.; Piga, M.; Massera, E.; Martinotto, L. On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario. Sens. Actuators B Chem. 2008, 129, 750–757. [CrossRef].
64. Guiry, J.J.; Van de Ven, P.; Nelson, J. Multi-sensor fusion for enhanced contextual awareness of everyday activities with ubiquitous devices. Sensors 2014, 14, 5687–5701. [CrossRef] [PubMed].