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A Smart-home Electronic-Nose for Detecting Hazardous Gases

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ABSTRACT

The idea of networking household appliances and technologies has been promoted for over a decade using smart home technology. The Smart Homes Association defines "the combination of technology and services" for a higher living level as "smart home technology" through home networking. Computer tools come in a variety. Systems can also be included in smart home systems. In this essay, we present. Systems for Smart Homes that can use or include several technologies. Automatic detection of dangerous substances, early fires, smoke, and gas leaks is provided by this ground-breaking device. E-nose can recognize seven different odors with the help of various gas sensors and several machine learning techniques. Finally, if a hazardous gas spread occurs, the system sends out an alarm message that is particular to the gas or occurrence. Support Vector Machine (SVM), Logistic Regression, and Decision Tree all received an F1-score of 98% from us. Random Forest and K-Nearest Neighbors both received perfect scores.

1. INTRODUCTION

1.1. Smart Homes

A home that uses Home Controller to integrate its many home automation devices is called a "Smart Home." Most Popular Home Controllers are connected to a Windows-based PC when in operation. They are just in charge of programming; the tasks related to home control are left to them. They can communicate with one another thanks to the integration of home systems. Another method is the home controller, which enables simultaneous single-button and spoken control of numerous home equipment in preprogrammed scenarios or while in operation [1]. In ambient-assisted living settings, sophisticated sensors are used to spot any problems that could endanger the resident. Specific smells associated with various risky living conditions could serve as an early indicator of an issue with the house. To implement these technologies in a residential setting, it is necessary to get through certain real acceptance barriers (particularly among the elderly), such as ease of use and privacy concerns [2].

1.2. Machine Learning Algorithms

Supervised learning is an area of study within Machine Learning and Artificial Intelligence. Sometimes referred to as Supervised Machine Learning. It is characterized by using labeled datasets to train algorithms capable of accurately classifying data or predicting outcomes. Classification methods include k-nearest neighbor (KNN). A majority vote of its neighbors determines the classification of a sample. A decision Tree is a tree-structured classifier with nodes that reflect dataset attributes, branches that represent decision rules, and leaf nodes that indicate the conclusion. Random Forest is a classifier that enhances the accuracy of projected predictions by averaging the results of numerous decision trees on varied subsets of a given dataset. Support Vector Machine (SVM), Support Vectors are data points that lie on hyperplanes, and we must identify the hyperplane with the greatest difference between the two classes. Logistic Regression is a statistical method for assessing a set of data. The Electronic Nose system incorporates all of these strategies.

1.3. Odor and Motion Sensors

In electronic equipment, odor sensors are designed to detect a particular odor, such as hydrogen or LPG. Due to its characteristics, each odour sensor, such as MQ sensors, reacts differently to distinct odors. When multiple odor sensors are included into a single system, the system's ability to detect scents is boosted. In addition to detecting motion close to heated surfaces, the ultrasonic sensor was also utilized to detect motion on such surfaces. When the sensor detects children's movement near the oven, for example, when they are close to the ultrasonic sensor, an abnormal movement is detected, and a warning is delivered to prevent the child from being damaged.

2. RELATED WORK

The goal of this study [3] is to classify fruit maturity. A gas sensor array mimics human olfaction to detect odors. Fruit-emitted Volatile Organic Compounds (VOCs) can be detected using an array of Metal Oxide sensors. The procedure was evaluated using bananas. The ripeness of a banana is used to categorize its maturity into four stages. The Electronic Nose is utilized daily to monitor the ripening of fruit. Sensor signals are transmitted to a laptop using a data acquisition (DAQ) card. Afterward, the data is processed using the NI Lab VIEW signal express application. Approaches employed in this study were PCA, KNN, and SVM. During the study, around 25 measurement data were obtained. The KNN and SVM approach achieved 100% and 96.66%, respectively. Since it was only tested on one type of fruit, the samples were the primary constraint (bananas).

