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Classification of Liquid Aroma Profiles Using Electronic Nose and Classical Machine Learning Methods

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Abstract This study addresses the automatic classification of liquid aroma profiles using classical machine learning methods with an electronic nose system. Therefore, the AI Nose Dataset 250 data set obtained from the Electronic Nose (E-Nose) system was used in this study. This dataset contains 7 features consisting of 6 chemical and environmental sensors and 5 different classes: Perfume, Air, Coffee, Tea, and Vinegar. The Naive Bayes (NB) algorithm was used along with Random Forest (RF), k-Nearest Neighbor (kNN), AdaBoost, and Decision Tree (DT) methods to classify these data. To analyze the classification performance of the models, the Confusion Matrix was used along with the metrics Accuracy, Precision, Recall, and F1 Score. The ROC Curve was used for a detailed analysis of the classification performance of the models. As a result of the training and testing of the models, classification performance close to 100% was achieved with the RF and kNN models. The highest classification performance was achieved with the RF model. When the results were examined, it was seen that the classification performance of all Machine Learning models was very close to each other.

Keywords: Electronic Nose, Machine Learning, Feature Extraction, Classification, Performance Analysis

Introduction

This study focuses on the use of machine learning models trained for the automatic diagnosis of liquids using E-Nose (Electronic Nose) systems. In this section, to establish our foundation, we examine the working principles of gas sensor arrays in electronic nose systems and the machine learning methods frequently used in these systems. Specifically, by examining data sets similar to the AI Nose Dataset 250, which can distinguish complex liquid vapors from time series data obtained from gas multi-sensor systems, the fundamental challenges encountered in E-Nose applications in the literature, and the critical methods used to overcome these challenges, we will be able to select the classification model that will be the focus of this project. There are many studies on this subject in the literature. Most of those related to the study we examined are listed in order.

Wei, Dan et al. 2023 highlight their work in the field of food analysis and detection using Chromatography-Mass Spectrometry and Electronic Nose technology. Their studies

utilized Chromatography-Mass Spectrometry and E-Nose methods for food flavor components. They have demonstrated that the GC-Mass Spectrometry method has a wide detection range and high sensitivity, while the E-Nose method is practical and fast in application. With the system they propose, combining the two technologies shows potential for creating food flavor fingerprints and developing more accurate food aroma prediction models (Wei et al., 2023).

Ye, Liu et al. supported the latest developments in smart E-Nose (Electronic Nose) technologies with machine learning in their 2021 study. They used machine learning techniques such as neural networks for odor identification in E-Nose systems. They suggested that gas sensor drift compensation, extraction, modeling, and integration into E-Nose systems significantly increased the system's prediction accuracy and consistency. With the proposed system, they demonstrated that E-Nose technology could deliver high performance in many applications, such as robotics, food engineering, environmental monitoring, and medical diagnosis (Ye et al., 2021).

Anwar et al. analyzed previous studies conducted by Anwar et al. in 2023 that focused on food quality assessment using E-Nose systems. They emphasized that traditional methods are costly, time-consuming procedures and subjective. They used E-Nose technology as a quick solution to the problem due to its ability to detect and distinguish different odors. They used machine learning algorithms (artificial intelligence-based models) to analyze complex data for accurate identification and evaluation of food using odor as a marker. They suggested that their proposed system, unlike traditional methods, would offer effective solutions to quality issues in basic food categories such as meat, dairy products, edible oils, fish, tea, and coffee using E-Nose technology (Anwar et al., 2023).

Susanti et al. used the Backpropagation Artificial Neural Network Method with an Electronic Nose to detect Arabica and Robusta coffee powder in their 2023 study. In the study, four odor sensors, TGS 2602, 2610, 2611, and 2620, were used to capture the aroma of coffee. The architecture of the Backpropagation Artificial Neural Network was designed with four inputs from all sensors, a hidden layer with eight neurons, and two output neurons. The developed neural network showed an impressive accuracy of 91.90% during the training phase. They found that the TGS 2602 and 2611 sensors showed the most distinct differences among the three aroma types. They argued that the proposed system, integrating Electronic Nose and Artificial Neural Network, provides a sensitive method for detecting the aroma of coffee types (Susanti et al., 2023).

Jiménez-López, Molina-Quiroga, and others conducted a study in 2023 on the classification of tea types using various feature extraction properties in the signal dataset based on the Electronic Nose system developed by Jiménez-López and his team. The

researchers used an Electronic Nose device equipped with seven chemically resistant gas sensors to analyze a total of 34 unblended commercial tea samples (green, white, black, mint, lemon balm, mallow flower, etc.) divided into eight different categories. They produced the device entirely themselves. The data provided by the sensors was classified using ANN and (k-NN) algorithms, and the best classification success was achieved using a 10-fold cross-validation method. With the system they proposed, they provided the ability to quickly and objectively monitor and classify tea types according to their aromas (Jiménez-López et al., 2023).

