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AI BASED AUTONOMOUS SOLUTION FOR THE MAINTENANCE OF PUBLIC CONVENIENCES USING EDGE COMPUTING

Geethapriya V, Dhanush V ,Kavitha J

[1] Rajalakshmi Engineering College, Chennai, India

dhanush.v.2024.mees@rajalakshmi.edu.in

Abstract

This concept suggests an IoT-based self-sufficient autonomous system intended to efficiently maintain and keep an eye on public amenities. The system uses a variety of sensors to continuously measure air parameters like temperature and humidity as well as the amounts of smell gases. For monitoring and analysis in real time, the sensor data is gathered by an ESP32 microcontroller and sent to an IoT cloud platform. The cloud technology makes it possible for supervisors or maintenance workers to get automated alerts and notifications, guaranteeing prompt cleaning and effective administration. The use of machine learning algorithms that evaluate the gathered data and forecast maintenance requirements using a Raspberry Pi enhances decision-making and minimises manual intervention. Battery power powers the entire system, offering dependability and energy economy. By improving cleanliness, operational effectiveness, and user pleasure in public restrooms, this scalable and ecologically friendly solution helps create more intelligent, sustainable, and clean public infrastructure.

Keywords: Iot, Cloud, Machine Learning

1. INTRODUCTION

Public conveniences are necessary amenities that are vital to upholding hygienic standards and guaranteeing a higher standard of living, especially in metropolitan and semi-urban areas. Yet, there are a number of significant issues with typical public restrooms, including inadequate upkeep, unsanitary conditions, erratic cleaning schedules, excessive water use, unpleasant odour's, and the lack of real-time monitoring systems. Open defecation and associated health risks are exacerbated by these issues, which also make them less usable and deter people from using them. Intelligent, autonomous, self-sustaining systems that can maintain cleanliness, reduce manual intervention, maximize resource use, and permit real-time monitoring are highly desired in order to meet these difficulties. The development of renewable energy sources and Internet of Things (IoT) technologies has made it feasible to create intelligent public amenities that can operate with little human oversight. An automated sanitation system that combines IoT- enabled sensors, and intelligent control mechanisms is the goal of the proposed project, "IoT Based Self-Sustained Autonomous Solutions for the Maintenance of Public Conveniences." In addition to automating tasks like flushing, floor cleaning, ventilation, and lighting, the system will be able to track occupancy, water levels, air quality, and cleanliness in real time. Authorities may remotely monitor the condition of the facility, get immediate notifications when repair is necessary, and adjust cleaning schedules in accordance with consumption statistics thanks to cloud connectivity. Furthermore, the system's self-sufficient operation will greatly lessen reliance on labour, raise standards of hygiene, save resources, and support sustainable urban growth. To sum up, this project intends to address one of the most important issues in contemporary sanitation infrastructure by providing an economical, environmentally responsible, and scalable solution for the intelligent maintenance of public conveniences.

2. METHODOLOGY

This Paper describes the creation of a self-sufficient, Internet of Things-based system for the independent upkeep of public conveniences. To monitor cleanliness, gas leaks, usage frequency, and odour levels, the system incorporates a number of sensors. For predictive maintenance, the Raspberry

Pi conducts sophisticated analysis using machine learning, while the ESP32 microcontroller manages initial data collecting and local processing. Through online or mobile applications, the processed data is sent to the IoT cloud, allowing for real-time alerts, centralised monitoring, and reporting. By utilising battery storage, the system functions without the need for external power, providing a dependable, environmentally sustainable, and expandable solution to enhance public conveniences' efficiency and cleanliness.

a. Block Diagram

The smell and gas detection system block diagram is displayed in Figure.1. The procedure starts with gas sensors, which detect unusual or dangerous gases in the ambient air. The main processing and communication unit, the ESP32 microcontroller, receives the signals that have been detected. After being transmitted by the ESP32, the data is stored and made available for additional analysis on an IoT cloud platform.