The objective of this study [4] is to categorize fruit ripeness. To detect odors, a gas sensor array mimics human olfaction. The array consists of several Metal Oxide sensors that can detect Volatile Organic Compounds (VOCs) emitted by fruit. Bananas were used to test the approach. Based on its ripeness, there are four distinct stages of banana maturity. Each day, the Electronic Nose is used to monitor the ripening of fruit. A data acquisition (DAQ) card communicates sensor signals to a laptop. The data is then processed with the NI Lab VIEW signal express application. PCA, KNN, and SVM were utilized in this investigation. Approximately twenty-five measurement data were obtained during the study. The KNN and SVM approach attained 100% and 96.66%, respectively. It was only tested on a single type of fruit. Therefore, the samples posed the greatest limitation (bananas).

This research [5] aims to identify food degradation in tomato-based Filipino cuisines using an Electronic Nose. This study is to construct a device with an array of sensors for detecting the gases emitted by spoiled tomato-based Filipino dishes and an Artificial Neural Network for classifying sensor data readings. The data for an Artificial Neural Network is trained via the Stochastic Gradient Descent approach and the Backpropagation algorithm. The Filipino dish made with tomatoes is placed beneath the sensor chamber to identify the gas sensors emitted by the dish itself. The discovery could be useful for assessing whether food has degraded. According to the confusion matrix, the error rate of the Electronic Nose system is 3.85%.

The electronic nose is one of the technical models that can be exploited to its fullest capacity using Machine Learning. In this study [6], Phunvira Chongthanaphisut, Thara Seesaard, and Teerakiat Kerdcharoen developed the Electronic Nose, which consists of four gas sensors based on functionalized single-walled carbon nanotubes (f-SWNTs) and polymer composites, to serve as a portable monitoring device for microbiological spoilage and contaminants in canned food. The gas-detecting signals were utilized as early warning indicators of spoilage, aiding in preventing adverse effects on human health. The tuna sample in mineral water was opened and cooled to room temperature (25 degrees Celsius). Using an e-nose, the odor associated with decomposing tuna in a car was identified for ten days. Principal component analysis (PCA) was used to visualize the discrimination of microbial canned tuna spoilage status and analysis of the smell-print of a specific level of ammonia contamination, demonstrating its applicability for quality assurance of canned food in the daily life of a smart home resident. Based on the gases produced by the food sample, it may be possible to predict whether or not a particular food sample has spoiled.

An electronic nose is utilized to classify the quality of various chili sauces in the research [7]. E-nose is capable of analyzing the material according to its fragrance. Researchers have used five distinct types of metal oxide semiconductor (MOS) gas sensors manufactured by several companies (TGS2620, TGS 813, TGS 822, TGS 2600, and TGS 2602 series). They used the Baseline manipulation method, the maximum value approach for feature extraction, and the main Component analysis technique for data analysis. Six chili sauce samples of differing quality were evaluated using the Electronic Nose as a data source. PC1 earned 92%, but PC2 earned 5.8%, resulting in 97.8% for both participants. This research is limited mainly because the publication is poorly organized and worded.

The paper [8] attempts to detect food degradation in a smart home context. They employed five perishable commodities, including homogenized milk, cream, yogurt, eggs, and sour cream, that were purchased fresh and stored at room temperature for seven days, with spoiling occurring on the seventh day. Twelve metal-oxide sensors were utilized to develop the Electronic Nose system. The Electronic Nose caught odor using a syringe to retrieve 2.0mL from the vial, which was then put into the sensor chamber and recorded every 0.5s for two minutes, yielding 12 conductivity against time curves. On day one, categories are divided and distinct from one another; on day seven, however, the similarity between the three samples rose.

Using eight metal-oxide sensors, TGS-813, TGS-821, TGS-822, TGS-824, TGS-825, TGS-842, TGS-2201, and TGS-2620, the researchers developed an Electronic Nose system [9] to detect a change in the quality of wheat. They employed both PCA and neural network approaches for qualitative and quantitative detection. From 120 samples, they chose 90 training samples and 30 testing samples. The method achieves an accuracy rate of greater than 90 percent when wheat is mixed with mildew and pests and a rate of 100 percent when wheat is both normal and subject to qualitative change.