In 2023, Lu, Shi, and colleagues conducted a study advocating the combination of portable Metal Oxide Matrix-Based E-Nose systems with machine learning techniques for multi-beverage classification systems. The aim of the study is to quickly and accurately identify different beverages (in terms of aroma profiles). The researchers used a Metal Oxide sensor array to detect volatile organic compound profiles. They created a machine learning model to process the data from the sensors and classify the beverages. They stated that the proposed portable system offers a fast, non-destructive, and highly accurate approach for evaluating beverage quality. They also argued that the integrated approach has great potential in areas such as food fraud detection (Lu et al., 2024).

In this review conducted by Sanislav et al. in 2025, they have comprehensively reviewed the current status of sensor-based Electronic Nose systems in terms of food quality and food safety. They emphasize the vital importance of the Electronic Nose in automating food evaluation. Current studies have shown that portable and low-cost Electronic Nose systems combined with pattern recognition algorithms achieve over 90% accuracy in determining quality levels. For the analysis of sensor data, researchers suggest methods such as machine learning, Principal Component Analysis, Linear Analysis, and Artificial Neural Networks. The challenges, however, have been highlighted in the compilation in terms of the authenticity and reliability of sensor drift (Sanislav et al., 2025).

In their 2023 study, Cascos, Lozano, and others aimed to compare the electronic nose and gas chromatography for evaluating the quality of green coffee beans. The main objective of this study was to evaluate and distinguish various volatile organic compound characteristics to classify the quality of fresh products. It was found that high-quality coffee contains more alcohol and aromatic compounds, while low-quality samples contain common negatively associated compounds such as carboxylic acids, pyridines, and pyridines. The classification of electronic nose data was performed using Partial Least Squares Discriminant Analysis (PLS-DA), and coffee quality was successfully classified with 96.9% accuracy. Furthermore, the PLS chemometric approach using fruity aroma showed a

correlation of 0.88. From this situation and measurements, the Electronic Nose device is a sensitive, low-cost tool for distinguishing different coffee qualities during processing. The results support the use of the electronic nose as an accurate, low-cost method for distinguishing coffee qualities during processing (Cascos et al., 2023).

Wang, Zhang, and colleagues conducted a study in 2021 on the optimization of an Electronic Nose sensor array. The aim of the research was to determine the most suitable sensor array for detecting tea aromas. Wang and others used fundamental methods such as correlation coefficient and clustering analysis in the optimization of the sensor array. Wang et al. first calculated the correlation of each sensor's output for different tea samples using the Hamming and Euclidean distance methods. Subsequently, sensors with similar performance were grouped together, and unnecessary sensors were removed through sensor cluster analysis. As a result of this optimization, it was proven that five of the ten metal oxide sensors were sufficient. Wang et al. demonstrated that their proposed optimization could significantly reduce the complexity and cost of the Electronic Nose system while maintaining its net analytical accuracy (Wang et al., 2021).

In their 2024 study, Jara-Cornejo, Peña-Bedón, and colleagues aimed to develop an electrochemical sensor using smart materials in food samples. The researchers fabricated the sensor by depositing molecularly imprinted polymers (MIPs) and multi-walled carbon nanotubes (MWCNTs) onto a glassy carbon electrode using the drop-casting technique. The synthesized materials were characterized using Fourier transform infrared spectroscopy and electrochemical methods (cyclic voltammetry and differential pulse voltammetry). The developed electrochemical method demonstrated a limit of detection (LOD) for curcumin. This proves that the method is highly sensitive. Therefore, this study demonstrates that it provides an effective solution for rapid and accurate analysis in the food industry (Jara-Cornejo et al., 2024).

Çetin, Özer et al. classified different food aromas using chemical odor data collected from Electronic Nose devices using machine learning methods in their 2024 study. The researchers collected data sets for each odor class, including examples such as chocolate, clove, cinnamon, ginger, and odorless ambient aroma, using the Electronic Nose system. In the study, Decision Tree Classifier (DTC), Multi-Layer Perceptron (MLP), k-NN, and Linear Discriminant Analysis (LDA) machine learning models were tested. For the calculated classification results, it was observed that the Decision Tree Classifier (DTC) model provided over 90.00% accuracy in predictions and yielded the most successful results. It was noted that the second most successful model was the Multi-Layer Perceptron (MLP). These

results demonstrate that the Electronic Nose is an effective method for quickly, economically, and reliably distinguishing food quality and aroma (Çetin et al., 2024).

