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A Technique Based on Ensemble Machine Learning for The Analysis of Electronic Nose Signals

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Abstract*—Numerous applications have been documented for electronic nose (e-nose) devices, which are valued for their speed, affordability, and lack of invasiveness. The e-nose scheme is a useful instrument for analyzing volatile chemicals as a distinct 'fingerprint,' especially in the meat industry. The pattern identification algorithm's capacity to decode e-nose signals is crucial to the e-nose system's effectiveness in a wide variety of uses. However, positive results using ensemble approaches have been reported in a number of data types. In this study, an ensemble learning strategy is proposed for e-nose signal analysis, particularly for evaluating beef quality. Not only are learning algorithms and sensor array optimization using ensemble approaches. Ensemble FSA is created by combining three filter-based feature selection algorithms (FSAs)—reliefF, chi-square, and Gini index—for sensor array optimization. When using a single FSA on a collection of homogenous e-nose data for beef quality monitoring, it is common for the results to be inconsistent or unexpected. In addition, multi-class regression and categorization problems are handled by using ensemble learning techniques. We use bagging and boosting algorithms, shown here by Random Forest (RF) and Adaboost. Both a support vector machine (SVM) and a decision tree are used as independent learners, and their results are compared to those of the ensemble. Experiments show that our ensemble method is effective and generalizable for e-nose signal processing. Optimized sensor combination using filter-based FSA consistently outperforms previous methods in both classification and regression. Additionally, despite using a reduced sensor complement, Adaboost as a boosting algorithm yields the highest quality prediction.

IndexTerms—E-nose, Machine Learning, Random Forest, Statistical Analysis

I. INTRODUCTION

In past few decades, e-nose devices have found widespread use in the food manufacturing, agricultural, medical, and other sectors. Due to its low cost per analysis, speed, ease of assessment, non-invasiveness, and ability to be performed in real time, it shows great potential for use in a wide range of sectors [1]. The use of electronic noses in analytical tools has been documented for a wide range of applications, such as, but not limited to, steak quality assessment and monitoring, meat cut recognition, bacterial population forecasting, identifying pork counterfeiting in beef, non-invasively diagnosing diabetes, etc. Moreover, painless alternatives to the frequent pricking that patients must endure are essential [2].

For these reasons, e-nose might be evolved into a non-invasive technology useful in a variety of settings. Like a human's olfactory system, the e-nose can detect odours in open air or within a hermetically sealed container. The heart of every electronic nose is an array of gas sensors, and the brain is some kind of pattern recognition algorithm. The gas sensing device consists of many individual gas sensors, each having its own unique selectivity. Separate gas sensors operate in combination to transform the chemical information of various gas mixtures into a measurable signal.Several gas sensors, each having its own unique selectivity and sensitivity, work together to provide a complex multivariate response. As an added bonus, a pattern matching unit uses this data to do classification and regression analyses on the signals.Depending on the task at hand, one sample may provide a profile of volatiles that is distinct from that of another. Because of this, the sensor array will likely end up with a varied distribution of gas detectors. Various gas sensor configurations are required for different tasks; for instance, a gas sensor array designed to differentiate between tea samples will be varied from one designed to do the same for coffee. Each sample, thus, calls for a unique set of gas detectors to detect its unique biomarker. The use of a large number of gas detectors to cover all gas sensitivities is not a practical option for developing a reliable and cost-effective electronic nose [3]. The resulting overlap in selectivity, high electrical power needs, heavy network traffic, computational overhead, etc. are only a few of the issues this presents. Using less sensor gas, on the other hand, may reduce manufacturing costs, power consumption, and the overall size of the device.

Therefore, an optimization process for sensor arrays is required before an electronic nose system can be created. Several papers have discussed this issue and provided various approaches for optimizing sensor arrays. There are several sensor array optimization issues, and FSAs are a frequent approach for dealing with them [4]. Developing a classifier also requires a good learning algorithm. Prediction errors are more likely to occur in a machine learning model that is not robust. Success using ensemble approaches has been documented across a variety of data sets in recent years. The term "ensemble method" is used to describe the process of using numerous models or algorithms together. In most cases, it outperforms with only one model. This research is driven by a number of factors, including the ones listed below [5]. Here, we leverage the most reliable FSAs from our prior research to construct an ensemble FSA consisting of measures including reliefF, chi-squared, and the Gini index [6].

