# Predicting Mosquito Repellent for Smart home system Utilizing Intelligent Machine Learning Model

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**Abstract.** The importance of good insect repellents is underscored by the significant threat that mosquito-borne diseases represent to global health. Machine learning applications to classify insect repellents and assess their efficacy have increased recently. The Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), K-Nearest Neighbor (KNN), and Naive Bayes (NB) algorithms are used in this study to investigate the classification of insect repellents. Machine-learning techniques are used to classify mosquito repellents by training multiple machine-learning classification models with a labeled dataset where each repellent is assigned a specified level of effectiveness. These algorithms can recognize trends and categorize the effectiveness of a specific repellant by looking at a range of characteristics such as chemical composition, concentration, duration of protection, and environmental factors. E-nose technology has many advantages, including high sensitivity and selectivity, rapid analysis, non-invasiveness, portability, comprehensive data analytics capabilities, affordability, and versatility. Here, we have proposed a non-selective gas sensor array consisting of eight MQ series sensors, followed by intelligent analytics to monitor the types, concentration, and use of five distinct mosquito repellents that are routinely used in real-world situations. The sensor node prototype was subjected to every possible disinfectant for a duration of 20 minutes at a time in order to generate the experimental dataset. Then, using this dataset as training data, numerous machine learning models were trained to correctly classify ambiguous data samples. The accuracy of the KNN & RF and DT-based models was only 97.97% and 90.71%, respectively. The performance was evaluated using the error metrics as well.

**Keywords: -** Electronic Nose, Pattern Recognition, Machine Learning, Normalization, Sensor Array, Gases/Odors Classification

## 1 Introduction

Nowadays, Internet of Things (IoT)-based intelligent sensor systems are pretty popular to make the home and city bright. The application area and the used sensor elements may be different but share the same objective to facilitate society on the economical and sustainability ground. Out of several categories of sensors, metal-oxide-based gas sensors are one of the multipurpose sensor elements [1, 2]. However, such gas sensors are non-selective which poses challenges while classifying the gases/odors accurately. To enhance the performance even with this inevitable issue, intelligent sensor signal processing is applied [3, 4]. Such processing techniques are not only beneficial to obtain outperformance but also open the door to applying deep learning techniques on gas sensors [5–7]. Various deep-learning methods are utilized for prediction and classification [8, 9] Moreover, using the referred techniques intelligent gas sensing systems can also be designed for resource-constrained applications (e.g., mini robots, drones, unmanned aerial vehicles, etc.) [10, 11].

With this introduction of utility of gas sensors, we have aimed a crucial application paradigm for smart healthcare. We have proposed an "Intelligent Mosquito Repellent System" to curb the adverse effects of mosquito-borne diseases. For example, the Zika virus, dengue fever, and malaria are major illnesses that are mosquito-borne. Mosquitoes are flying-carriers of such diseases, i.e., these diseases have high spread-ability. Therefore, the development and effective application of insect repellents is crucial for protecting people from diseases that mosquitoes spread. In addition to being bothersome insects, mosquitoes can spread diseases like West Nile, Zika, dengue, and malaria. Therefore, it is essential to protect ourselves from mosquito bites, especially in locations where mosquito-borne diseases are common. In this sense, mosquito repellents are essential since they lower the risk of disease transmission and prevent mosquito bites. A growing number of people are considering utilizing machine learning algorithms to classify and evaluate the efficiency of different insect repellents, as was previously mentioned [12, 13]. In order to categorize mosquito repellents, machine learning techniques are applied. A model is trained using a labeled dataset in which each repellent is given a specific level of effectiveness. These algorithms may identify trends and predict a certain repellent's effectiveness by looking at a range of characteristics like chemical composition, concentration, duration of protection, and environmental factors [14, 15]. Several works have been developed in the context of mosquito repellent. A review of a few significant works has been incorporated under the forthcoming subsection of related work.

### 1.1 Related Works

Burning indoor mosquito coils results in smoke that effectively wards off insects. Currently, this tradition is carried out widely in households throughout Asia, Africa, and South America. Nevertheless, the smoke might contain dangerous pollutants. Four famous mosquito coil brands from China and two well-known brands in Malaysia were subjected to an experiment to determine their emissions. They used mass balance equations to determine the emission rates of polycyclic aromatic hydrocarbons (PM2.5, or fine particles), aldehydes, and ketones [16]. They discovered that pollutant concentrations brought on by burning mosquito coils could significantly exceed air quality regulations or recommendations by using these established emission rates to anticipate interior concentrations under realistic room settings. The tested Malaysian mosquito coils produced more measurable pollutants than the tested Chinese mosquito coils under the same combustion conditions.