Incegul, Ozkan et al.'s 2022 study is a review of studies on the use of Electronic Nose Metal Oxide Semiconductor (MOS) sensors in food analysis. The authors noted the increasing demand for Electronic Nose systems, highlighted by the growing interest in fast and low-cost techniques. Although systems that mimic the human olfactory mechanism have different sensor technologies, Metal Oxide Semiconductor (MOS) gas sensors are used particularly in the medical, chemical, agricultural, and food industries due to their rapid response, low cost, durability, and portability. The review shows that studies using MOS sensors in food analysis focus on food quality, shelf life, microbial contamination, food spoilage, fraud, classification, and decomposition. It is stated that this technology can serve as an alternative to existing food analysis techniques and offer an opportunity to validate the results obtained (İncegül et al., 2022).

Astuti et al.'s 2024 study developed an effective method for classifying coffee roasting degrees by integrating the E-Nose device with an artificial neural network (ANN). The study was carried out using an Electronic Nose based on ten metal oxide semiconductor sensor arrays to analyze the coffee aroma formed at the end of different stages of roasting time, as well as some physical and chemical changes (weight loss, density, moisture content). It was concluded that artificial neural networks provide very high reliability in predicting roasting time and coffee quality parameters obtained from sensor data to predict the identity of coffee roasting degree using artificial neural network models (GRNN). It was stated that this system is an effective way to enable the automation of current production processes where coffee roasting degree evaluation is largely based on observation (Astuti et al., 2024).

In the 2008 study by Borah and Hines, it was observed that the ANN-based Electronic Nose system was effective for classifying tea aroma. In their studies on collecting aromatic data for tea types, the researchers used 14 sets of Electronic Nose consisting of Metal Oxide Semiconductor (MOS) sensors. The sensor data presented to distinguish tea types from each other was processed through artificial neural networks combined with an MLP structure. This system performed qualitative classification of teas and showed that it distinguished them with an accuracy of 97.5%. As a result, their study revealed that Electronic Nose technology integrated with artificial neural networks is a fast and reliable quality control classification tool in the tea industry (Borah et al., 2008).

In the study conducted by Romani, Cevoli et al. in 2012, Romani et al. investigated the integration of E-Nose with Artificial Neural Network (ANN) for Offline Quality Control in coffee roasting. The researchers used an Electronic Nose system with ten tin oxide (SMOX)

sensors to identify volatile components according to roasting degree. They observed the physical and chemical changes (weight loss, density and color (L value)) that occurred during the roasting process and correlated these data with Electronic Nose signals. The study was evaluated with two different artificial neural network models, Generalized Regression Neural Network (GRNN) and Multilayer Perceptron (MLP). The GRNN model showed the highest reliability with an accuracy classification of over 95 percent. These findings confirm that the integration of Electronic Nose and neural network offers the coffee industry a fast, inexpensive and automated approach to evaluating roasting quality (Romani et al., 2012).

In a study conducted in 2024 by Iswanto, Muflih et al., a Low-Cost Electronic Nose System was combined with a 1-D CNN to classify Robusta and Arabica coffee varieties. The researchers used an Electronic Nose designed with Metal Oxide Semiconductor (MOS) sensors to detect the aromas and volatile components of coffee beans. CNN was used to extract the complex patterns of sensor response data during the classification process, achieving a high accuracy of 99.30%. Compared to classical laboratory methods, the potential of the Electronic Nose system for fast, accurate, low-cost and even coffee variety classification applications was investigated (Iswanto et al., 2024).

According to research in the literature, the contributions of this study can be listed as follows:

1. The aim is to determine and implement the most suitable machine learning model to address the challenges in the literature, particularly in classifying volatile organic compounds emitted by liquids, using real-time sensor data such as the AI Nose Dataset 250.
2. As shown in the literature (Iswanto et al. 2024; Cascos et al. 2023), the aim is to create an E-Nose system using low-cost metal oxide semiconductor (MOS) sensor arrays, providing an alternative to expensive and time-consuming methods such as traditional GC-MS, and to finalize its ability to classify volatile organic compounds with high accuracy.
3. The aim is to increase the prediction and reliability of the classification model by processing time series data obtained from E-Nose sensors, especially in neural networks (ANN, RNN, 1-D, CNN), to extract complex and unique aroma fingerprints in the responses of the sensors (slip compensation, etc.). • It was considered that suggestions could be offered to determine the minimum number of sensors required for maximum classification accuracy by modeling previous sensor optimization studies in the literature, thus contributing to reducing the complex structure and production cost of the E-Nose system.

4. The aim was to demonstrate that the developed model can be used as a fast and reliable tool for important quality control applications such as food identification, gelatin type detection, roasting degree, or aroma classification, especially when trying to identify volatile organic compounds.

The rest of the study is planned as follows: The third section presents the materials and methods, the methods used, and performance metrics along with the datasets used in the study; the fourth section presents the experimental results obtained from the study; and the fifth section presents the contributions and application areas along with the results.

Methodology

The main objective of this study is to classify different aroma classes with high accuracy using machine learning (ML) algorithms with the AI Nose Dataset. In this section on e-Nose applications, the dataset on which the study is based, the ML methods used for classification, and the metrics used to evaluate the performance of the models are explained in detail. The results of this data are evaluated using complexity matrix and k-NN validation.