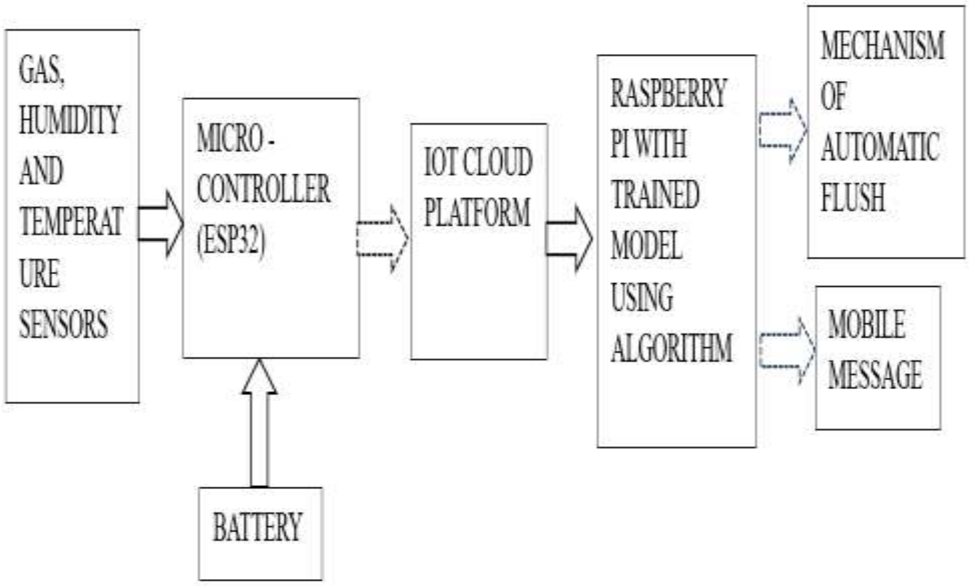

Figure.1 Functional block diagram

A Raspberry Pi carries out sophisticated analysis and machine learning-based predictive maintenance, while the ESP32 microcontroller analyses the data locally for prompt decision-making. The Battery is used for the giving power supply to ESP32 microcontroller. For centralised monitoring, data logging, and real-time alerts through mobile or online applications, processed data is transferred to an IoT cloud platform. It sends the information to supervisor or maintenance person through mobile message. It provides a scalable and effective maintenance solution and guarantees continuous, and self-sustaining operation.

The figure.2 shows the technique of the suggested model. The system begins by initialising its sensors, which include gas and smell sensors that continuously scan the surrounding area for offensive or dangerous smells. The ESP32 microcontroller receives the gathered data and serves as the main interface for preprocessing and sensor communication. The IoT cloud platform receives the processed data after processing, allowing for remote access and storage for additional decision-making. The Raspberry Pi, which trained the machine learning model that has been developed, is used to analyse the cloud data. This model assesses if the detected data points to the existence of an unusual odour or gas leak. To ensure a prompt response and remedial action, the system instantly generates and sends a mobile alert to the concerned personnel if it detects a scent event. The system keeps monitoring in a loop if no unusual circumstance is found. This approach guarantees remote accessibility, real-time detection, and automated alerts, which makes the system useful for preserving public conveniences. By facilitating quick contact between maintenance personnel and the mobile message notification system, manual inspection efforts are decreased, and prompt action is ensured for better hygiene and user satisfaction in public facilities.

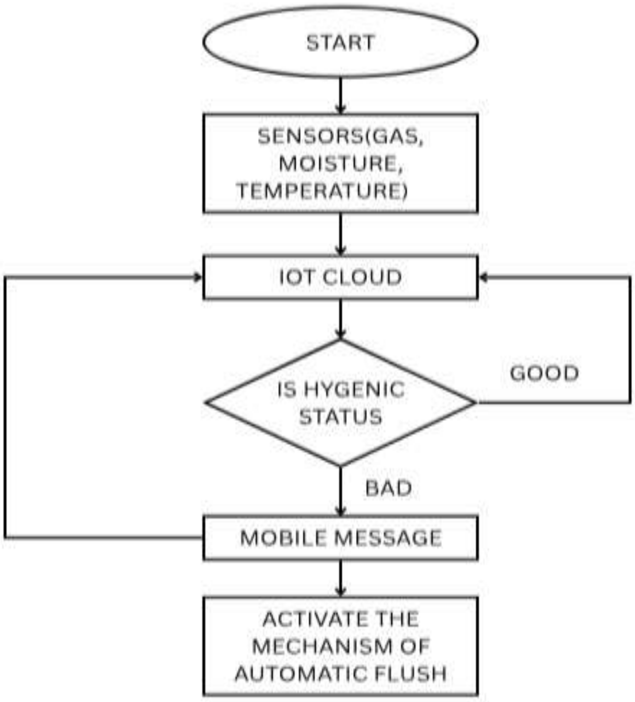

Figure 2: Flow chart of proposed work

b. DATA COLLECTION

The hardware setup (Figure) represents the real-time data acquisition system designed for monitoring environmental conditions in public conveniences. It consists of an ESP32 microcontroller connected with a DHT11 temperature and humidity sensor and an MQ135 gas sensor.

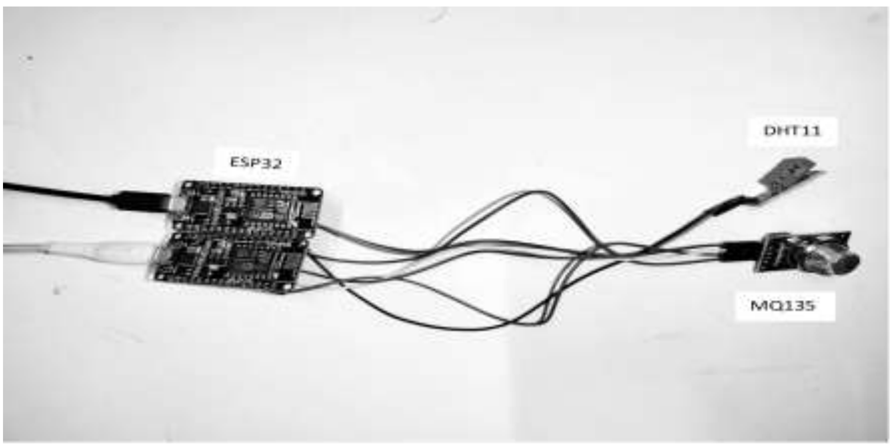

Figure3: Data collection through Hardware

The ESP32 acts as the central processing and communication unit, responsible for collecting sensor data and transmitting it wirelessly to the IoT cloud for real-time monitoring. The range of sensors should be explained (Table.1) and the hardware measuring the range based upon the value.