In [17] Long-lasting insecticide-treated nets (LLINs), indoor residual spraying (IRS), and insecticide-treated materials (ITMs) are a few examples of product forms that may contain spatial chemical actives. The goal was to determine how mosquito coils and emanators affect mosquito behaviors that lessen human-vector interaction and to suggest a scientific consensus on terminology and evaluation methodology. A few examples of the databases available are PubMed, MEDLINE, LILAC, the Cochrane Library, IBECS, and the Armed Forces Pest Management Board.

Improvements in statistical reporting of research and a common understanding of the procedures and terminologies employed through standardized testing criteria were found to be necessary. To repel mosquitoes and purify the air, one of the research offers a novel method in which a sensor automatically detects the mosquito population before adjusting the amount of fumes released by our specific herbal solution [18]. They experimented with different compositions and insect densities, and the results convinced us that their approach is superior to other commercially available mosquito repellents.

A system that employs a solar panel as its energy source to power a rechargeable 12V battery that powers an Arduino UNO to turn on and off the mosquito-repelling system was proposed [15].

The remainder of the paper is structured so that Section 2 outlines the technique for the project under consideration. Here, we outline the database and experimental setup. The examination of the database of insect repellents is presented in Section 2 sub-section. The results of this projected effort are presented in Section 3, and finally, the conclusions of this research work and its future directions are mentioned in Section 4.

## 2 Experimental Setup and Data Description

The E-Nose-based Mosquito Repellent System (EMRS) used for collecting the dataset comprises an ESP8266 module along with eight metal-oxide gas-detecting sensors and temperature-humidity (DHT22) sensor. To create the EMRS, we have gathered an appropriate database. The eight non-selective sensors that make up the developed EDMS are MQ2, MQ3, MQ4, MQ5, MQ6, MQ8, MQ9, MQ135, and DHT22. Fig.1 shows the experimental setup built in our laboratory for the collection of data.