AI Nose Dataset

In this study, the AI Nose Dataset 250 dataset obtained from the Kaggle platform was used (Krishna, 2025). This dataset records sensor results obtained from a gas multi-sensor device exposed to many Volatile Organic Compounds (VOCs). The dataset consists of 5 different classes of volatile organic compounds (Perfume, Air, Coffee, Tea Vinegar) with 1940time steps and observations in each class. Each measurement records the response of 6 chemical and environmental sensors (Humidity, Temperature, NO2, Ethanol, VOC, CO) as a change in electrical resistance. The data connection is shown in Figure 1. As shown in the figure, the data type is multivariate time series data. The data includes time series measurements of the odors of different liquid types, chemical and electrical responses in the sensor array. The dataset consists of CVS files where measurements belonging to different liquid classes are recorded. Each sensor server represents the change in the sensor, creating an odor fingerprint of a liquid. This data forms the basis for developing machine learning models. The aim is to test the model's ability to accurately classify a new type of liquid based on sensor results (İncegül et al., 2022).

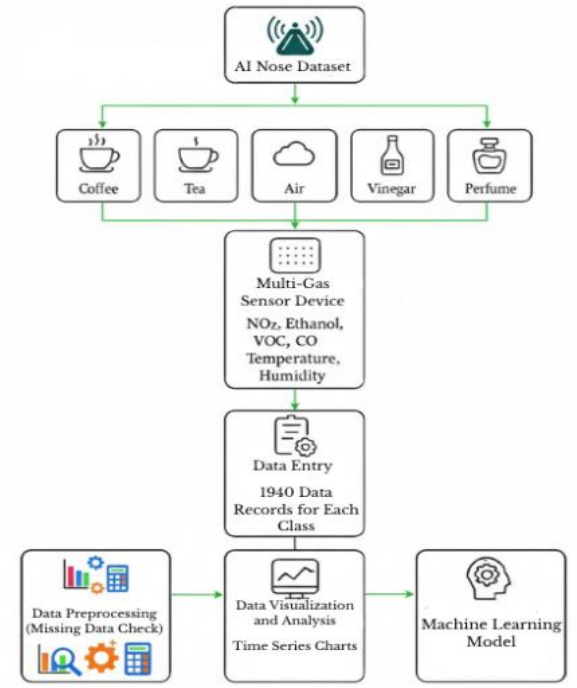

Figure 1 AI Nose Dataset

Machine Learning

In our study, traditional machine learning and deep learning approaches were used for the classification of data obtained in the E-Nose system. This integrated approach allowed us to analyze the data from a different perspective. Traditional Machine Learning methods were used as the basic comparison in the classification of data, especially from the E-Nose feature extraction stage. Algorithms such as those frequently encountered in E-Nose applications and showing high success were evaluated in this context (Çetin et al., 2024).

K-Nearest Neighbor (k-NN)

Although k-Nearest Neighbor (k-NN) is a simple, non-parametric algorithm that assigns a data point to the majority class of its nearest neighbors, it has demonstrated flawless classification success (F1 Score: 1.000) based on similar odor profiles in E-Nose data and is among the most successful models studied. (Ye et al., 2021) (Susanti et al., 2023).

Random Forest (RF)

It is one of the ensemble learning algorithms. It offers generalization by combining the results of multiple decision trees. It was included in our study because it generally offers one of the highest classification successes in E-Nose data, along with its high dimensionality and noise resistance (Sen and Taspinar, 2024; Lu et al., 2024).

Desicion Tree

It has a simpler interpretable structure because it creates simple rules and classifications by looking at the features in the dataset. It was included in our study because it helps in determining critical thresholds in this way (İncegül et al., 2022; Jiménez-López et al., 2023).

AdaBoost

The Decision Tree model creates simple rules and performs classification by looking at the features in the dataset, thus providing a structure whose results are easier to interpret. It was included in our study because of its transparent structure, which helps to determine the critical thresholds and decision points for odor classification in E-Nose data and shows a high classification success (F1 Score: 0.998) (Taspinar et al., 2023).

Navie Bayes

The Naive Bayes algorithm is a probabilistic method based on Bayes' theorem and the conditional independence of features. It was used in our study because of its computationally fast speed and its suitability as a reference model in multivariate systems such as E-Nose, and it showed a good initial success (F1 Score: 0.977) in the classification task (Wang et al., 2021; Ye et al., 2021).

Performance Metrics

To evaluate the classification performance of machine learning algorithms more objectively, commonly used standard metrics were utilized (Ye et al., 2021). With these metrics, the aim was to measure not only the accuracy of the model but also its prediction and inter-class discrimination capabilities (Adak, 2016).