The electronic nose proposed in [10] has a significant application in smart homes for detecting harmful circumstances and warning the tenant. Twelve metal-oxide gas sensors (MOGS) were utilized to detect the odor of five distinct food samples heated at 50 degrees Celsius for five minutes to concentrate the odor. In Electronic Nose analysis, they utilized fuzzy C-means (FCM) and Artificial Neural Network (ANN) clustering. To minimize overtraining in Artificial Neural Network, the dataset is separated into a 60% training set, 20% validation set, and 20% testing set.

In the study [11], the outdoor air quality performance of three Electronic Nose systems utilizing only semiconducting gas sensors, only amperometric gas sensors, or both types of sensors are examined. Three semiconducting gas sensors and three amperometric gas sensors were ultimately employed to detect nitrogen dioxide, Sulphur dioxide, Ozone, and carbon monoxide. They have utilized the PLS and SVM regression algorithms. MATLAB software was used to do the calibration. The information was gathered over six days. The O3 and SO2 prediction findings indicated that slightly lower RMSE values may be reached with only amperometric sensor responses in model calibration construction.

The Electronic Nose system has been proposed in work [12] for detecting the amount of polluting gas in the environment. The researchers' hardware consists of three MOS sensors (MQ3, MQ6, and MQ135), an ARM controller, a MAX3232 processor, and an RF ZigBee model. Back Propagation Neural Network has been proposed for software, and the Neural Network is trained using the pattern recognition technique Multi-Layer Perceptron (MLP). ARM processors are used for real-time data collection. At a load of 2,200 kilowatts, all sensors perform satisfactorily and produce output following their specifications. The system's limitations are that it requires labeled training data and a longer training period.

Utilizing an array of gas sensors and a Raspberry PI MCU, the project [13] aims to learn more about Azotemia through urine utilizing the Electronic Nose. Regarding software, the KNN method was utilized for precise classification and prediction, and the PCA technique was employed for visualization and charting. According to the findings, the study has a 90% Accuracy and a 10% error rate. The only significant limitation is the ML Algorithms they employed.

The purpose of this paper [14] is to determine whether or not the participants in this experiment have schizophrenia. The researchers collected breath samples from the person and identified them using a Raspberry PI MCU's array of gas sensors. SVM classifier is then used to process this data. Five people with schizophrenia and five non-schizophrenic people were tested for the trial. This study has an accuracy rating of 80%. This experiment's dataset was insufficient to validate their system completely.

Satetha Siyang and Teerakiat Kerdcharoen developed an electronic nose [15] as an alternate method for detecting diabetes based on direct urine odor (E-nose) monitoring. Utilized data analysis techniques, including principal components analysis (PCA) and cluster analysis (CA). Based on this preliminary experiment, our laboratory-made Electronic Nose may be a promising technology for detecting diabetes by directly monitoring urine odor with applied temperature (>45 °C).

Using a fuzzy KNN algorithm, the researchers of [16] desired to develop an Electronic Nose system to detect early fire stages within structures. The created Electronic Nose was utilized to capture the odors of the fire vials, effectively classifying the fire origins and materials. The datasets are odor signals acquired from an in-house, low-cost indoor air quality (IAQ) system utilizing metal oxide gas sensors. The classification system has an average classification precision of 96.15 percent. The sole limitation identified was their disorganized workflow.

