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RESEARCH ARTICLE

A LOW-COST ELECTRONIC NOSE DEVICE

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ABSTRACT

The ability of electronic nose to detect and identify volatile organic compounds makes them a promising technology for a variety of purposes. The study presents an inexpensive electronic nose system that can detect and classify Carbon-Monoxide, and Ethylene gases based on their levels of concentration. The system uses advanced algorithms to analyze and interpret the data generated by the E-nose sensors. By applying pattern recognition techniques, the electronic nose provides a more sensitive and accurate detection system. The study provides an overview of electronic nose technology and reviews various models, including gradient-boosting trees, light gradient-boosting machines, and support vector machines. The research also describes the feature extraction process, which involves principal component analysis, elastic-net, and fast Fourier transforms. The extracted features are then used to train linear regression, K-nearest neighbors, light gradient boost, and gradient boost regressor models. Overall, this research demonstrates the feasibility of developing a low-cost electronic nose system that has several applications in the real world.

INTRODUCTION

Electronic nose (E-nose) technology has received considerable interest in recent years due to its numerous uses in a variety of industries, including food processing, environmental monitoring, and medical diagnosis (Julian, 1994). The development of low-cost electronic nose devices can increase the accessibility of this technology and open up new potential applications. One of the shortcomings of the E-nose is its high cross-sensitivity. A significant advancement in E-nose technology is the use of machine learning algorithms to address the high cross-sensitivity of the metal oxide gas sensors ((Jean Bartlett, 2000; Magdalena, 2017). These algorithms can analyze large amounts of data generated by the E-nose sensors and provide accurate and reliable results (Cosimo Distante, 2002). An ideal platform for testing and prototyping the E-nose is the Arduino Nano because of its small size, lightweight, and ease to use (Arduino Nano Documentation, 2021). Instead of transferring the data to a distant server for inference, on-board inferencing is a technology used in electronic nasal devices to execute inferences on the device itself. This method can speed up reaction times while reducing the quantity of data that has to be transferred. Other important components of the electronic nose technology include preprocessing, feature extraction, and the use of machine learning algorithms (Zhenyi Ye, 2021).

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Preprocessing involves cleaning and filtering the data generated by the E-nose sensors to remove noise. Feature extraction involves identifying the most relevant features in the data and using them to train machine learning models. This paper's goal is to discuss the implementation and use of a low-cost electronic nose system that can identify and categorize ethylene and carbon-monoxide gases according to their concentration levels (Miguel Macías, 2013). Previous studies have explored various applications of electronic nose technology, demonstrating its potential in diverse fields. In the field of medicine, electronic nose has been used for the diagnosis and monitoring of respiratory diseases such as asthma and chronic rhinosinusitis (Silvano Dragonieri, 2018). E-nose has also shown promise in the detection of urinary tract infections (Carlos E. Sanchez, 2019) and the identification of specific diseases like tuberculosis (Silvano Dragonieri, 2007). (Yan Jia, 2015) emphasized the significance of feature extraction techniques, in their review, for enhancing the performance of electronic nose systems and how it plays a crucial role in obtaining relevant information from sensor responses with reduced redundancy, thereby improving subsequent pattern recognition algorithms. The emphasis on feature extraction aligns with the goal of this research which also takes into account the computational requirements (Xi Wang, 2023) focus on the application of electronic nose based on low-dimensional metal oxides in areas like illness diagnosis, environmental evaluation, coal mine risk assessment, and food quality.

The research highlights difficulties that electronic nose systems have, including inadequate capacity to recognize mixed gas signals and sensor drift brought on by environmental conditions. Advanced algorithms, such as conventional algorithms for gas recognition and neural network-based algorithms, are investigated as potential remedies. Support vector machines, a traditional technique, have been frequently applied in the past, while recent developments in neural networks, like convolutional and recurrent neural networks, are highlighted as promising for gas recognition. This study uses gradient-boosting algorithms to address this challenge (Miguel Macías, 2013) majored in the creation of a lightweight, affordable electronic nose based on a mbed microcontroller. Pumps, electro-valves, an mbed, an LCD, and four TGS Figaro gas sensors are all included in the gadget. By evaluating the ethanol content in synthetic wine matrices, the performance of the system is assessed. The electronic nose in combination with a classifier using neural networks, successfully discriminates wine samples with varying alcohol content, demonstrating high accuracy for aroma detection. The use of neural networks can be expensive computationally for an onboard inference on the Arduino Nano, a lightweight algorithm was considered in this study.