date	time	Gas sensor ppm	Humidity percent	Temperature °c	condition	status
2025-09-18	00:00:00	12.69	58.3	22.38	Good	Door_Close
2025-09-18	00:30:00	13.41	54	22.63	Good	Door_Close
2025-09-18	01:00:00	14.46	50.4	22.74	Better	Door_Close
2025-09-18	01:30:00	8.13	48.2	22.61	Good	Door_Close
2025-09-18	02:00:00	11.13	43.1	22.47	Good	Door_Close
2025-09-18	02:30:00	10.06	48.9	22.57	Good	Door_Close
2025-09-18	03:00:00	13.99	51.1	24.13	Better	Door_Close
2025-09-18	03:30:00	8.55	48.5	24.28	Good	Door_Close
2025-09-18	04:00:00	8.48	52.3	23.59	Good	Door_Close
2025-09-18	07:00:00	23.73	57.9	23.4	Better	Door_Open
2025-09-18	07:30:00	30.56	63.4	23.71	Bad	Door_Open
2025-09-18	08:00:00	28.22	61.8	23.87	Bad	Door_Open

Table.1 Real Time Data Collection

The DHT11 sensor measures temperature and humidity levels, while the MQ135 sensor detects the concentration of harmful and odour-causing gases such as ammonia, carbon dioxide, and sulphur compounds. This collected data is used to analyze the air quality and hygiene status of the environment.

The above figure which have a (Table.2) real time data collection from the variety of sensors like gas, humidity, temperature. The Sensor name and range are mentioned in below table. In that table sensor type, range , working and detection as explained. The accuracy of each and every sensor should explain in table.

Table.2 Details of sensor

SENSOR ID	SENSOR NAME	RANGE	ACCURACY	DETECTION
MQ135	GAS	(10-1000)ppm	20sec	Nitrogen Oxide
DHT11	TEMPERATURE	0ºC-50 ºC	± 2ºC	Cold and Warm
	HUMIDITY	20%-80%	± 5%RH	Dry and wet

The MQ135 sensor acts as a gas sensor which detects a nitrogen oxide gas. The DHT11 sensor acts as a temperature and humidity sensor which detects a cold and warm and also detects a dry and wet condition.

c. FLOWCHART

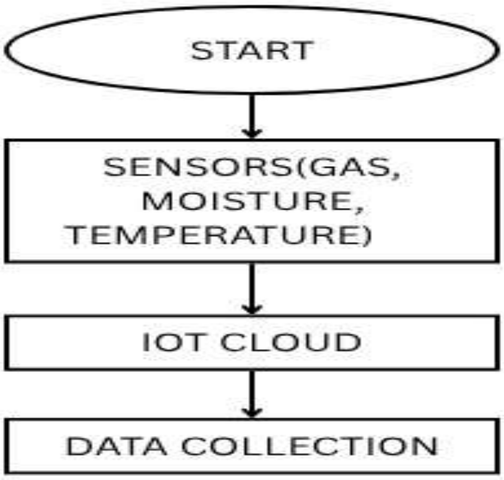

Figure.4 Flowchart for data collection

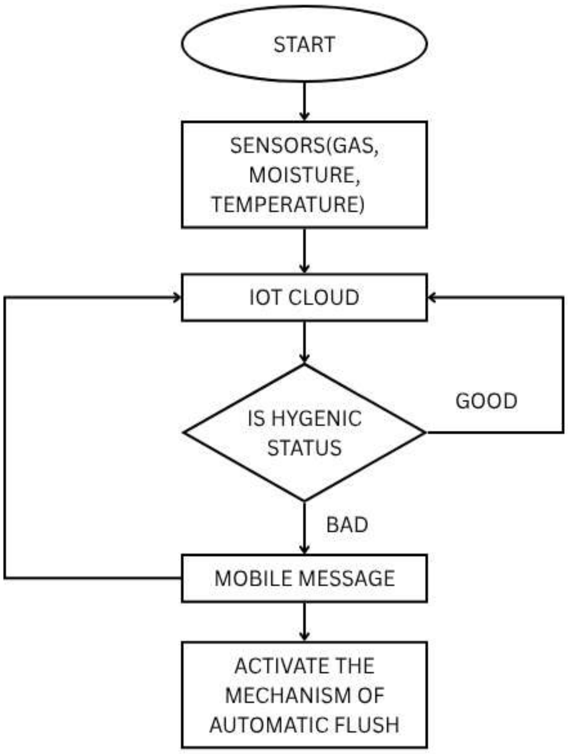

Figure.5 Flowchart for Testing

d. RANDOM FOREST ALGORITHM

One effective supervised machine learning method for classification and regression applications is the Random Forest algorithm. To increase prediction accuracy and manage overfitting, it builds a lot of separate decision trees during training and then combines their outputs. To ensure tree diversity and improve model robustness, each tree in the forest is trained using a random subset of the dataset and characteristics. Each decision tree offers a class or value during prediction, and the final result is decided by average (for regression) or majority vote (for classification). Large datasets, missing values, and accuracy even in the presence of noisy or unbalanced data are all reasons why Random Forest works so well. When compared to single decision trees, its ensemble nature offers superior generalisation, which makes it broadly relevant in real-world issues including environmental prediction systems, health monitoring, and sensor data analysis. The Machine Learning algorithm used to Reduces overfitting compared to a single decision trees. Its more stable data and performs well with large dataset. The algorithm used mainly for high dimensional data and also maintain the handles missing data.