TABLE I: Summary of related works

Paper name	Detection scope	Detected odors	Algorithms	Dataset
Electronic nose	Detecting fruit ripeness	Ethylene gas	KNN	Data acquired
Monitoring of Food Spoilage with Electronic nose: Potential Applications for Smart Homes	Detecting food spoilage in smart homes	Odour of five different food samples	MDA and ANN	Data acquired
Application of electronic nose technology in the detection of wheat quality	Detecting wheat quality and degree of change	Methane, Ethane, Butane, Hydrogen, Alcohol, Toluene, Xylol, Ammonia, Sulfide, Hydrocarbon, Nitrogen-oxides, Alcohol, Toluene, Carbon oxide and ISO-butane	Backpropagation	Data acquired
Intelligent Electronic Nose Systems for Fire Detection Systems Based on Neural Networks	Detecting fires at an early stage	Ammonia, Ethanol, Alcohol, Hydrogen, Freon, Hydrocarbon, Methane, Cooking vapor	K-means and backpropagation	Data acquired
Identification of Food Spoilage in the Smart Home based on Neural and Fuzzy Processing of Odour Sensor Responses	Detecting spoiled food in smart homes	Odour of five different food samples	PCA, FCM, and back propagation	Data acquired
Development of an electronic-nose system for fruit maturity and quality monitoring	Detecting fruit maturity	Volatile Organic Compounds (VOCs)	PCA, KNN, and SVM	Data acquired
Monitoring and Detection of Fruits and Vegetables Spoilage in the Refrigerator using Electronic Nose Based on Principal Component Analysis	Detecting fruits and vegetables spoilage	Odour of four different food samples	PCA and KNN	Data acquired
Early detection of fish degradation by Electronic Nose	Detecting fish degradation	Three odours of fish smell	PCA	Data acquired
Determining spoilage level against time and temperature of tomato-based Filipino cuisines using electronic nose	Identify food degradation in tomato-based Filipino cuisines	Ammonia, Ethanol, Carbon Monoxide, Toluene, Propane, Methane, Hydrogen Sulfide, Benzene	ANN and Confusion Matrix	Data acquired
Prediction of Rice Odor by Using an Electronic Nose and Artificial Neural Network	Distinguish between various types of rice	the odor of four different rice types of jasmine rice, white rice, sticky rice, and brown rice	PCA, KNN and RBF neural networks	Data acquired
Detecting moldy bread using an E-nose and the KNN classifier	Detecting rotting bread	VOC	PCA, KNN, ANN and SVM	Data acquired

Monitoring of Microbial Canned Food Spoilage and Contamination Based on E-Nose for Smart Home	Detecting microbial spoilage in canned food	VOC	PCA	Data acquired
Hand Held Electronic Nose System Using Machine Learning and Predictive Modeling Techniques-A supervised classification-based approach		Methane, Ammonia and carbon Dioxide	KNN, SVM, Random Forest, Logistic Regression and PCA	Data acquired
Quality Classification of Chili Sauce Using Electronic Nose with Principal Component Analysis	classify the quality of different chili sauces	Alcohol, hydrogen, iso-butane, CO, air, Methane, propane, butane, lammable gases, n-hexane, benzene, ethanol, acetone, pollutant gases, Hydrogen sulphide, ammonia, toluene	PCA	Data acquired
Portable Gas Detection and Warning System for Olfactory Disabled People	detect the presence of harmful gases	liquid petroleum gas (LPG), methane (CH4), butane (C4H10), carbon monoxide (CO) and hydrogen sulfide (H2S)	N/A	Data acquired
Identification of Toxic Gases using Electronic Nose	Detecting toxic gases in polluted air	Alcohol checker, breathalyzer, LPG, propane, iso-butane, CO2, NO, NH3, smoke, and benzene	Backpropagation Neural Network	Data acquired
Gas concentration analysis of resistive gas sensor array	Analyze gas concentration	H2, LPG, C3H8, CH4, Alcohol, CH4, CO2, NH3, H2S, LPG, CH4	Backpropagation Neural Network	Data acquired
Urban Monitoring of Unpleasant Odors with a Handheld Electronic Nose	Validating chemical spoilage	Phenol and VOC	CNN Deep learning algorithm	Data acquired
Semi-supervised Gas Detection Using an Ensemble of One-class Classifiers	Detecting gas	Acetone, Ethanol and 1-propanol	OCNN, OCGM and MOCM	Data acquired
Evaluation of the Electronic Nose Used for Monitoring Environmental Pollution	Validating polluted gas on human health and the environment	H2S, CO, SO2, Fumes from food, General air contaminants, Combustible gases	PLS and SVM	Data acquired
An Overview of IoT Hardware Development Platforms	Detecting the amount of pollutant gas in the environment	LPG, Propane, and Hydrogen	MLP and backpropagation Neural Network	Data acquired
Application of Electronic Nose for Diagnosing Azotemia from Urinalysis Using Principal Component Analysis	Diagnosing Azotemia through urinalysis	Combustible Gas, Carbon Monoxide, Hydrogen Gas, and Air Quality	KNN and PCA	Data acquired
Determination of schizophrenia using electronic nose via support Vector Machine	Detecting schizophrenia	Pentane, Alcohol, Carbon Monoxide, Ammonia	SVM	Data acquired
Diabetes diagnosis by direct measurement from urine odor using electronic nose	Detecting Diabetes	Ammonia	PCA and Cluster analysis	Data acquired
Fuzzy K-Nearest Neighbor (FKNN) Based Early Stage Fire Source Classification in Building	Detecting fire sources in the early stage	Oxygen, Volatile organic compounds, Carbon dioxide, Ozone, and Nitrogen dioxide	Fuzzy KNN	Data acquired