Overall, previous studies on feature extraction techniques for metal oxide e-nose have explored various methods. These methods seek to extract useful characteristics from sensor response data to enhance e-nose's classification and discriminating abilities. Further research in this area is needed to explore novel feature extraction methods and optimize the combination of feature extraction techniques with machine learning algorithms for more advanced e-nose applications. The rest of this paper is structured as follows: The content and procedures are described in Section 2. The outcomes of the suggested fixes are shown in Section 3, and the study's conclusion and some recommendations for further research are provided in Section 4.

MATERIALS AND METHODS

Arduino Nano: A tiny and adaptable microcontroller board called the Arduino Nano was created for applications that need to be low power and have a small form factor. It is based on the ATmega328P microprocessor and has features comparable to those of the well-known Arduino Uno board in a more compact design. The Nano board is part of the Arduino ecosystem, which provides an easy-to-use platform for creating interactive electronic projects. It includes an ATmega328P microcontroller, which operates at 16MHz and consists of 2 KB of RAM and 32 KB of flash memory for storing programs. Despite its compact size, the Nano board offers a sufficient number of I/O pins, including digital I/O pins (both PWM-capable and non-PWM), eight analog input pins, and UART (serial communication) pins, allowing it to be connected to various sensors, actuators, and other electronic components.

The Dataset: The data used for the implementation of this project was obtained from a public repository. 16 chemical sensors that were exposed to gas mixed at various concentration levels were used to get the data. The dataset was sampled 100 times per second. A 60 ml measuring vessel with a constant flow rate of 300 ml/min contained the sensor array. The information was gathered at a gas delivery platform facility at the University of California, San Diego's Chemo Signals Laboratory in the Bio Circuits Institute. The data contained 19 columns and 4208261 rows. The first column denotes the timestamp. The second and the third columns contain concentration values for Carbon-Monoxide and Ethylene respectively. The 4th column to the 19th column contain the sensor readings in response to the gases. The gas sensor readings were obtained in the following arrangement: TGS2602, TGS2602, TGS2600, TGS2600, TGS2610, TGS2610, TGS2620, TGS2620, TGS2602, TGS2602, TGS2602, TGS2600, TGS2600, TGS2610, TGS2610, TGS2620, TGS2620.

Feature Extraction: Feature extraction is the process of transforming the raw sensor data from an electronic nose into a lower-dimensional representation that can be used to classify scents and recognize patterns. Principal Component Analysis (PCA) is a commonly used method for reducing the number of dimensions in data while retaining the most crucial information. It has been used to classify odors successfully in e-nose systems (Cosimo Distante, 2002). With the help of this, the characteristics of the dataset were reduced from 16 to 8 components, or half its original size. Fast Fourier Transform (FFT): FFT is a widely used technique for analyzing the frequency content of a signal. It has been used in e-nose systems to extract frequency-based features from the sensor response (Yan Jia, 2015). The dataset was sampled at a frequency of 100Hz, making it a frequency domain dataset. FFT was used to convert from time domain to frequency domain, and then used to extract significant frequency components.

Another popular approach for feature extraction is the use of the elastic-net regularization method. The elastic-net combines the advantages of both the lasso and ridge regression, allowing for simultaneous feature selection and regularization. Lasso and Ridge's regression is also referred to as L1 and L2 regularization respectively. L1 regularization encourages sparsity and feature selection by driving coefficients to zero, while L2 regularization encourages small coefficient values without enforcing sparsity. Several studies have shown the elastic-net's usefulness for feature extraction. For instance, (13) offered a clear framework based on a reliable elastic-net feature learning technique and its iterative resolution. This approach extracted a set of coefficients from each feature which minimizes the combination of L1 and L2 regularization terms while fitting the data. The coefficients were used to determine which features have a high impact.

Model Training: The model-building process is a crucial step that requires careful consideration. The goal is to build and train a model that can accurately detect and classify different odors using a limited set of sensors. To achieve this, the dataset was split into train and test samples in ratio 80 to 20 respectively. The training sample of the dataset was trained on Linear regression, KNearestNeighbors, Light Gradient Boost, and Gradient Boost Trees.