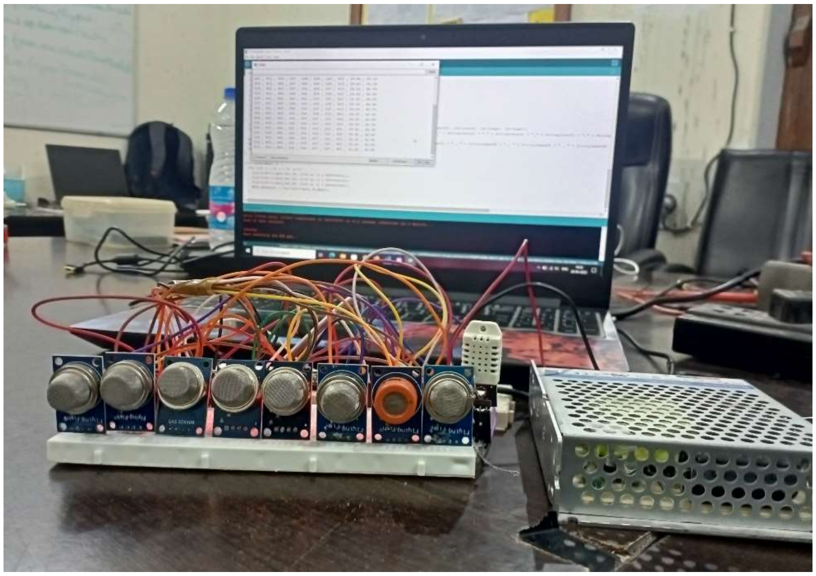

**Fig. 1.** Experimental setup for data collection.

We have used an eight-channel analog multiplexer to take input from all the eight gas sensors and interfaced it with the ESP8266 module, the temperature and humidity sensor (DHT22) is directly interfaced with the ESP module, the framework for which is shown in Fig. 2. Eight metal-oxide gas-detecting sensors, an ESP8266 module, a temperature sensor, and a humidity sensor are all parts of the created E-Nose system for gathering the dataset. Due to its versatility and simplicity, the ESP8266 is a low-cost, Wi-Fi-enabled microcontroller module that has gained popularity for use in Internet of Things (IoT) projects. It is a highly integrated system-on-chip (SoC) that combines a microcontroller unit (MCU) with Wi-Fi capabilities, making it ideal for creating Wi-Fi-enabled projects or for establishing connections between devices and the internet. The equipment used to collect the dataset consists of eight sensors that detect metal-oxide gas as well as sensors for temperature and humidity. Fig. 2 shows the structure for gathering data. The sensors MQ2, MQ3, MQ4, MQ5, MQ6, MQ8, MQ9, and MQ135 are employed, together with a DHT22. The experimental setup created at our NCC laboratory for data collection is shown in Fig. 1 and Framework in Fig. 2.

### 2.1 Gas Sensor

To generate or create electrical signals, gas sensors distinguish between the appearance of various gases. Gas sensors based on Metal Oxide Semiconductor (MQ) technology are the ideal choice since they are the smallest, least expensive, respond quickly, and have a longer lifespan. Many experiments have been carried out based on this sensor and their sensitivity as described in [19, 20]. The Multimodal Gas Data provided in the research is a new set of concurrent data samples obtained utilizing a thermal imaging camera and seven distinct MQ gas-detecting sensors as described in [21].

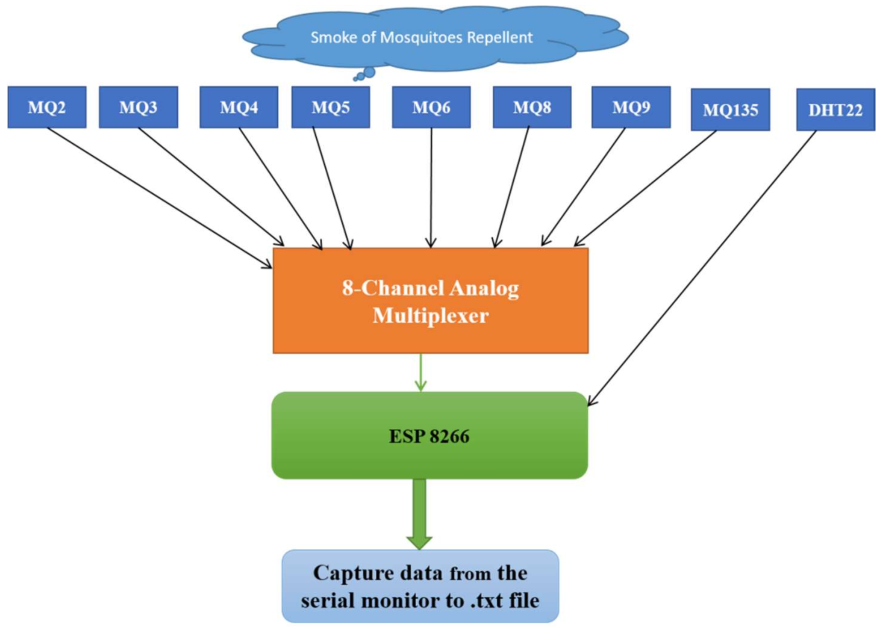


**Fig. 2.** Framework for data collection.

**Table 1.** Gas sensors and their applications.

| Gas sensor | Target gases |
|---|---|
| MQ2 | Methane ($CH_4$), Butane |
| MQ3 | Alcohol, Ethanol, Smoke |
| MQ4 | Methane ($CH_4$), CNG gas |
| MQ5 | Carbon Monoxide (CO), Natural Gas |
| MQ6 | LPG, Butane |
| MQ8 | Hydrogen Gas ($H_2$) |
| MQ9 | LPG, Butane |
| MQ135 | Air Quality (CO, Benzene) |
| DHT22 | Temperature and Humidity |

## 2.2 DATASET COLLECTION

The dataset for this study was gathered utilizing a variety of commercially available insect repellents, including coils, sprays, incense sticks, Hit Spray, and liquids. The several gas sensors were exposed to various compounds while being kept 10 mm apart from one another during the experiment. By running the system for 20 minutes, data for all the classes were collected. Keeping such materials in contact with the setup. The equipment (EMRS) was first allowed to run in a fresh-air environment to collect data. Second, data for the Goodnight Fast Card was gathered by burning it close to the sensors, data for the Hit Spray mosquito repellent was gathered by intermittently spraying it over the sensor array, and data for incense sticks and mosquito coil were also gathered in the same manner as for the Fast Card, Liquidator, and Hit Spray.

