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RESEARCH ARTICLE

Application of a Low-Cost Electronic Nose to Detect of Forest Tree Pathogens: Fusarium oxysporum and Phytophthora plurivora

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ABSTRACT The presence of forest tree pathogens may lead to substantial problems and their early detection during seed storage or in nurseries may be critical for the choice of appropriate management strategy. A new construction of a low-cost electronic nose was tested on the samples of pathogenic fungi and oomycetes of *Fusarium oxysporum* and *Phytopthora plurivora*. The electronic nose uses Figaro Inc. TGS series sensors with applied heater voltage modulation. Such a mode of electronic nose operation may be more appropriate for application for constant monitoring of seeds storage, when we compare it to the method making use of modulation of the gas concentration. A rectangular shape of the sensors' heater voltage modulation pattern, with a shallow drop of the heater voltage from the nominal voltage, was proposed. Data visualization using the principal component analysis method and the random forest machine learning technique was used to build classification models. A classification accuracy of 97% was obtained by a fusion of data collected by TGS 2610 and TGS 2602 sensors.

INDEX TERMS Electronic nose, odor classification, VOC, volatile organic compounds, fungi, oomycetes.

I. INTRODUCTION

A main motivation for conducting the research is the transition of crop protection in Europe from chemical pest control to integrated pest management (IPM), in which physical and biological methods play an important role. In this situation, new tools are needed to support this strategy to ensure expected yields while improving environmental quality. One such innovative direction is the use of scents to identify insect pests and pathogens. Detection of odours can be done by different techniques of chemical analysis of gases. First of all, most information can be obtained by classical chemical analysis techniques, including gas chromatography-mass spectrometry. This approach provides the most objective and reliable identification of individual chemical components and their relative concentrations. However, due to the significant cost of equipment and the need for highly skilled personnel, this method is usually limited to applications under laboratory conditions.

The concept of the electronic nose is to use a series of nonspecific gas sensors [1], [2], [3]. In this approach, the individual chemical components of the measured gas are not identified; instead, odors are classified and recognized using pattern recognition techniques supported by machine learning algorithms.

Several applications for electronic noses have been proposed, focusing on forestry and agriculture [4], [5], [6], [7], [8], [9]. In addition, applications for fungal species detection and identification have recently been explored by Mota *et al.* [10].

Gas sensors based on various physical phenomena can be used to construct electronic noses, such as electrochemical [11], gravimetric [12], optical [13]. However, when simple, low-cost devices are proposed, they are usually based on commercially available metal oxide (MOX) sensors.

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In this research, we describe a low-cost electronic nose recently constructed in our laboratory. Unlike the previously reported constructions from our lab [14], [15], which were based on the same types of Figaro Inc. MOX type gas sensors, the new electronic nose applies a method of sensor heater modulation.

Multiple research groups reported electronic nose constructions based on such a principle of sensors operation. Numerous papers report new sensors construction, but also there is a large body of research, in which commercially available sensors were used. From the perspective of the electronic nose construction, an important aspect is the choice of the pattern of the sensor heater modulation profile.

Huang *et al.* [16] used a rectangular shape of of 20 mHz modulation applied to a single SnO_2 sensor for detection of organic VOC. Hosseini-Golgoo *et al.* [17], [18], [19] investigated a staircase-like mounting profile from 1 to 5 V. Similar modulation profile was used by Liu *et al.* [20] in p-type NiO sensor. Sensors' response to increasing heater voltage by rectangular steps of various high was studied by Amini *et al.* [21] and Gosangi and Gutierrez-Osuna [22]. A rectangular heating voltage profile with a constant high but varying base voltage level was applied by Hossein-Babaei and Amini [23] in a low-cost, tin oxide-based, generic gas sensor. Yin *et al.* [24] applied triangular saw teeth-like modulation of TGS 2602 and TGS 2620 sensors. Oates *et al.* [25] presented a low-cost electronic nose with sinusoidally heated standard commercially available sensors for the classification of oil types, and recently [26] demonstrated application to basic detection of different foodstuffs. He *et al.* [27] applied a spike-like pattern with a modulated frequency of spikes during the measurement procedure. A triangular modulation profile was used by Krivetskiy *et al.* [28]. Yuan *et al.* [29] used triangle and rectangle-like profiles, with baseline at low sensor temperature conditions. Zhao *et al.* [30] applied rectangular temperature modulation to SnO_2 sensor for the detection of toxic and flammable gases. Iwata *et al.* [31] proposed to use modulation profile with amplitude and frequency periodically changed. Vergara *et al.* [32] reviewed optimized feature extraction for temperature-modulated gas sensors.