Model Evaluation: Evaluation of a machine learning model is the process of assessing its performance and accuracy. Determining a model's applicability for a particular situation and its capacity to generalize to new data requires evaluation.

An over-fit model to training data may perform poorly on new data and unseen data. On the other hand, a model that is under-fit may have poor performance on both the training and validation data. The trained models were evaluated using the test samples in an attempt to predict the target features. The results were evaluated using the following metrics which include: Mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R squared).

Model Deployment: This step involves integrating the trained model into a microcontroller, specifically the Arduino Nano microcontroller for this research. By integrating the model into a microcontroller, it becomes possible to use the model for real-time applications, such as in an electronic nose or other Internet of Things (IoT) devices. The Arduino Nano microcontroller is an ideal platform for model deployment due to its low power consumption, high processing speed, and compatibility with various sensors and peripherals. The process of integrating the model into the microcontroller involved exporting the trained model using the micromlgen library in the Python programming language, and programming the Arduino Nano using the Arduino Integrated Development Environment.

RESULTS AND DISCUSSION

Figure 1 and Figure 2 present eight extracted features by PCA from the 16 sensor readings. Figure 3 presents the selected features using Elastic-Net while Figure 4 presents the extracted features using Fast Fourier Transforms. Table 1 presents a comparison of the model

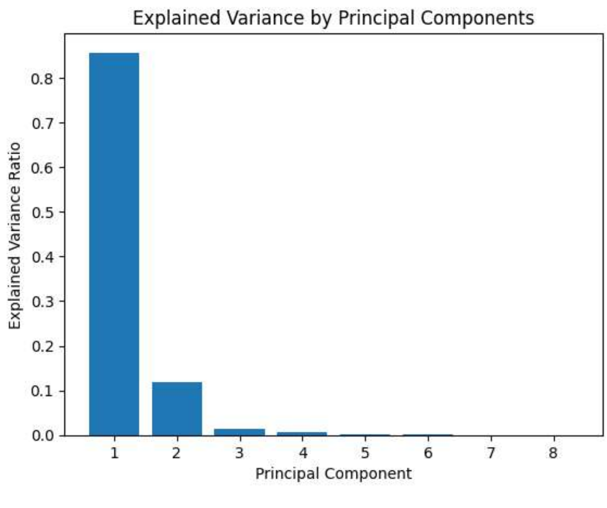

Fig. 1. A plot of the extracted features from the dataset

The analysis of feature extraction techniques revealed distinct strengths in transforming raw sensor data into informative features. Principal Component Analysis (PCA) effectively reduced data dimensionality, capturing the most significant variance, while the sensors selected using Elastic-Net resulted in better performance. The Fast Fourier Transforms extraction method presented promising results. These findings offer researchers the flexibility to choose appropriate feature extraction methods based on specific e-nose applications and classification requirements. The evaluation of various machine learning models showcased the strengths and trade-offs of each algorithm.

K-Nearest Neighbors (KNN) demonstrated strength in detecting the underlying pattern but was computationally heavy compared to the other algorithms. Linear Regression demonstrated its simplicity in handling large datasets which guarantees that it will not over-fit on the data. The Light Gradient Boost algorithm proved to be a better algorithm for handling a very large dataset and still providing good results. However, Linear Regression was deployed to the Arduino Nano due to its lightweight.