3. METHODOLOGY

3.1. Proposed System Overview

The Electronic Nose system is illustrated in FIGURE 1. There are four sections within the Electronic Nose. Arduino-Uno is utilized to assemble the hardware components. Arduino-Uno is a microcontroller that is used to collect inputs from many sensors. An array of Mx Sensors on the microcontroller is paused to detect different gases. The sensor mechanism generates voltages based on the measured gases. The microcontroller will then use the analog signals received to detect any contamination in the atmosphere.

The microcontroller-collected data is subjected to the pre-processing phase, which comprises multiple stages. Normalization is the process of converting the numeric column values of a dataset to a common scale. Then there is the standardization process, which entails transforming data into a standardized format that facilitates data study. The data are then scaled to standardize the data's independent variables range. Then, we conducted feature selection using the correlation matrix for features.

Following this, we construct and process our model using either Training/Testing Split or Cross-Validation. A dataset is divided into two subgroups in the training or testing split procedure. The training dataset is the initial subset utilized for model fitting. The second subset is not used to train the model; rather, the input element of the dataset is provided to the model, which then makes predictions and compares the estimated parameters. A cross-validation is a resampling approach for evaluating and training a model across multiple iterations using diverse data chunks. Primarily employed when the objective is to predict how well a predictive model will function in practice.

Additionally, the Odors are categorized to produce the output. The sensors validate their accuracy by comparing the sensor outputs to the data sets. This process classifies which gas the sensors detected.

In the last phase, if any unexpected occurrences occur, an alert message will be sent to the user via an Android mobile application in which each user has a unique account and may view all detected alerts.