Accuracy (CA)

Accuracy is the ratio obtained by dividing the number of samples correctly predicted by a classification model by the total number of samples tested. This metric was used as a key indicator in our study to evaluate model success, as it provides a quick idea of the model's overall classification performance and shows how frequently it makes correct predictions across all tested classes (Taspinar et al., 2022).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Precision (Prec)

Accuracy measures the degree to which the model accurately predicts a particular odor class, within the cases where it does so. This metric was used in our study because it indicates whether the model has a low tendency to incorrectly identify a class and allows us to assess the prediction reliability for each odor class (Dagli et al., 2022).

$$\text{Precision} = \frac{TP}{TP+FP}$$

Sensitivity (Recall-Rec)

Sensitivity indicates how many of the samples that are actually positive (belonging to the relevant class) are correctly assessed as positive by the model. This metric was included in our study because it allows us to assess the model's tendency to erroneously miss a class (false negative) and measures the success of detecting each odor class in the E-Nose data (Taspinar, 2025).

$$\text{Recall} = \frac{TP}{TP+FN}$$

F1 Score

The F1 score is the harmonic mean of the Accuracy and Sensitivity metrics. This metric was used as one of the key performance indicators in our study, particularly because it requires a balance between correct and incorrect classification metrics and provides a reliable and comprehensive result even in the case of possible class imbalances in the dataset (Koklu et al., 2022).

$$\text{F-1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision+Recall}}$$

Confusion Matrix

It is a fundamental tool that demonstrates the model's performance. By comparing the model's predictions with actual data, it shows the correct and incorrect prediction results in each class. It consists of four basic result types (TN, TP, FP, FN) that form the basis of all evaluation metrics. It was used in the study because it shows which classes the model confused with each other (Sen and Taspinar., 2025).

Estimated / Real	Coffe	Tea	Air	Vinegar	Perfume
Coffe	TP (Coffee)	FN	FN	FN	FN
Tea	FP	TP (Tea)	FN	FN	FN
Air	FP	FP	TP (Air)	FN	FN
Vinegar	FP	FP	FP	TP (Vinegar)	FN
Perfume	FP	FP	FP	FP	TP (Perfume)

Figure 2 Confucion Matrix

Matthews Correlation Coefficient (MCC)

Matthews Correlation Coefficient (MCC) is a comprehensive correlation coefficient that takes into account the four basic outcome types (True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)) of a classification model and has a value range of -1 to +1. This metric was used as an important indicator in determining model success in our study because it provides a reliable and consistent performance assessment, especially in datasets where class imbalance is possible. Therefore, MCC is important in model identification (Taspinar et al., 2022).

$$\mathrm{MCC} = \frac{(TP \cdot TN) - (FP \cdot FN)}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}}$$

Area Under the Curve (AUC)

The Area Under the ROC Curve (AUC) is used as a measure of a classifier's accuracy at all possible thresholds, regardless of the threshold value. The closer this value is to 1, the higher the model's ability to accurately distinguish a positive sample from a random negative sample. Because it evaluates this critical ability, it was used as an important metric in determining model performance in our study (Taspinar et al., 2021).

Cross Validation

To prevent overlearning of models and to test them reliably, the K-Fold Cross-Validation technique was used. In this study, a 5-Fold Cross-Validation approach was adopted, where the dataset was randomly divided into 5 equal parts. In this process, one of the folds in each cycle was used as the test set and the rest as the training set. The final performance of the model was obtained by averaging the 5 results (Taspinar, 2023).

Result and Discussion

In this study, k-NN, AdaBoost, RF, NB, and DT methods were used to perform multi-classification analysis on collected E-Nose sensor response data in order to reliably identify four different classes of chemical liquids using E-Nose sensor data. These experiments aimed to evaluate the potential of E-Nose systems in chemical analysis and quality control applications. An ASUS TUF Gaming Notebook FX506LU computer was used in the studies. This computer includes an Intel Core i5 processor (typically at a base speed of 2.5 GHz), 8GB of DDR4 RAM, and an NVIDIA GeForce GTX 1660 Ti graphics processor (GPU). This

hardware was chosen specifically to effectively manage the computationally intensive requirements of ensemble algorithms and cross-validation processes, such as Random Forest.

All coding and analysis were performed using the open-source Python 3.10 programming language and popular scientific libraries (NumPy, Pandas, Scikit-learn, TensorFlow/Keras). This approach ensures easy reproducibility by independent researchers. For all applied machine learning methods, multiple parameters were set to achieve optimal performance and minimize overfitting.

Model training and testing were performed using the Cross-Validation method. In this method, the k value was set to 10. All process steps applied in the study are shown in Figure 3. For the RF method, the forest depth was set to 25 and the number of trees within it to 150. These parameters were optimized to reduce the risk of over-learning and increase the stability of the model. For the AB method, Decision Tree was used as the basic estimator, and the number of estimators (n_estimators) was set to 100. The learning rate was fixed at 1.0. This ensemble method aimed to better learn samples close to the classification boundary. For the k-NN method, the parameters number of neighbors 5, metric euelidean, and weight uniform were used. These settings showed robust classification performance based on the proximity between local data points. For the NB method, the Gaussian Naive Bayes classifier was used, appropriate to the distribution of the dataset. For the DT method, the maximum depth of the tree was limited to 10, which kept the complexity of the model under control and prevented over-learning. The Gini coefficient was used as the partition criterion.