e. CLUSTERING

Clustering is an unsupervised machine learning technique used to group similar data points together. It automatically identifies patterns in data and forms meaningful groups called clusters.

- Partition-Based Clustering
- Hierarchical Clustering
- Density-Based Clustering
- Model-Based Clustering
- Grid-Based Clustering
- Spectral Clustering
- Fuzzy Clustering

f. PARTITION-BASED CLUSTERING

Partition-Based Clustering is a type of unsupervised learning algorithm that divides a dataset into a set of non-overlapping clusters, where each data point belongs to exactly one cluster.

K-means Clustering

A popular partition-based unsupervised learning approach, K-Means clustering divides data into a predetermined number of clusters according on similarity. It seeks to maximize the separation between various clusters and reduce the distance between data points and their respective cluster centers. The first step in the process is to choose k initial centroids, where k is the number of clusters. The centroids are then computed as the mean position of the points within each cluster after each data point is assigned to the closest centroid using the Euclidean distance formula. Until the centroids stabilize a sign that the clustering process has converged—this assignment and update procedure is repeated iteratively. K-Means' primary goal is to reduce the within-cluster sum of squares (WCSS). mathematically represented as J=∑i=1k∑xj∈Ci‖xj−μi‖2J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2J=∑i=1k∑xj∈Ci ‖xj−μi‖2, where xjx_jxj denotes a data point and μi\mu_iμi represents the centroid of the ithi^{th}ith cluster. The algorithm is simple, fast, and efficient, making it suitable for large datasets and spherical cluster shapes. However, it has limitations, such as requiring prior knowledge of the number of clusters, being sensitive to the initial placement of centroids, and struggling with overlapping or irregularly shaped clusters. Compared to other methods, K-Means performs better for large and well-separated data, while hierarchical and density-based methods handle complex or noisy data more effectively. Overall, K-Means clustering remains one of the most popular techniques for discovering hidden patterns in data and is widely applied in areas such as customer segmentation, pattern recognition, image compression, and data analysis.

Two-Cluster Clustering (K = 2)

In two-cluster clustering, the entire dataset is divided into two main groups. This is the simplest form of clustering and is useful when the data has clear separation into two categories. For example, in tire fault detection, the algorithm can separate images into “normal texture” and “faulty texture.” Similarly, in customer analysis, it can divide users into “low spenders” and “high spenders.” This method works best when only two natural patterns exist in the data.In K-Means clustering, data points that share similar characteristics are grouped together into the same cluster, while those that differ significantly are placed in other clusters — all without using any predefined class labels. This makes K-Means an unsupervised learning algorithm that discovers patterns purely based on data similarity. For example, when the number of clusters is set to $K = 2$, the algorithm divides the dataset into two distinct groups. The objective of K-Means is to minimize the total distance between each data point and its corresponding cluster centroid. The objective function is expressed as J=∑k=1K∑xi∈Ck||xi−μk||2J = \sum_{k=1}^{K} \sum_{x_i \in C_k} ||x_i - \mu_k||^2J=∑k=1K∑xi∈Ck||xi−μk||2, where ||xi−μk||2||x_i - \mu_k||^2||xi−μk||2 represents the squared Euclidean distance between a data point xix_ixi and its cluster centroid μk\mu_kμk, and CkC_kCk denotes the set of points assigned to the kthk^{th}kth cluster. The algorithm iteratively updates the centroid positions to minimize this error function until convergence is achieved. As a result, the final clusters contain data points that are closely related to each other, effectively representing meaningful patterns or groupings within the dataset.

Three-Cluster Clustering (K = 3)

Three-cluster clustering divides the data into three well-defined groups. This is especially useful in datasets where information naturally falls into three levels or categories. For example, customer spending patterns often include low, medium, and high spending groups. Similarly, tire defects may appear as normal, slightly damaged, and heavily cracked patterns.In K-Means clustering, each group of data points is represented by a **centroid**, which acts as the central point of that cluster. Every data point in the dataset is assigned to the group whose centroid is nearest to it, based on a distance measure. The primary objective of the K-Means algorithm is to **minimize the within-cluster sum of squares (WCSS)**, which ensures that data points within the same cluster are as close as possible to their centroid. When the number of clusters is set to $K = 3$, the algorithm partitions the dataset into three distinct groups, each with its own centroid. The optimization function used in K-Means can be mathematically expressed as

J=∑k=1K∑xi∈Ck||xi−μk||2J=\sum_{k=1}^{K} \sum_{x_i \in C_k} ||x_i - \mu_k||^2J=k=1∑Kxi∈Ck ∑||xi−μk||2
where ||xi−μk||2||x_i - \mu_k||^2||xi−μk||2 represents the **squared Euclidean distance** between a data point xix_ixi and its cluster centroid μk\mu_kμk, and CkC_kCk denotes the **set of points assigned to the kthk^{th}kth cluster**. During the clustering process, centroids are continuously updated by calculating the mean of all points within each cluster until there is no significant change in their positions. This iterative adjustment helps in achieving optimal cluster separation. As a result, K-Means produces three well-defined clusters with data points that exhibit high internal similarity and clear separation from other groups, making it an efficient and interpretable method for analyzing structured datasets.