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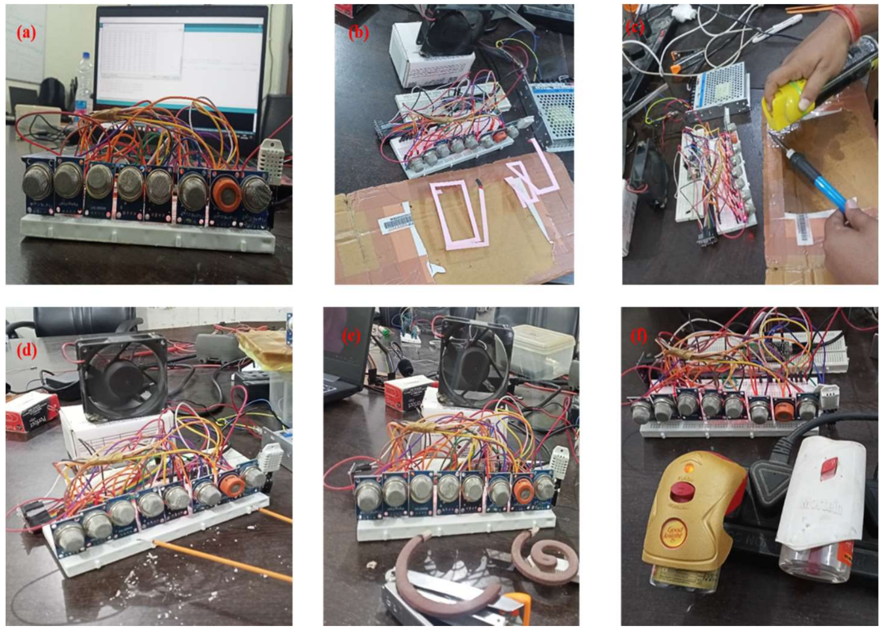



**Fig. 3.** Data collection of (a) Fresh air, (b) Fast card, (c) Hit spray, (d) Incense stick, (e) Coil, and (f) Liquidator.

## 2.3 Data Analysis and Standardization

We standardized the features by reducing the mean to zero and the variance to unity because the output range of all the sensors was 0 to 1023 and each sensor had a varied sensitivity. Calculating the standard score is as follows:

$$(\sigma)^2 = \sum_{i=1}^{N} \frac{x_i - \mu}{N-1} \qquad (1)$$

Where $x_i$ represents each data point, μ is the mean of the dataset, N is the number of data points, and σ is the variance of the data point.

Data pre-processing, classification, and pattern recognition are the basic fundamental components of every E-Nose system, as discussed by [22–25].

We have standardized the features by converting mean to zero and variance to unity

$$z = \frac{x - \mu}{\sigma} \qquad (2)$$

Where $x$ represents data, μ is the mean of the dataset, Z is the Score, and σ is the variance of the data set.

## 2.4 Building Model for Classification

We have divided our dataset into train and test sets for the purpose of developing the model, and we have determined that the ratio for these sets should be 80:20. However, before dividing the dataset, we have shuffled it such that both the train and test set receive an adequate quantity of all sorts of data.