To boost the efficiency of ML models, ensemble learning techniques are used on data sets including e-nose signals from beef quality monitoring systems. Bagging and boosting are two of these techniques, and they are used to construct a robust model for classification and regression tasks such as distinguishing beef grade and predicting the microbial population in beef samples [7]. To the best of our knowledge, using ensemble learning in e-nose signal analysis is a novel and uncommon practice.

Rather of relying on just one algorithm, the ensemble approach pools the data produced by many approaches to get more comprehensive and accurate findings. There have been reports in recent years [8-9] of ensemble approaches being used to handle a wide range of problems. Although the ensemble approach is most often employed for classification tasks, it may also be successfully used to feature selection issues [10-11]. We present many different signals processing techniques, including a noise filtering procedure, an FSA ensemble, an ensemble model for categorization and regression, and an assessment.

The rest of the paper is organized as follows: The second part discusses relevant research. Materials and techniques, including the experimental design, data collection, and our suggested methodology, are discussed in Section 3. Section 4 presents the findings and discusses them. Finally, this investigation is summarized in Section 5.

II. Literature Survey

Among the many applications of an electronic nose are optimizing sensor arrays and developing algorithms for classification. Multiple approaches have been proposed to optimize sensor arrays. Wrapper FSAs are constructed using heuristic techniques, and big, heterogeneous data sets are optimized for several objectives. Using a GA, we can optimize sensor combination for a wide variety of disparate datasets. As an added measure, a sensor array's individual sensor weight (a continuous value between 0 and 1) is evaluated using a combination of particle swarm optimization (PSO) and GA to detect wound infection. On the other hand, the number of sensors has remained constant [12].

The other studies investigate the use of sensor tuning in the determination of tea quality. A reduction from 30 sensors in the array to 13 or even 8 might increase classification accuracy by more than 3%. Filter-based FSAs were employed in this case to achieve optimal sensor array performance. [13].

Furthermore, the use of a rough set to optimize sensor arrays for black tea categorization is explored. Due to the accuracy of this method, data from as many as four gas sensors may be downscaled simultaneously. The size of the sensor array may be decreased by using a filter-based analysis of feature selection techniques. Using a quick correlation filter, the optimal configuration of gas sensors for beef grade classification was established. The process may be used to disable up to four gas sensors at once. This method combines neural networks with random forest to choose gas sensors. When reducing the size of a gas sensor array, cluster analysis is also performed. Gas sensors for indoor air contaminants were chosen using logistic regression analysis and kernels principal component analysis. Using this method, we might potentially reduce the size of one of the four gas sensors. However, it has been proven that non-searching FSA improves performance on regression tasks. A response surface has also been used to optimize the application of a sensor array for the determination of strawberry freshness. The vast majority of studies have shown that decreasing the number of gas sensors in a system increases its performance. In contrast, principal component analysis (PCA) has seen extensive use in e-nose technologies and meat rotting detection. A favorable outcome was reported [14-22]. Alternatively, principal component analysis may be used to reduce massive data sets to more manageable proportions. As a result, there has been no change in the overall number of sensors.

As a consequence, ensemble methods are now being used in contexts where they weren't initially conceived. Combining bagging ensemble learning with long short-term memory (LSTM) neural networks improves prediction accuracy. Ensemble classifiers have been used by medical practitioners for fibrillation diagnosis from ECG data because to their classification results of 99.37% in recognizing 16 types of fibrillation. Estimation of type 1 diabetes are also made using a variety of ensemble methods. The Ensemble method was also used to provide forecasts about the air quality. Its advantage over a single model has been experimentally confirmed. Using a well selected feature subset in selecting features with a various classifier has been found to greatly improve the classification accuracy score when used to audio recognition. The concept of an ensemble was also used to the feature-selection procedure, not only the learning procedure. Ensemble FSA was developed in large part as a solution to the instability issue. Several research have shown the usefulness of Ensemble FSA for high-dimensional data. Evidence suggests that an ensemble of FSAs is preferable than a single FSA. Even now, researchers see machine learning as a promising field for further exploration [15]. Only a few few studies within the e-nose field have even broached the topic of ensemble ideas. For instance, the Adaboost model has been used to accurately recognize Chinese herbal remedies. Data from experiments shows that it is superior to stand-alone classifiers. The soft-voting procedure was also used to estimate several other types of odours and their concentrations. Multimodal logarithmic extrapolation, multilayer perceptron, and SVM are all components of the approximation model (SVM). The boosting method was also able to distinguish between the two coffee varieties when trained on an e-nose dataset. Ensemble learning was shown to be applicable for both classification and regression problems in beef evaluation.