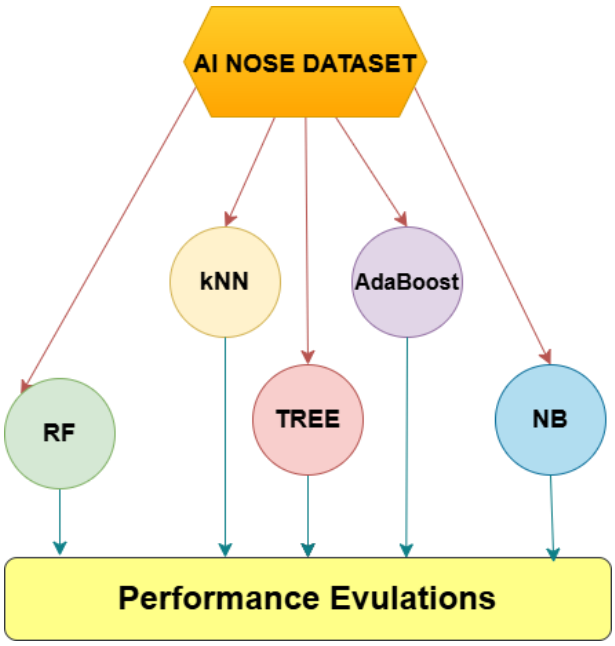

Figure 3 Experimental Resaults

In our dataset, 6 features obtained from each data point were given as an introduction to machine learning methods with 1940 different outputs, and training was performed. The complexity matrices obtained by the machine learning method are given in order. The complexity matrix obtained by the K-NN method is shown in Figure 4.

	Air	Coffe	Perfüme	Tea	Vinegar
Air	**368**	**0**	**0**	**0**	**0**
Coffe	**0**	**111**	**0**	**0**	**0**
Perfüme	0	0	492	0	0
Tea	0	0	0	470	0
Vinegar	0	0	0	0	498

Figure 4 k-NN in the complexity matrix

According to the complexity matrix presented in Figure 4, the k-NN model's performance is flawless because all predictions are concentrated on the main diagonal, and all values outside the diagonal are zero (0.0). The model correctly classified 368 data points belonging to the air class, 111 data points belonging to the coffee class, 492 data points belonging to the perfume class, 470 data points belonging to the tea class, and 498 data points belonging to the vinegar class as their true classes. This means that there were no misclassifications in any of the 1939 test samples in total; for example, all 368 data points belonging to the air class were correctly predicted, and there were no data points misclassified as coffee, perfume, tea, or vinegar. The same excellent situation applies to all other classes, indicating that the model performs with 100% accuracy on this test set.

	Air	Coffe	Perfüme	Tea	Vinegar
Air	93	68	68	68	68
Coffe	20	28	20	20	20
Perfüme	91	91	125	91	91
Tea	87	87	87	119	87
Vinegar	92	91	92	92	126

Figure 5 AdaBoost in the complexity Matrix

The Complexity Matrix presented in Figure 5 correctly classified only 93.7% of the 368 data points belonging to the air class, while incorrectly assigning the remaining 274.3 data points equally to the other four scents (coffee, perfume, tea, vinegar). Similarly, the coffee class performed the weakest; only 28.3% of the 111 data points were correctly predicted, and 82.7% were misclassified. The number of correct classifications was also significantly lower in the perfume (125.3% correct out of 492 samples), tea (119.7% correct out of 470 samples), and vinegar (126.8% correct out of 498 samples) classes compared to the total number of correct classifications in the actual class. The density of red areas, particularly outside the diagonal, indicates that the model has serious problems distinguishing one scent from another and generally exhibits performance close to random guessing, with mispredictions spread across almost all other classes.

	Air	Coffe	Perfüme	Tea	Vinegar
Air	367	0	0	0	0
Coffe	0	109	0	1	0
'erfüme	0	0	488	1	1
Tea	0	0	1	466	0
/inegar	0	0	1	0	495

Figure 6 shows the RF complexity matrix.

The Complexity Matrix in Figure 6 demonstrates that the model operates with high accuracy. Of the 368 data points in the air category, 367.3 were correctly predicted, while the remaining 0.3 were misclassified as tea and 0.4 as vinegar. Of the 111 data points in the coffee category, 109.7 were correctly predicted, with 0.1 misclassified as perfume and 1.2 as tea. Of the 492 data points in the perfume category, 489.9 were correctly predicted, while 0.2 were misclassified as coffee, 0.8 as tea, and 1.1 as vinegar. Of the 470 data points in the tea category, 465.2 were correctly classified, with 0.6 air, 1.0 coffee, 2.7 perfume, and 0.5 vinegar. Finally, of the 498 data points in the vinegar category, 496.6 were correctly predicted, with

0.3 air, 0.5 perfume, and 0.6 tea misclassified. Correct classification rates are high across all classes, and the number of misclassified samples is quite low.