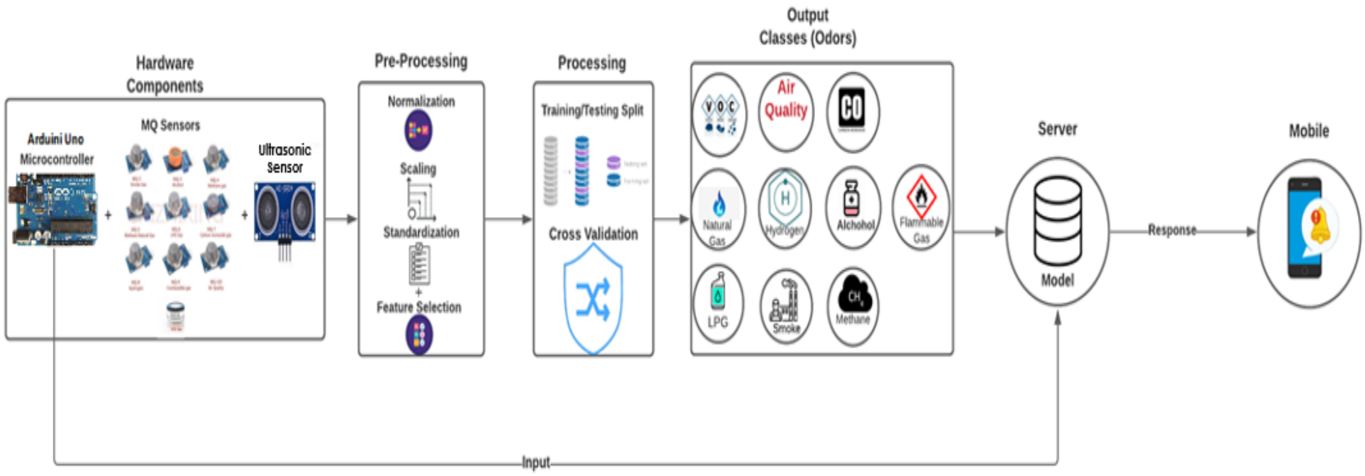

FIGURE 1: System Overview

3.2. Hardware Design

3.2.1 Gas Sensors

MQ gas sensors are utilized in the construction of the Electronic Nose. They detect Smoke, LPG Gas, Natural Gas, Hydrogen Gas, Flammable Gas, and Air Quality. According to TABLE 1 [14], each sensor detects various chemical components with varying concentrations and detection ranges. When a chemical component is discovered, the resistance falls, and the voltage rises to indicate the change in density measurements.

3.2.2 Micro-controller

The Micro-Controller is the device's brain and controls the operation of all other system components. The device employs an AVR Atmega 328P 8-bit Microcontroller IC [13]. It offers 14 digital input/output pins (of which 6 can be used as PWM outputs), six analog inputs, a 16 MHz ceramic resonator, a USB port, a power jack, an ICSP header, and a reset button.

3.2.3 Software Development

C/C++ is the most common programming language, and the IC has an integrated bootloader for uploading and executing code from the integrated development environment (IDE). 1) Arduino IDE The Atmega 328P module is programmed with the Arduino IDE. In addition, the software supports a large number of additional electronic modules and has a user-friendly interface.

2) Processing Software: Processing is a flexible programming language and software sketchbook for the visual arts [15]. Processing employs the Java programming language with further simplifications, such as new classes. In addition, it offers a graphical user interface to facilitate compilation and execution. The data-gathering phase was used to collect sensor readings from the Arduino IDE serial monitor into a .csv file.

3.2.4 Classification Algorithms

1) KNN is the fundamental pattern recognition and classification algorithm used in machine learning. The classification of a sample is determined by the majority vote of its K neighbors. The sample would be placed in the category with the greatest quantity.

2) Support Vector Machine (SVM): SVM classification, the hyperplanes that provide the greatest margin between two substantially identical classes. The data on the hyper planes are referred to as support vectors, and we must identify the plane that gives the greatest difference between the two classes.

3) Decision Tree: A decision Tree is a supervised learning technique that may be applied to both classification and regression issues, while it is most commonly employed to solve classification problems. It is a classifier with a tree-like structure, where internal nodes represent the features of a dataset, branches represent the decision rules, and each leaf node reflects the conclusion.

4) Random Forest: Random Forest is a classifier that includes several Decision Trees on various subsets of a given dataset and takes the average to increase the predictive accuracy of that dataset. Instead of depending on a single Decision Tree, the Random Forest forecasts the ultimate output based on the prediction of each tree and the majority vote of predictions.

5) Logistic Regression: Logistic Regression is a classification approach acquired from statistics by machine learning. Logistic Regression is a statistical method for assessing a dataset whose outcome is determined by one or more independent factors. Logistic regression aims to identify the model that best describes the connection between the dependent variable and the independent variable.

3.2.5 Mobile Application

A Flutter Mobile Application is where users receive forthcoming notifications, with each user having a unique account that allows him to track all alerts received, as seen in FIGURE 2. In addition, users can view their notifications' history together with the warning's location, as shown in FIGURE 3.