SVM was utilized for both classification and regression. To further identify air pollutants, SVM was utilized as a foundation classifier for ensemble. As shown by the findings, an ensemble classifier is superior to a single classifier in terms of recognition accuracy and generalization. Ensemble classifier was also considered for use in mitigating the effects of gas sensor drift. This previous research[16], shows the feasibility of using ensemble approach in e-nose data. However, these programmes can only be used to create simple models for classification and regression. Our research differs from theirs in that we suggest utilizing an ensemble approach to do more than just construct a classification or regression model; we also use ensemble FSA to find the optimal sensor combination in the array.

III. Materials And Methodology

Figure 1 shows the e-dissected nose's parts in great detail. There are two sections to this container. There are 4 gas sensors in the first chamber's sensor box, all of which have their specifications shown in Table 1. The wireless communication module is housed in the control box located in the second room. The box's gas sensor signal is sent to the computer once every minute. During each cycle of the experiment, raw data is retained continuously for almost 288 minutes. Within that time frame, beef goes from being fresh or good to being rotten. Having a way to counteract each round would be quite helpful. The first thing to do is use a powerful fan to thoroughly clear out both of the e-nose box's chambers. Second, you'll need to let the container air out for three to six hours to get rid of any leftover smell from the prior trials. A total of 24540 points were earned, with about 2080 points allocated to each of twelve different cuts of beef. In all cases, 150 g of meat was found to be on display. Dolt, morbidly obese, bull, top steak, short tenderloin, sirloin, flaps meat, prime rib, from within, skirt mutton, and shin are only few of the beef cuts included. The total amount of microorganisms inside a beef cut is used to determine the quality differential.

Fig. 1. E-nose setup

TABLE I. Sensor Specification

Gas Sensor	Selectivity	Detection Range
MQ136	ALCOHOL	10-1100 PPM
MQ2	BENZENE	20-900 PPM
MQ4	METHANE	50-500 PPM
MQ9	CO, METHANE	30-3000 PPM

As a result, optical density is measured with a spectrophotometer set to a 1000-fold dilution. Additionally, a hemocytometer may be used to count the individual red blood cells that make up the microbiological population inside a beef cut. The foundation of this experiment is the fusion of traditional and time-limited methods. In order to standardize the quality of beef throughout Australia and New Zealand, the Agricultural and Resource Management Council created a system based on total viable count (TVC) with four sensory classes. Specifications are summarized in full in Table 2.

TABLE II. Steak standard according to Bacterial Colony Forming Unit (BCFU)

Standard	BCFU in 1 g of beef.
Outstanding	<4
fine	4-5
Allowable	5-7
Impaired	>7

Using these standards, we may confidently classify the information at hand as consistent. Because the same results keep occurring, that's why. However, the pattern is obscured by the noise introduced by the fluctuating humidity. The reliability of an analysis also depends on how much variance there is in the feature selection process and how small the sample size is. Noise, homogeneity, and almost zero dimensionality are only some of the characteristics of the experimental e-nose data sets used to assess beef quality. Uncertainty stems from the fact that measurements get skewed whenever there is a change in humidity in the sample chamber. In order to solve this issue, the noise filtering architecture was developed. Since the data sets are similar, they may be analyzed using the same methods in the same environment. In addition, the data dimension has a significant impact on the total number of sensors used in an experiment. Eleven gas sensors, eleven inferior features. However, the sensitivity of the optimization problem will increase as the number of sensors in the sensor array grows. Adding additional sensors to a device requires the power company to do more work, store more data, and deploy more personnel. We use twelve distinct data sets in this experiment. One slab of beef may have 12,040 different patterns. In a situation when just a few records are available, this is a good enough number to work with. In addition, it would take more time and effort to build many variants of the sensor array, each tailored to tracking a different cut of meat. As a result, testing the stability of FSA is a practical approach to solving sensor array optimization problems.