Four-Cluster Clustering (K = 4)

Four-cluster clustering is used for datasets with higher variation and multiple hidden patterns. In this approach, the model creates four groups that describe more specific differences in the data. For example, in customer ordering behavior, four clusters may represent morning buyers, afternoon buyers, night buyers, and rare buying patterns. In tire texture analysis, four clusters may represent normal textures, small cracks, medium cracks, and severe damage.In K-Means clustering, each group of data points is represented by a **centroid**, which serves as the central point of that cluster. Every data point in the dataset is assigned to the group whose centroid is closest to it, based on a distance measure such as the **Euclidean distance**. The main objective of K-Means is to **minimize the within-cluster sum of squares**

(WCSS), ensuring that data points within the same cluster are closely grouped together and distinct from those in other clusters. When the number of clusters is set to *K = 4*, the algorithm divides the dataset into four separate groups, each having its own centroid that represents the mean of the points within that cluster. The mathematical formulation of the objective function is expressed as

J=∑k=1K∑xi∈Ck||xi−μk||2J = \sum_{k=1}^{K} \sum_{x_i \in C_k} ||x_i - \mu_k||^2J=k=1∑Kxi∈Ck∑||xi−μk||2

where ||xi−μk||2||x_i - \mu_k||^2||xi−μk||2 denotes the **squared Euclidean distance** between a data point xix_ixi and its corresponding cluster centroid μk\mu_kμk, and CkC_kCk represents the **set of data points assigned to the kthk^{th}kth cluster**. During the clustering process, the centroids are recalculated after each iteration as the mean of all the data points in their respective clusters. This iterative process continues until the centroids stabilize and the clusters become clearly separated. With *K = 4*, the final result forms four distinct clusters, each containing data points that share similar features, making K-Means a powerful and efficient technique for pattern recognition, data segmentation, and unsupervised data analysis.

3. SIMULATION RESULTS OF RANDOM FOREST ALGORITHM

The simulation of the proposed machine learning model using the Random Forest algorithm was carried out to evaluate its performance on the trained dataset. The trained data demonstrates that the model effectively captures the relationship between the input parameters and the target output, resulting in high prediction accuracy and stability(Fig3). During the training phase, the Random Forest classifier achieved consistent convergence with minimal error variation across multiple iterations, indicating strong learning capability and robustness against overfitting. The graphical representations of the trained data illustrate that the predicted outputs closely match the actual values, confirming the reliability of the model. Furthermore, the performance evaluation metrics such as accuracy, precision, recall, and F1-score indicate that the Random Forest algorithm performs efficiently in handling non-linear data relationships. The Feature Importance which explains the comparison of sensors. The overall simulation results validate that the developed model provides improved classification and decision-making performance compared to conventional algorithms, thereby proving its suitability for the intended application.

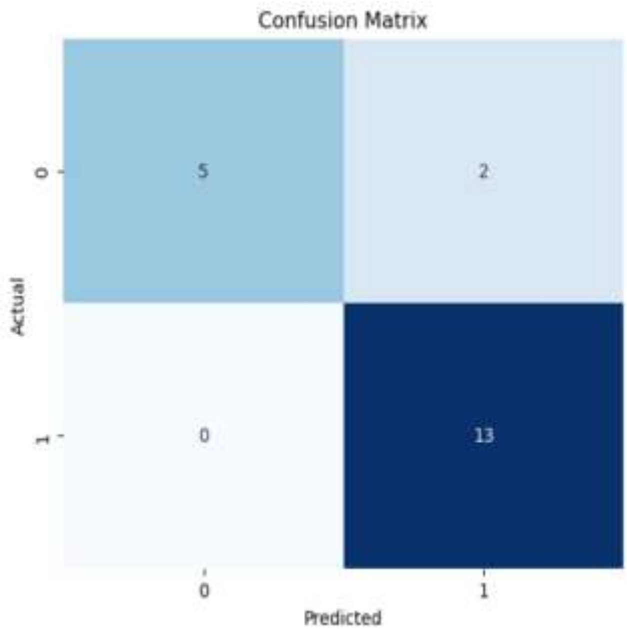

Figure.6 Confusion Matrix

Table.3 Classifier performance parameters

Performance parameters		value	Macro Average	Weighted Average
Accuracy		0.90	______	_______
Precision	0	1.00	0.93	0.91
	1	0.87		
Recall	0	0.71	0.86	0.90
	1	1.00		
F1-Score	0	0.83	0.88	0.90
	1	0.93		

A confusion matrix(Figure) is a performance evaluation tool used in machine learning and classification problems to show how well a model's predictions match the actual data. It provides a detailed breakdown of correct and incorrect predictions, helping to identify where the model performs well and where it makes errors. The confusion matrix is structured into four categories:

- True Positive (TP**):** Correctly predicted positive instances
- True Negative (TN): Correctly predicted negative instances
- False Positive (FP): Incorrectly predicted positive instances
- False Negative (FN): Incorrectly predicted negative instances

CALCULATIONS

Accuracy = (True Positive + True Negative) / Total.