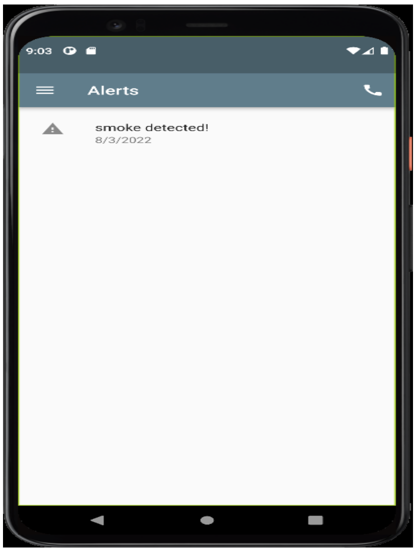

FIGURE 2: Alerts Page

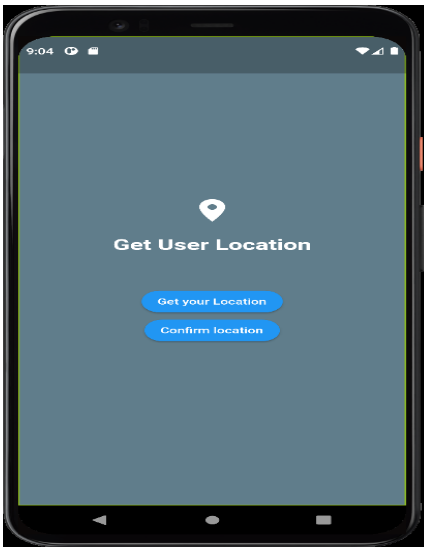

FIGURE 3 : Location Page

4. DATA DESCRIPTION

A dataset was acquired for the MQ sensors using Arduino UNO Microcontroller, Arduino IDE, and Processing Software. The size of the Acquired Dataset is approximately 41,000 instances. The gathered data will be used to differentiate between seven gas classes (types) and identify which gas is dominant and widely distributed among them, in addition to a link between the measured density of contaminated atmospheres and time. These datasets will be utilized to train the machine learning model to provide the most accurate predictions possible. FIGURE 4 depicts the visualization of the dataset.

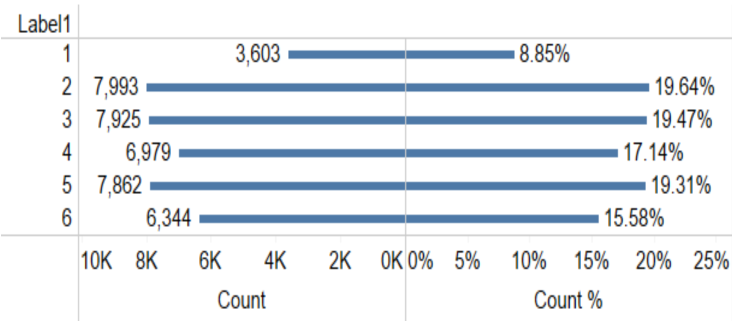

FIGURE 4: Insight of Data Instances Count

5. EXPERIMENT

Our experiments are conducted using the data we collected. The K Nearest Neighbor, Support Vector Machine with a linear kernel, Random Forest, Decision Tree, and Logistic Regression classifiers machine learning models are developed using the Python programming language. All studies were performed on a 16 GB RAM-equipped Intel CoreTM i7 laptop. The dataset is divided into two sections, training and testing. A training set of size 70% is provided to the models to update their parameters, and a testing set of size 30% is used to categorize which gas is dominating and heavily distributed among the remaining six gases (classes). The purpose of feature scaling and log normalization is to rescale the numeric attributes into a 0 to 1 range and to normalize the features as much as feasible. Five machine learning methods, K Nearest Neighbor, Random Forest, Decision Tree, SVM, and Logistic Regression, were applied to the dataset, with Random Forest attaining the highest accuracy. The Confusion matrices for the SVM, Logistic Regression, Decision Tree, Random Forest, and K Nearest Neighbor algorithms are depicted in FIGURES 5, 6, 7, and 9 accordingly.