Feature selection algorithms - There were 12 distinct types of beef utilized in this experiment, and each kind was represented by a single data set. The reliefF, chi-squared, and Gini indices are utilized as the three filter-based FSAs. In earlier investigations it has been found that these algorithms provided the most consistent results when applied to these e-nose datasets [17].

The goal of ReliefF is to evaluate how effectively a set of characteristics distinguishes between pairs of similar cases. Based on l randomly chosen cases, ReliefF finds its nearest hit H and miss M from the same class and a different class, respectively. It is possible to calculate a score for feature $X_k$quality estimate using (1).

$$F_{score} = \frac{1}{d}\sum_{i=1}^{m}\left(\frac{1}{h_i}\sum_{x\in MH_i}(x_{ik} - x_{rk}) + \sum_{y\neq y_i}\frac{1}{n}\frac{ratio_y}{1-ratio_y}\sum(x_{ik} - x_{rk})\right) \quad (1)$$

Chi-squared- To determine whether a feature is dependent on the class label, the chi-squared feature selection does an independence test. A high chi-square score suggests that a given characteristic is important. The chi-squared statistic may be calculated as follows, given a single feature fi and a set of n possible feature values:

$$X_l = \sum_{i=1}^{p} \sum_{j=1}^{d} \frac{(n_{ij} - \partial_{ij})^2}{\partial_{ij}} \quad (2)$$

Where n_{ij} represents the number of scenarios, with the ith feature value from the feature X_l; $\partial_{ij} = \frac{n_i * n_j}{n}$

Gini-Index- For the Gini Index, also known as the Gini Impurity, one takes the difference between the total squared probabilities for each class and one. Because of how easy they are to construct; it mostly benefits bigger divisions. Basically, it determines how likely it is that a certain characteristic was erroneously categorized

The Gini Index may take on values between 0 and 1, with 0 indicating perfect classification and 1 indicating an evenly distributed set of variables. When the Gini Index is 0.5, it indicates that all classes have an equal number of each element.

$$G = \sum_{i=1}^{d} (pr(i) * (1 - pr(i))) \quad (3)$$

The Gini Index can only conduct a binary split since it uses category variables and reports its findings in terms of success or failure. Unlike its sibling, Information Gain, it requires less processing power. As the Decision Tree iterates, it maximizesa number called Gini Gain, which is derived from the Gini Index and used to determine how close to optimal a CART is.[18]

IV. Results

We explain our feature-selection, classification, and regression findings from the experiments here. At first, an ensemble FSA is constructed using the outputs of three standard FSAs. ReliefF's WAFA rating is shown on Figure2.

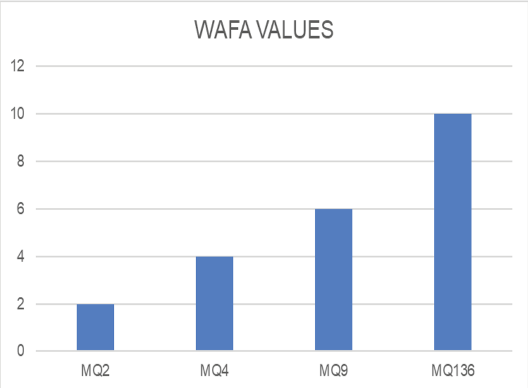

Fig. 2. ReliefF outcomes

High-scoring features are used to pick the sensors that will be represented in the feature subset. The sensors are MQ136, MQ2, MQ4, and MQ9 based on data from twelve similar datasets. Using the same method, Figure3 shows that the chi-square result for a subset of sensors MQ136, MQ2, MQ4, and MQ9.