= (5+13)/20 = 18/20 = 0.90 = 90%.

Precision = True Positive / (True Positive + False Positive).

= 5/(5+0) = 5/5 = 1.

Recall = True Positive / (True Positive + False Negative).

= 5/(5+2) = 5/7 = 0.71.

F1 Score = 2 * (Precision * recall) / (Precision + Recall).

= 2*(1*0.71)/(1+0.71) = 2*(1.71)(0.71) =2.42.

4. SIMULATION RESULTS OF CLUSTERING ALGORITHM

TWO GROUP CLUSTERING

The two-group (K=2) clustering output graph makes it evident how the dataset is split into two different clusters according to how related the data points are.

To visually divide the groupings, a distinct color is used for each cluster in the graph. All of the data points are grouped together if they have similar traits or distances. The graph clearly displays the centroids of the two clusters, indicating each group's center point. The average location of the data points inside each cluster is shown by these centroids. The graph's division of the two groups attests to the algorithm's ability to recognize the dataset's natural patterns. All things considered, the two-group clustering result successfully illustrates how the data divides into two significant and distinct groups according to their feature values.

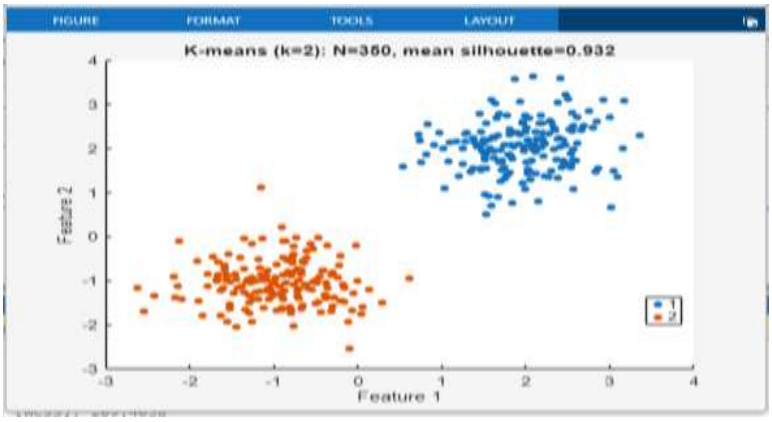

Figure.7 Output of two group clustering

THREE GROUP CLUSTERING

The output graph of three-group (K=3) clustering shows how the dataset is separated into three distinct clusters based on the similarity of data points. To make the boundaries between the groups easy to see, each cluster is depicted using a distinct color. Each point is assigned to the closest centroid by the algorithm, which finds natural patterns in the data.

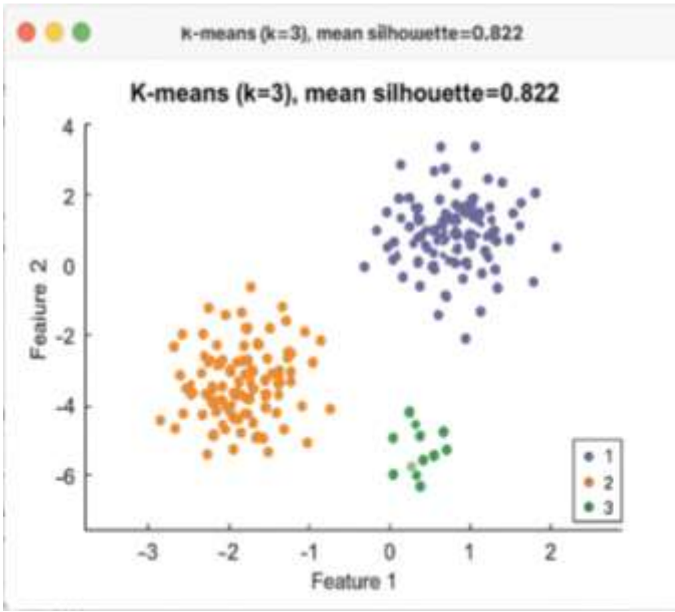

Figure.8 Output of three group clustering

The graph's three centroids, which show the average position of the data in each group, serve as the centre reference points for the corresponding clusters. Three significant patterns or regions may be seen in the dataset by looking at the distribution of points around these centroids. Each cluster's dispersion and separation on the graph show how the data varies. Overall, the three-group clustering output shows that there are three distinct, well-organized groups in the data.

FOUR GROUP CLUSTERING

The dataset is separated into four distinct clusters according to the similarity of feature values, as seen in the output graph of four-group (K=4) clustering.