	Air	Coffe	Perfüme	Tea	Vinegar
Air	367	0	0	1	0
Coffe	0	110	0	1	0
Perfüme	0	0	492	0	0
Tea	0	0	1	469	1
Vinegar	0	1	0	0	497

Figure 7 shows the Tree complexity matrix.

The Complexity Matrix (Tree method) in Figure 7 demonstrates the model's high success rate in the odor classification task. Of the 368 data points in the air category, 367.0 were correctly predicted, with the remaining 1.0 being misclassified as tea. Of the 111 data points in the coffee category, 110.0 were correctly predicted, with the remaining 1.0 being misclassified as tea. All 492 data points in the perfume category, i.e., 492.0, were correctly predicted, demonstrating flawless performance in this category. Of the 470 data points in the tea category, 469.0 were correctly classified, with the remaining 1.0 being misclassified as vinegar. Finally, of the 498 data points in the vinegar category, 497.0 were correctly predicted, with only 1.0 being misclassified as perfume. Overall, the vast majority of the 1939 samples were correctly classified, with a total misclassification rate of only 4.0.

	Air	Coffe	Perfüme	Tea	Vinegar
Air	353	0	0	8	5
Coffe	0	102	0	8	0
Perfüme	0	0	488	0	2
Tea	0	20	11	437	0
Vinegar	14	0	0	1	481

Figure 8 shows the NB complexity matrix.

The Complexity Matrix in Figure 8 shows that the model is generally successful in odor classification but experiences significant confusion in some classes. Of the 368 data points

in the air class, 353.7 were correctly predicted, while the remaining 8.7 were misclassified as tea and 5.7 as vinegar. Of the 111 data points in the coffee class, 102.6 were correctly predicted, while the remaining 8.4 were misassigned as tea. Of the 492 data points in the perfume class, 488.3 were correctly predicted, while 0.2 were misclassified as air, 1.3 as tea, and 2.2 as vinegar. Of the 470 data points in the tea class, 437.8 were correctly classified, but significant confusion was observed in this class, with 0.4 being misclassified as air, 20.6 as coffee, and 11.1 as perfume. Finally, out of 498 data points belonging to the vinegar category, 481.6 were correctly predicted, but 14.4 were misclassified as air, 0.1 as coffee, and 1.3 as tea. The biggest challenge for the model was distinguishing between tea and coffee/perfume scents, and between vinegar and air odor. Performance metrics for each method were calculated using the data on complexity matrices obtained from the methods. These metrics are shown in Table 1.

Table 1: Model of Performance Matrices

MODEL	F1	Prec	Recall	MCC
Tree	0.998	0.998	0.998	0.997
Random Forest	1.000	1.000	1.000	1.000
k-NN	1.000	1.000	1.000	1.000
AdaBoost	1.000	1.000	1.000	1.000
Naive Bayes	0.977	0.977	0.977	0.977

According to Table 1, the most successful models are Random Forest, k-NN, and AdaBoost, all with a score of 1.000. The model with the lowest classification success is Naive Bayes with a score of 0.977. The Tree model has a classification success of 0.998. When other performance metrics are examined, it is seen that the F1 Score, Precision, and Recall metric values show a complete parallel with the classification success of the models. When the classification successes and F1 Score, Precision, and Recall metrics are examined, it can be said that all models show a success rate of 97.7% and above.