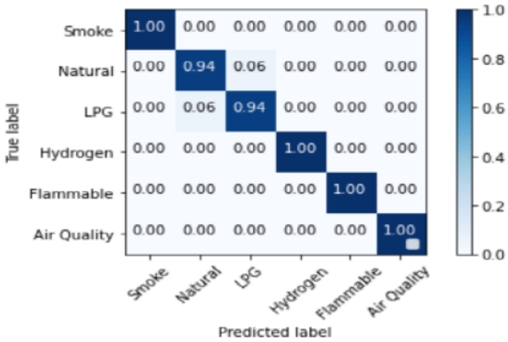

FIGURE 5: Support Vector Machine Algorithm Confusion Matrix

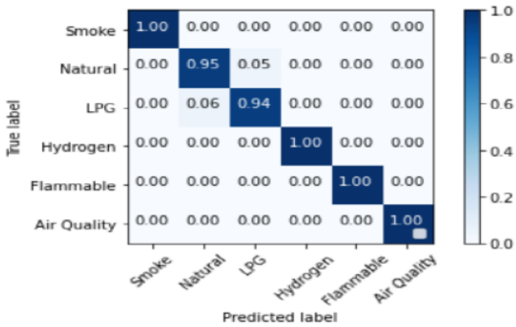

FIGURE 6: Logistic Regression Algorithm Matrix

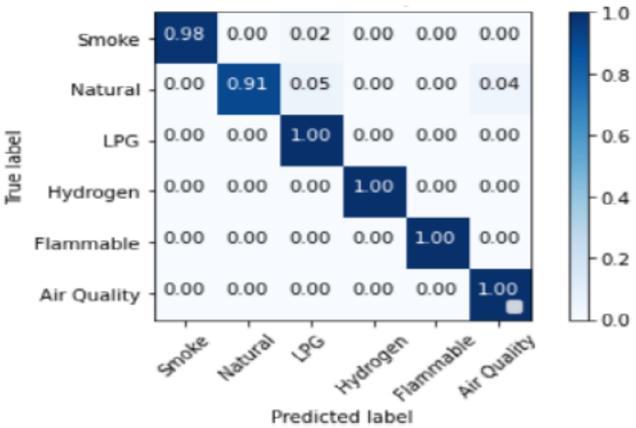

FIGURE 7: Decision Tree Algorithm Matrix

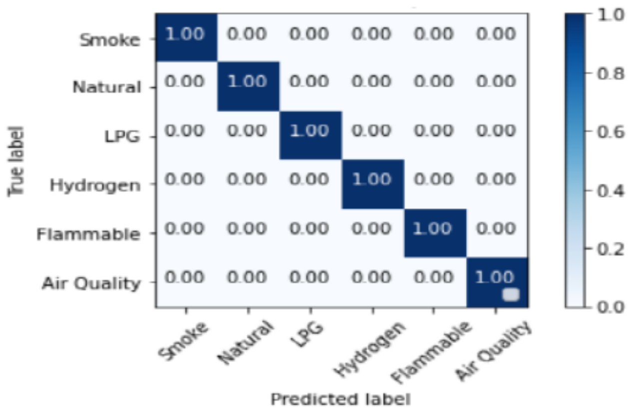

FIGURE 8: Random Forest algorithm Matrix

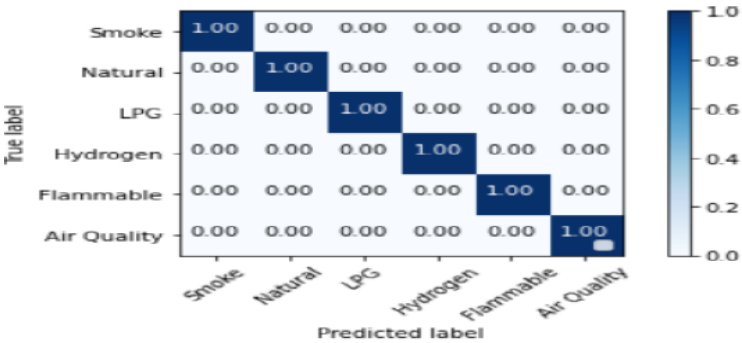

FIGURE 9: K Nearest Neighbor algorithm Matrix

6. CONCLUSION

We suggested Electric Nose device uses an array of nine MQ-sensors to detect any unexpected gas leakage. The user is notified using a mobile application when an anomaly is found. The retrieved sensor values are then classified into seven classifications by our machine-learning model using a variety of algorithms. The proposed system is a smart-home device that keeps the entire family secure.

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