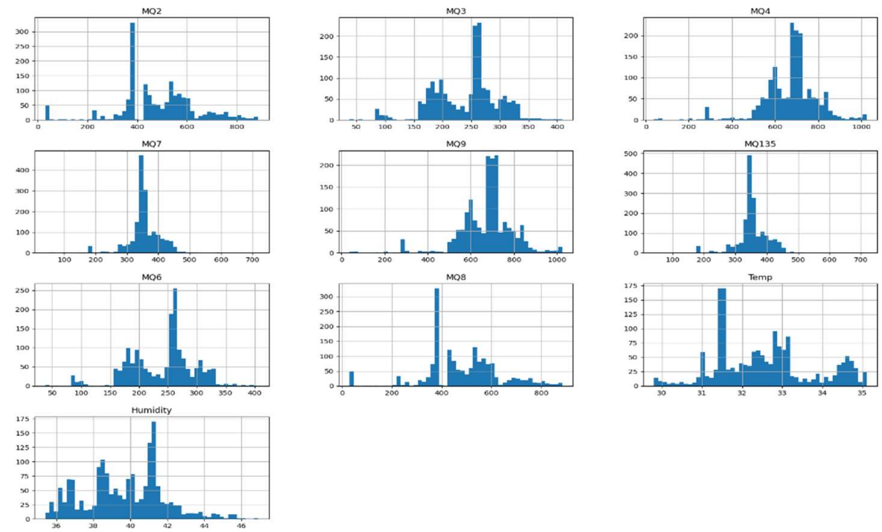



**Fig. 4.** The sensor response dataset's histogram graphs.

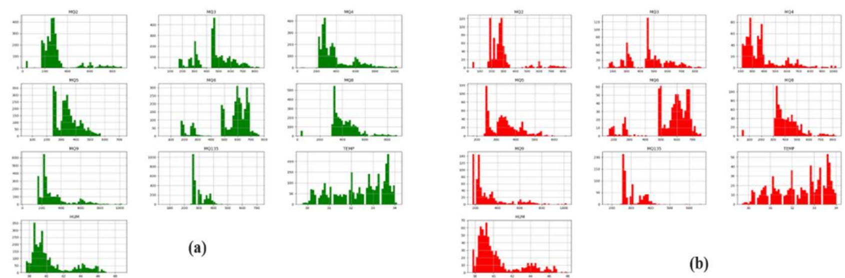



**Fig. 5.** Histograms for (a) Training set, and (b) Test set.

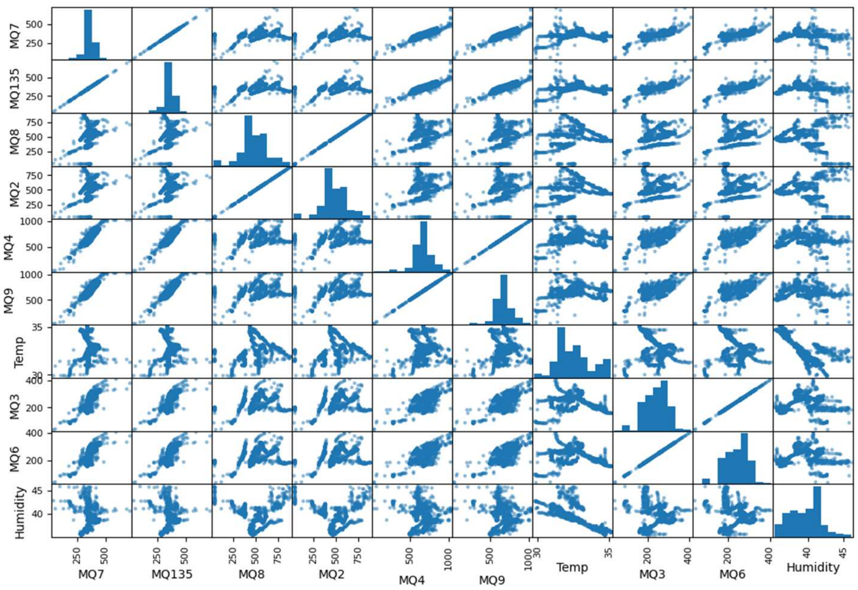



**Fig. 6.** Scatter plots for all the sensor responses dataset.

## 3 RESULTS AND DISCUSSION

We have compared these five alternative machine learning methods based on their Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error, and R2 Score when training various models on our training set. We discovered that the KNN plus DT approach, out of all these five techniques, has the least error and hence best fits our classification issue. Additionally, RF and LR both have accuracy scores of 97.97 and 97.71. We also determine each classifier's Confusion Matrix. Eight MQ sensors' responses are recorded in the E-Nose, along with other sensor output responses. 1700 instances of average reactions from various 8 tin oxide gas sensors are included in the data set. The room where the embedded sensors are located. The range of the goal value is from 0 to 4, which corresponds to the outputs. The data collection has 1700 entries with a Range Index of 0 to 1700, and its data columns are 10. Multiple non-selective MQ sensors that are wired in series were employed in the self-developed E-Nose Sensor array system. The dataset was acquired and recorded from our own custom-built EMRS, which is only available for this study project. The LR, DT, RF, KNN, and NB sklearn modules were imported, and a model was developed for the classifier to get accuracy. We also calculated the performance measures that were taken into consideration. In training various models on our training set we have compared these different machine learning algorithms based on their Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and their R2 Score. Out of all these 5 algorithms we have found that K-Nearest Neighbour Algorithm has the least error and thus it best suits our classification problem.