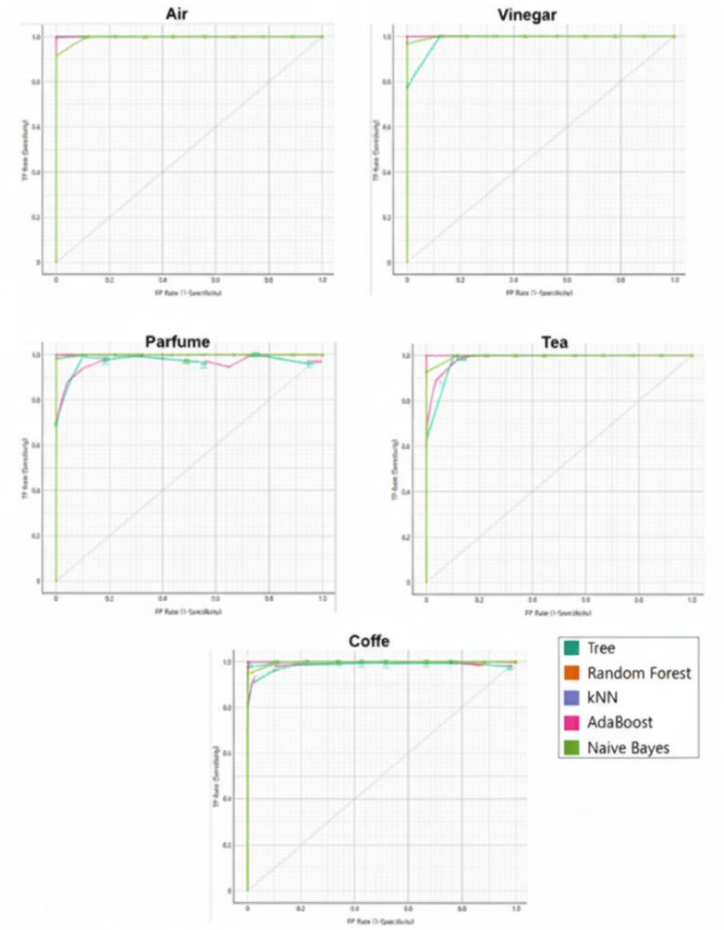

Figure 9 ROC CURVE

Examining Figure 9 (ROC Curves) and the related performance metrics table reveals a strong correlation between classification success and the learning levels of the models. Random Forest, k-NN, and AdaBoost are the best-learning models with an F1 score of 1.000. Naive Bayes is the least-learning model with an F1 score of 0.977. In conclusion, the classification success of the models is revealed by their learning rates; the flawless ROC curves confirm that the models with the highest metrics generalize the data without error.

Discussion

This study analyzes the performance of different Machine Learning (ML) algorithms in classifying time series data. The accuracy rates obtained for separating five different liquid classes (Perfume, Air, Coffee, Tea, and Vinegar) show that the sensor data contains distinct odor profiles among the classes. The applied 5-Fold Cross-Validation procedure revealed that the models produced generalizable results, not just data-specific ones. In particular, the good performance of the RF, kNN, and AdaBoost algorithms in Accuracy, F1 Score, and MCC metrics indicates that these algorithms are suitable for E-Nose-based classification

problems. Although the Decision Tree (DT) model exhibited lower performance, its high accuracy of 99.4% shows that the dataset has distinctive features and that successful results can be produced with the classification algorithms. These findings support the idea that E-Nose data is a reliable input source for machine learning-based approaches and can be effectively used in aroma classification problems. In this way, the study results reveal that the integration of E-Nose and ML offers significant practical advantages in applications such as quality control and aroma detection prevention in production and consumption processes.

Conclusion

This study presented a comprehensive evaluation of classical machine learning algorithms for network intrusion detection using the NSL-KDD benchmark dataset. The primary objective was to develop a reliable and efficient classification framework capable of accurately distinguishing normal network traffic from multiple attack categories, namely DoS, Probe, R2L, and U2R. Extensive experimental analyses demonstrated that ensemble-based approaches, particularly Random Forest and AdaBoost, significantly outperformed other models in terms of Accuracy, F1-score, Recall, Precision, MCC, and AUC. The Random Forest model achieved the highest overall performance with 99.5% classification accuracy, 0.996 F1-score, and 0.993 MCC, confirming its robustness and superior generalization capability in complex network environments. The findings highlight that the rich set of 41 network features contained in the NSL-KDD dataset provides strong discriminative power for identifying diverse intrusion patterns. Furthermore, the results clearly indicate that traditional linear classifiers such as Logistic Regression are less effective when dealing with non-linear and highly complex cyber-attack behaviors. In contrast, ensemble learning techniques demonstrate remarkable resilience against noise, class imbalance, and overfitting, making them particularly suitable for real-world intrusion detection systems. Despite the strong performance achieved, several limitations of the present study must be acknowledged. First, NSL-KDD, although widely used as a benchmark, does not fully reflect the evolving nature of modern cyber-attacks and real network traffic conditions. Second, the experiments were conducted in an offline environment, which does not capture latency constraints and dynamic traffic behavior encountered in operational networks. Additionally, while high detection accuracy was achieved, the computational cost of ensemble models may pose challenges for deployment in resource-constrained systems. Future research directions should focus on validating the proposed framework on more recent and large-scale datasets such as UNSW-NB15 and CICIDS2017, as well as on live network traffic. The integration of hybrid architectures combining classical machine learning with deep learning models is expected to further enhance detection capabilities,

especially for previously unseen attack patterns. Moreover, the incorporation of online learning mechanisms and adaptive feature selection strategies would allow the system to continuously evolve alongside emerging cyber threats. In conclusion, this study confirms that machine learning-based intrusion detection systems, particularly those built upon ensemble learning, offer a highly effective, scalable, and reliable solution for safeguarding modern network infrastructures. The proposed approach provides a solid foundation for next-generation intelligent cybersecurity systems capable of delivering autonomous, real-time, and high-precision threat detection.

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