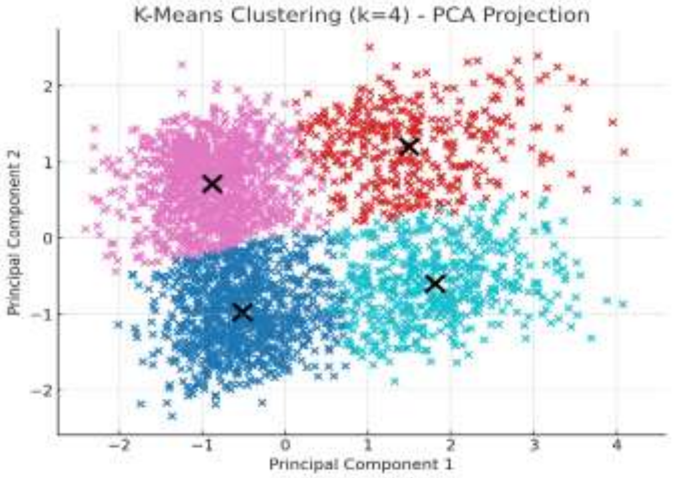

Figure.9 Output of four group clustering

To make it easier to distinguish across clusters, each group is displayed in a distinct color. Each of the four centroids that the algorithm finds indicates the average location of all the data points that make up that specific cluster. The data's distribution around these centroids on the graph illustrates the internal organization and variance within each group. The algorithm's four clusters allow for a more thorough dataset segmentation that captures minute variations between data points. The graph's distribution pattern shows that the dataset has four natural groupings, and the clustering technique successfully arranges the data into useful categories.

k. COMPARISON

TABLE.4 Comparison of Group Clustering

S. NO	GROUPS CLUSTERING	K-RANGE	SILHOUTTE RANGE
1	TWO GROUP CLUSTERING	K=2	0.932
2	THREE GROUP CLUSTERING	K=3	0.822
3	FOUR GROUP CLUSTERING	K=4	0.362

l. COMPARISON OF REAL TIME DATA VS BROWSER DATA IN RANDOM FOREST ALGORITHM

The Parameters of real time data and browser data of random forest algorithm are mentioned in the below table

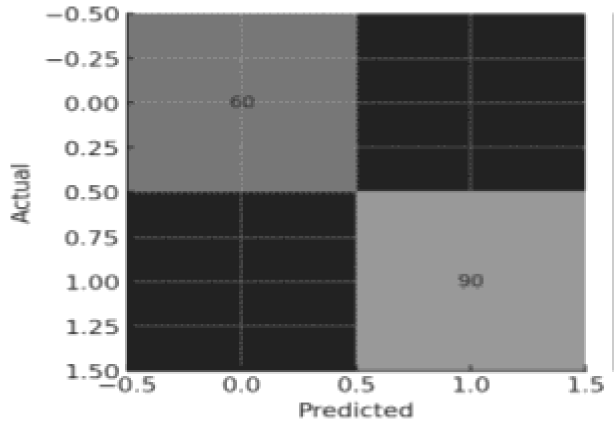

Figure.10 Real time data in random forest algorithm

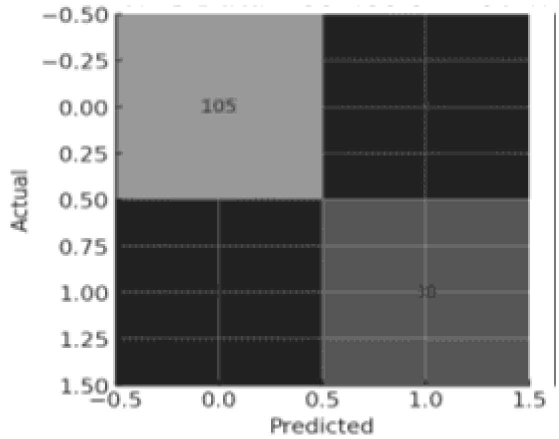

Figure.11 Confusion Matrix of browser data

The Confusion Matrix of browser data asShown below

Table.5 COMPARISON OF DATA WITH RANDOM FOREST ALGORITHM

S No	PARAMETERS	REAL TIME DATA	BROWSER DATA
1	ACCURACY	0.9931	1.00
2	PRECISION	1.00	1.00
3	RECALL	0.9743	1.00
4	F1-SCORE	0.9870	1.00

COMPARISON OF REAL TIME DATA VS BROWSER DATA IN CLUSTERING ALGORITHM

The Parameters of real time data and browser data of clustering algorithm are mentioned in the below table

Table.6 comparison of data with clustering algorithm

S No	METRICS	REAL-TIME DATA	BROWSER DATA
1	SILHOUTTE RANGE	0.6487	0.5543
2	DAVIS-BOULDIN INDEX	0.5906	0.6156
3	CALANSKI-HARABASZ SCORE	982.42	1120.96