### 3.1 Confusion Matrix (CM)

A confusion matrix is a simple way to measure the performance of a classification algorithm. It is also used to define parameters such as precision score, recall score, and F1 score. The Confusion matrix for DT, KNN, LR, RF, and NB classifiers is shown in Fig. 7.

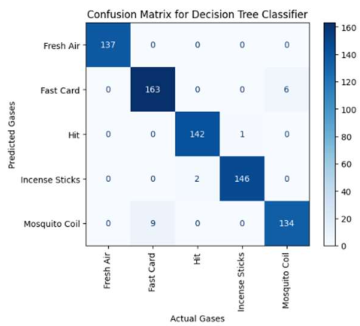
$$Precision\ Score = \frac{TP}{TP + FP} \qquad (3)$$

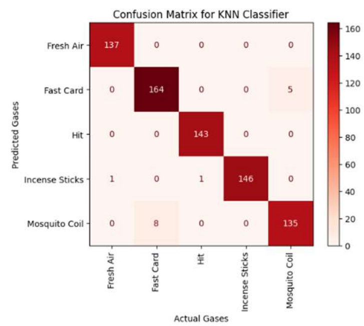
$$Recall\ Score = \frac{TP}{TP + FN} \qquad (4)$$

$$F1\,Score = 2 * \frac{precision * recall}{precision + recall} \quad (5)$$

### 3.2 Decision Tree (DT) classifier

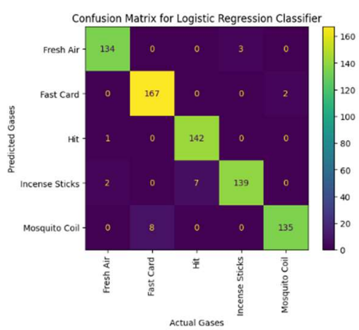
It is a machine-learning algorithm that is used for both regression and classification tasks. Recursively dividing the input data into subgroups depending on the values of various qualities or features is how it works. The process continues until a stopping requirement is satisfied, such as reaching a specific depth, obtaining a minimum number of samples in a node, or when further splits do not enhance the classification performance. Each partition or subset serves as a node in the tree. Table 2 shows an accuracy of 97.7%.

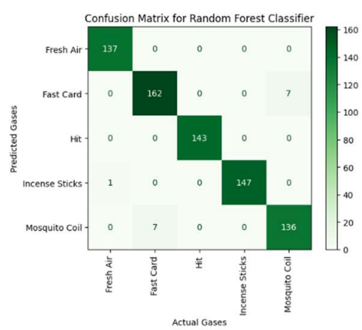



(a) DT Classifier CM.

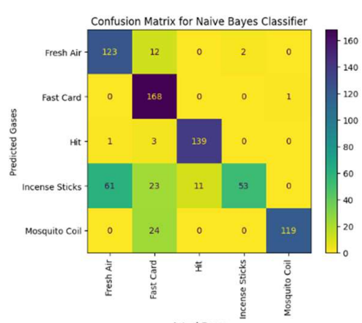
(b) KNN Classifier CM.




(c) LR Classifier CM.

(d) RF Classifier CM.




(e) NB Classifier CM.

**Fig. 7.** Confusion matrices (a) DT, (b) KNN, (c) LR, (d) RF, and (e) NB.

### 3.3 Decision Tree (DT) classifier

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**Table 2.** Classification report of DT classifier.

| Mosquito repellent | precision | recall | F1-score | support |
|---|---|---|---|---|
| Fresh Air | 1 | 1 | 1 | 137 |
| Fast Card | 0.953216 | 0.964497 | 0.958824 | 169 |
| Hit | 0.986111 | 0.993007 | 0.989547 | 143 |
| Incense Sticks | 0.993197 | 0.986486 | 0.989831 | 148 |
| Mosquito Coil | 0.957447 | 0.944056 | 0.950704 | 143 |
| accuracy | | | 0.977027 | 740 |
| macro avg. | 0.977994 | 0.977609 | 0.977781 | 740 |
| weighted avg. | 0.977048 | 0.977027 | 0.977016 | 740 |