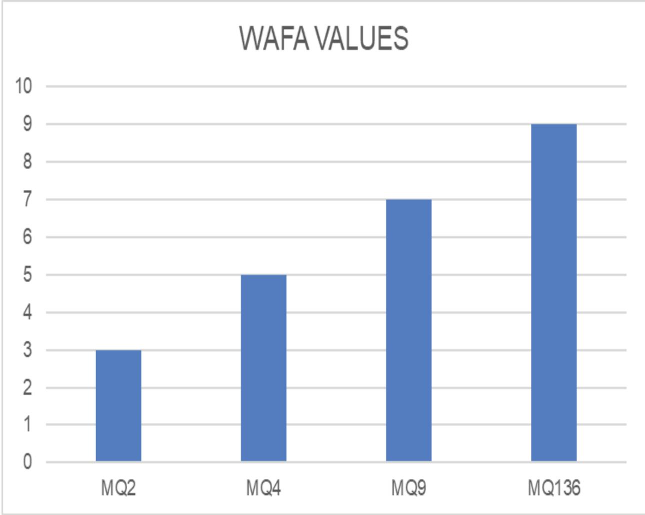

Fig. 3. Chi-Squared Outcomes

More so, Figure4 displays the suggested sensors, such as MQ136, MQ2, MQ4, and MQ9, depending on the Gini index. Using the chosen sensors for classification and regression tasks follows the performance of ensemble FSA for sensor array optimization. The data set is randomly split into a training data set (typically 70%) and a testing data set (30%) for the purposes of developing classification and regression models. This results in a total of 18,648 instances for use in training and a total of 7992 instances for use in testing. In addition, the experiment was split into two groups: one that made use of all available sensors and another that relied on the optimized sensors generated by the ensemble FSA. When all sensors are used, machine learning algorithms have 11 input characteristics from 4 sensors to work with.

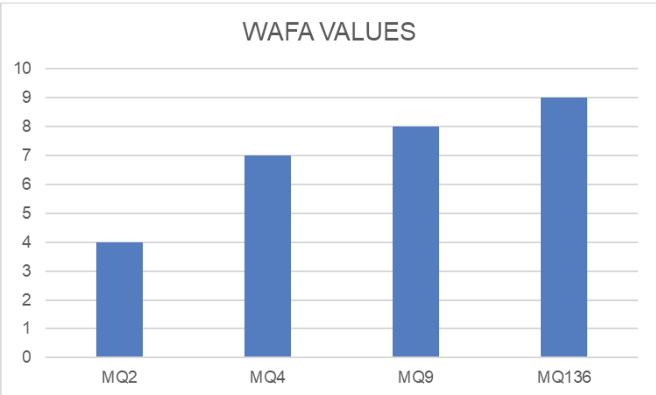

Fig. 4. Gini Index Outcomes

Using the chosen sensors for classification and regression tasks follows the performance of ensemble FSA for sensor array optimization. The data set is randomly split into a training data set (typically 70%) and a testing data set (30%) for the purposes of developing classification and regression models. This results in a total of 18,648 instances for use in training and a total of 7992 instances for use in testing. In addition, the experiment was split into two groups: one that made use of all available sensors and another that relied on on the optimized sensors generated by the ensemble FSA. When all sensors are used, machine learning algorithms have 11 input characteristics from 4 sensors to work with.

V. Conclusion

In this section, we discuss the results of our studies with the selection of features, classification, and regression. An ensemble FSA is first produced by taking the results of three regular FSAs and combining them. The WAFA rating for ReliefF is shown here in Figure 2. High-scoring features are used in the selection process for deciding which sensors will be included in the feature subset. According on the findings of twelve comparable datasets, the sensors are designated as MQ136, MQ2, MQ4, and MQ9. Figure 3 illustrates, via the use of the same methodology, that the chi-square result for a selection of sensors (MQ136, MQ2, MQ4, and MQ9). In addition to this, the Gini index is used to determine which sensors, such as MQ136, MQ2, MQ4, and MQ9, should be used, as shown in Figure 4. The following five gas sensors are proposed for use in the classification and regression procedures that will be performed on this data set. The performance of the ensemble FSA for sensor array optimization is followed by the use of the selected sensors for classification and regression tasks. For the purposes of creating classification and regression models, the data set is randomly divided into a training data set (usually consisting of 65% of the total) and a testing data set (consisting of 33% of the total). As a consequence of this, there are a total of 18,658 instances available for use in training, and there are a total of 7870 instances available for use in testing. In addition to this, the experiment was carried out with two distinct groups: the first used any and all of the sensors at their disposal, while the second depended on the optimized sensors that were produced by the ensemble FSA. When all of the sensors are employed, the data that the machine learning algorithms have to work with consists of 11 input characteristics from 4 sensors.

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