The Two group clustering of real time data as shown below

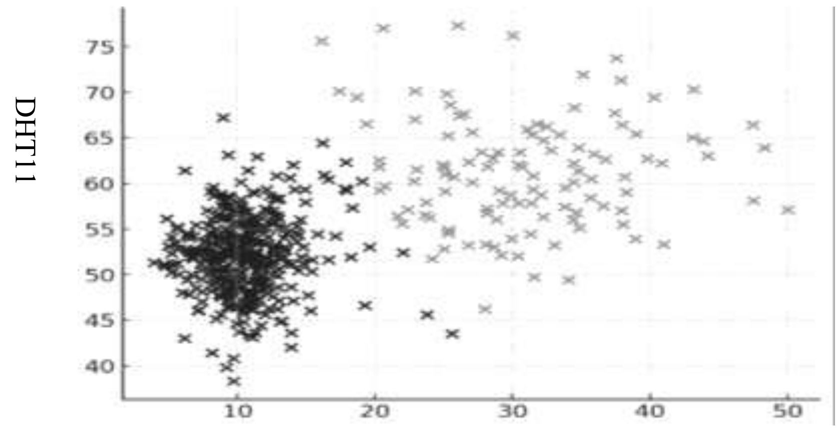

Figure.13 Two group clustering of real time data

The Two group clustering of browser data as shown below

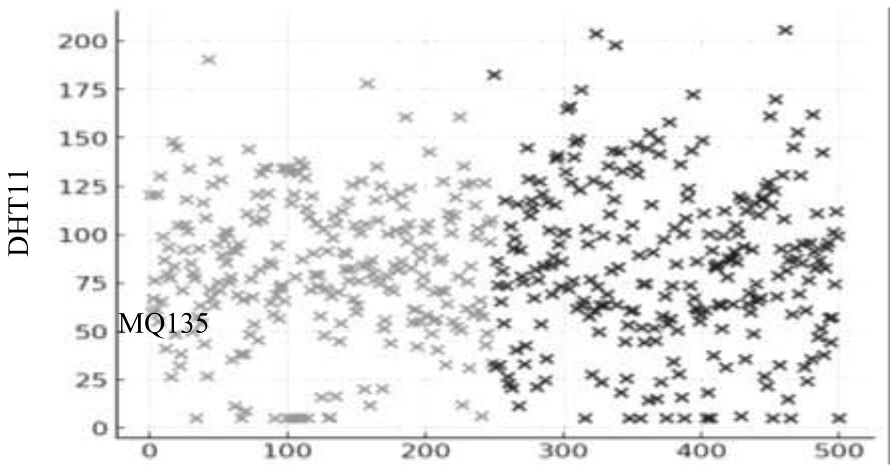

Figure.14 Two group clustering of browser data

5. CONCLUSION

The suggested AI-Based Autonomous Solution for the Maintenance of Public Conveniences utilising Edge Computing successfully combines machine learning and IoT technologies to provide intelligent and automated hygiene monitoring. The system effectively collects real-time data from public restrooms using an ESP32 microcontroller and a variety of environmental sensors, including gas, temperature, and humidity sensors. Training with a Random Forest algorithm makes it possible to accurately identify maintenance needs and classify hygiene levels in an effective manner. Additionally, the system can automatically identify patterns and abnormalities without human supervision thanks to the integration of clustering algorithms like K-Means, which facilitate unsupervised data analysis. The machine learning model's performance is validated by simulation results, which show that the system runs consistently with good accuracy, precision, and recall values. By enabling preliminary data processing at the local node prior to cloud transmission, edge computing integration reduces latency and improves responsiveness. Quick notifications, less reliance on constant internet connectivity, and effective energy management through battery-powered operation are all guaranteed by this hybrid cloud-edge design. The project as a whole shows how IoT-based sensor networks and sophisticated decision-making algorithms may greatly increase public sanitation facilities' sustainability, cleanliness, and efficiency. The strategy guarantees a cleaner and more hygienic environment for the general public while minimising human intervention and optimising resource use. The study's goals of creating a scalable, independent, and self-sustaining system for smart city sanitation management are effectively met.

6. FUTURE SCOPE

The project creates a number of opportunities for further research and practical implementation. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are examples of deep learning models that can be added to the system to improve anomaly detection and maintenance trend prediction. PIR motion detectors, water level sensors, and ammonia-specific detectors are examples of extra sensors that could be included to improve occupancy monitoring and environmental sensing accuracy. Future iterations may make use of edge AI hardware accelerators, like Google Coral or NVIDIA Jetson Nano, to enhance edge-level real-time processing capabilities. The system would be able to automatically optimise cleaning and servicing intervals based on past data trends if predictive maintenance scheduling using reinforcement learning was implemented. More broadly, mobile apps and cloud-based dashboard visualisation systems can be created to allow administrators to track maintenance progress, monitor several facilities at once, and evaluate performance indicators. Sustainability in remote or rural sites could be improved by integrating renewable power sources like solar panels, which could render the system entirely energy-independent. Furthermore, data-driven urban sanitation planning and the creation of clean, environmentally friendly public spaces can be facilitated by integration with government data portals and municipal smart city infrastructure. Future research must also incorporate cybersecurity and data protection measures to prevent unauthorised access to sent sensor and user data. All things considered, this research lays the groundwork for future autonomous public convenience management systems that integrate IoT, AI, and renewable energy to create more intelligent techniques.

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