**Table 3.** Classification report of KNN classifier.

| Mosquito repellent | precision | recall | F1-score | support |
|---|---|---|---|---|
| Fresh Air | 0.992754 | 1 | 0.996364 | 137 |
| Fast Card | 0.953488 | 0.970414 | 0.961877 | 169 |
| Hit | 0.993056 | 1 | 0.996516 | 143 |
| Incense Sticks | 1 | 0.986486 | 0.993197 | 148 |
| Mosquito Coil | 0.964286 | 0.944056 | 0.954064 | 143 |
| accuracy | | | 0.97973 | 740 |
| macro avg. | 0.980717 | 0.980191 | 0.980403 | 740 |
| weighted avg. | 0.979793 | 0.97973 | 0.97971 | 740 |

### 3.4 K-Nearest Neighbours

A machine learning technique used for classification problems is called the K-Nearest Neighbours (KNN) Classifier. It works on the premise that in a feature space, items or data points that are close to one another tend to belong to the same class. Since KNN is an instance-based learning or lazy learning algorithm, it doesn't explicitly construct a model during training. To make predictions at runtime, it instead memorizes the full training dataset. Table 3 shows an accuracy of 97.97%.

**Table 4.** Classification report of LR classifier.

| Mosquito repellent | precision | recall | F1-score | support |
|---|---|---|---|---|
| Fresh Air | 0.978102 | 0.978102 | 0.978102 | 137 |
| Fast Card | 0.954286 | 0.988166 | 0.97093 | 169 |
| Hit | 0.95302 | 0.993007 | 0.972603 | 143 |
| Incense Sticks | 0.978873 | 0.939189 | 0.958621 | 148 |
| Mosquito Coil | 0.985401 | 0.944056 | 0.964286 | 143 |
| accuracy | | | 0.968919 | 740 |
| macro avg. | 0.969937 | 0.968504 | 0.968908 | 740 |
| weighted avg. | 0.969381 | 0.968919 | 0.968835 | 740 |

**Table 5.** Classification report of RF Classifier.

| Mosquito repellent | precision | recall | F1-score | support |
|---|---|---|---|---|
| Fresh Air | 0.992754 | 1 | 0.996364 | 137 |
| Fast Card | 0.953216 | 0.964497 | 0.958824 | 169 |
| Hit | 1 | 1 | 1 | 143 |
| Incense Sticks | 1 | 0.993243 | 0.99661 | 148 |
| Mosquito Coil | 0.957447 | 0.944056 | 0.950704 | 143 |
| accuracy | | | 0.97973 | 740 |
| macro avg. | 0.980683 | 0.980359 | 0.9805 | 740 |
| weighted avg. | 0.979751 | 0.97973 | 0.979719 | 740 |

### 3.5 Logistic Regression (LR) Classifier

It is a statistical technique used in jobs involving binary and multiple-class categorization. Despite its name, it is more closely connected to logistic functions than linear regression. It forecasts the likelihood that a specific class will contain an instance, which is subsequently utilized to get a final classification determination. Table 4 shows an accuracy of 96.89 %.

### 3.6 Random Forest (RF) Classifier

The algorithm is a member of the ensemble learning family of machine learning techniques. It is based on the idea of building numerous decision trees and combining their predictions to increase overall accuracy and decrease overfitting. It is intended for both classification and regression problems. Table 5 shows an accuracy of 97.97%.

### 3.7 Naïve Bayes (NB) classifier

For classification tasks, it is a probabilistic machine learning algorithm. It takes as a given that characteristics are conditionally independent given the class and is built on the ideas of Bayes' theorem. Naive Bayes can be surprisingly effective despite its straightforward presumptions, especially for problems involving text categorization and other high-dimensional data. In Table 6 the accuracy of the NB classifier is 81.35%.

**Table 6.** Classification report of NB classifier.

| Mosquito repellent | precision | recall | F1-score | support |
|---|---|---|---|---|
| Fresh Air | 0.664865 | 0.89781 | 0.763975 | 137 |
| Fast Card | 0.730435 | 0.994083 | 0.842105 | 169 |
| Hit | 0.926667 | 0.972028 | 0.948805 | 143 |
| Incense Sticks | 0.963636 | 0.358108 | 0.522167 | 148 |
| Mosquito Coil | 0.991667 | 0.832168 | 0.904943 | 143 |
| accuracy | | | 0.813514 | 740 |
| macro avg. | 0.855454 | 0.810839 | 0.796399 | 740 |
| weighted avg. | 0.853338 | 0.813514 | 0.796415 | 740 |

Fig. 8 and Table 7 show the comparison of the five classifiers that were taken into consideration. It was found that the two classifiers, RF and K-NN, generated accurate results that were promising for classifying the different mosquito repellent as well as the response to the fresh air.