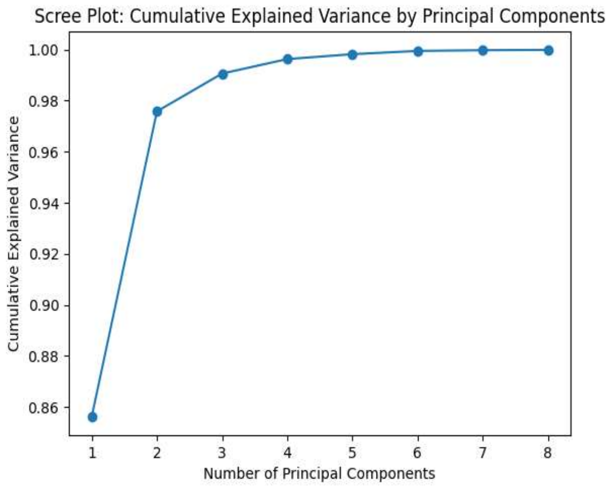

Fig. 2. A plot of Cumulative Variance of the Extracted Features

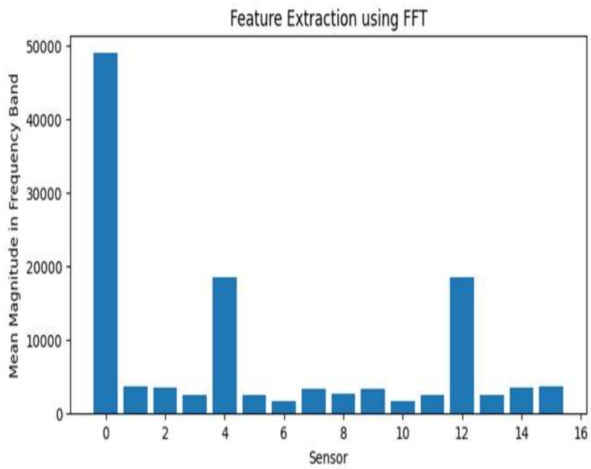

Fig. 3.A plot of feature extraction with FFT

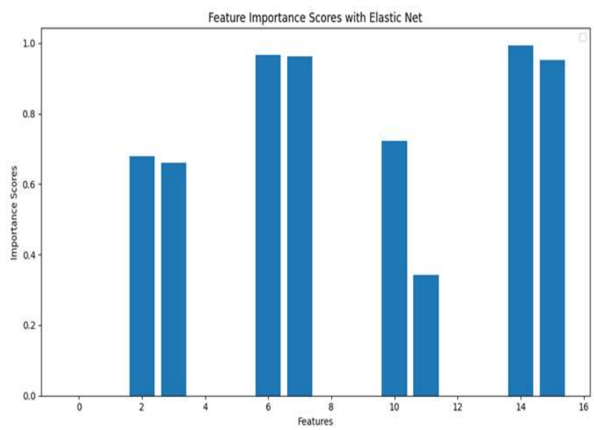

Fig. 4. A plot of feature selection with Elastic-Net

Table 1. Model performance in conjunction with the feature extraction methods

s/n	Models	RMSE(ppm)	MAE(ppm)	MSE(ppm)	R Squared
1	Elastic-Net with Linear Regression	48.36	30.34	4357.01	0.64
2	FFT with Linear Regression	49.69	30.38	4598.51	0.62
3	PCA with KNN	12.65	1.73	299.90	0.97
4	PCA with Light Gradient Boost	29.38	15.00	1605.84	0.86
5	PCA with Linear Regression	48.94	30.40	4466.28	0.64
6	PCA with Gradient Boost	40.58	22.39	3068.60	0.75

Table 2. Cost Implication of the Hardware System

Component	Cost ($)
TGS2600 (2 units)	29.98 (14.99 per unit)
TGS2610 (2 units)	20.00 (10.00 per unit)
TGS2620 (2 units)	21.9 (at 10.95 per unit)
TGS822 (2 units)	15.98 (at 7.99 per unit)
Arduino Nano board	7.98
1k Ohms Resistor (8 units)	0.616 (at 0.077 per unit)
Printed Circuit Board	6.59
Total	103.046

CONCLUSION

This study postulated a system that costs only around 100 USD as depicted in table 2. According to the E-Nose Market Size, Shares, Growth, Opportunities, and Forecast (2023) report, commercial electronic nose products are available at a range of prices, from 11,000 USD to 150,000 USD while the cost of the proposed electronic nose product ranges about 8,000USD to 82,000 USD. In comparison, the implemented system is a cost-effective solution that is more affordable and efficient. This paper delved into the exploration of Metal Oxide Electronic Nose (e-nose) technology with a focus on feature extraction and machine learning prediction. Through rigorous experimentation and analysis, significant findings were obtained, contributing to the advancement of e-nose technology and its potential real-world applications. Based on the study's findings and limitations, hybrid feature extraction techniques can be explored to enhance feature representations and improve e-nose discriminative capacity. Collaboration with industry partners to deploy the developed e-nose system in real-world applications like food quality assessment, environmental monitoring, and medical diagnostics is essential for validating the technology's effectiveness.

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