**Table 7.** Comparison of accuracy with different classifiers.

| Algorithm | Accuracy (%) |
|---|---|
| Naïve Bayes | 81.35 |
| Logistic Regression | 96.89 |
| Random Forest | 97.97 |
| Decision Tree | 97.71 |
| K-Nearest Neighbour | 97.97 |

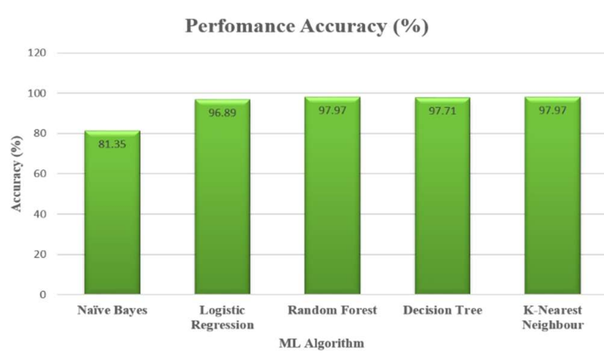


**Fig. 8.** Comparison of classification accuracy of different algorithms.

Several measures in Fig. 9 and Table 8 are used to evaluate the performance of these classifiers.

**Table 8.** Performance evaluation of different algorithms.

| Algorithm | MAE | MSE | RMSE | R2 Score |
|---|---|---|---|---|
| Naïve Bayes | 0.456757 | 1.23514 | 1.11137 | 0.363904 |
| Logistic Regression | 0.072973 | 0.197297 | 0.444182 | 0.898392 |
| Random Forest | 0.0608108 | 0.182432 | 0.427121 | 0.906047 |
| Decision Tree | 0.0594595 | 0.172973 | 0.4159 | 0.910919 |
| K-Nearest Neighbour | 0.0581081 | 0.171622 | 0.414272 | 0.911615 |

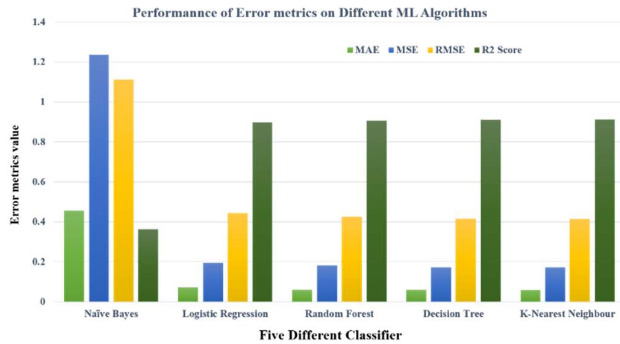


**Fig. 9.** Performance evaluation of different algorithms.

## 4 Conclusions

As a result, we tested various machine learning methods and got remarkable accuracy. When used to classify insect repellents, machine learning systems have shown positive results. By combining various features and training the model using labeled data, it is possible to determine an insect repellent's efficiency with accuracy. The quality and representativeness of the training data are essential for the classification model's success; it is imperative to keep this in mind. A diverse and comprehensive dataset including a range of insect repellents, environmental variables, and efficacy measures is necessary to produce accurate categorization findings. Additionally, there are opportunities to improve the accuracy and efficacy of classification models for mosquito-repellent products gratitude to current studies and advancements in machine learning approaches. Combining state-of-the-art algorithms, feature selection strategies, and ensemble methods can help the models be enhanced to make predictions that are even more accurate. Therefore, our recommended strategy demonstrates a sophisticated and affordable system for mosquito-repellent monitoring in homes and workplaces. Through our suggested (EMRS), we have demonstrated that an accurate classification of the mosquito repellent is attainable. It is a cheap, simple, and IoT-capable system. As a result, it can be applied to pandemic prevention programs and smart city scenarios. It is also feasible to establish an IoT network for simultaneous monitoring of a greater area.

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