In most of the cases of reported constructions of low-cost electronic noses, the MOX sensors used were not designed for operation in the temperature modulation mode. Furthermore, most of the research applied modulation on the temperature on a wide scale, reaching regions far from the nominal sensor working conditions. In addition, in most of the research, multiple periods of the modulation were applied and used for gas recognition. In our research, we report investigations of the possibility to use only one period of modulation with a relatively small change of the sensor heater voltage, close to its nominal working conditions.

The new electronic nose, presented in this manuscript, was applied to classify measured samples of fungi and oomycetes and differentiate them from non infested medium.

To achieve the above objectives, data visualization using principal component analysis and random forest technique of machine learning was used to build classification models showing the best classification accuracy of the modeling features based on the data extracted from the sensors. Different subsets of the data used for classification were tested to optimize the list of sensors in the electronic nose sensor array and the depth of the voltage modulation profile of the sensor heating.

II. MOTIVATION FOR DETECTION OF PATHOGENIC FUNGI AND OOMYCETES

As international trade in plants and plant materials increases, the accidental introduction of insects or pathogens into new areas becomes a serious problem. Their spread can lead to forest health problems at a very early stage, such as damage to plants in forest nurseries, resulting in a significant reduction in the number of seedlings and economic losses. One of the most frequently observed problems is caused by the pathogens of the so-called ''damping-off seedlings disease''.

Damping-off is a disease that causes death of germinating seeds and young seedlings, especially in forest nurseries [33]. This disease is caused by several organisms, such as: fungi *Fusarium*, *Rhizoctonia*, *Cylindrocarpon*, and oomycetes *Phytophthora* and *Pythium*. In Poland the genera *Fusarium* and *Phytophthora* represent the most numerous pathogens in forest nurseries. Their pathogenic soil-borne strains are among the most harmful microorganisms in the world due to their potential adaptability. They cause root rot, tuber blight and wilt [34], [35]. Pathogenic strains of the fungal species *F. oxysporum* particularly affect seedlings of coniferous species in nurseries. The most commonly observed symptoms are needle wilt and, in some cases, small root and stem rots. Seedlings lose their fine roots (in which case they are easily pulled out of the ground) or fall over due to infected stem tissue, which is usually damaged near the ground. The pathogen moves upwards from the roots to the stems and hinders water uptake, gradually clogging the xylem tissue, which leads to wilting of the plant, yellowing of the needles and death.

Pathogenic oomycetes of the genus *Phytophthora* pose an even threat to plants. When these organisms destroy the fine roots (< 2 mm), the plants die quickly. If the seedlings are raised in a water regime suitable for them, they often do not show disease symptoms (are asymptomatic), and chlamydospores are formed in the rhizosphere of the soil, which become active only when the plants are planted in moist habitats. Since they do not show external signs of disease, visual selection of seedlings is not effective, and the problem is shifted from the nursery to the forest plantation. Molecular diagnostic tests conducted in many countries have shown that infestation of plants prepared for planting in nurseries in Europe is high, sometimes reaching 80% [36]. In addition, fungicides are intended to control fungi, not oomycetes. Thus, if used improperly, they only mask the disease, which is usually the case in nurseries. Therefore, it is critical to identify the organisms that foresters and arborists are dealing with there, and accurate and rapid analysis with e-nose would be very useful for this purpose. Currently, the recomended method for detecting oomycetes in soil is the baiting using plant material [37]. The currently recommended method for detecting oomycetes in soil is baiting with plant material [37]. In this approach, the organisms sought grow on oak, beech, or rhododendron leaves as bait, and the infected leaf pieces are usually placed on selective media (e.g., PARP) [38]. This approach requires several days, if not weeks, to obtain pure cultures of pathogens that can be identified by classical (microscopic) or molecular (DNA sequencing) methods. From an economic perspective, forestry and ornamental nurseries need to develop a rapid method for detecting pathogens that primarily cause damping-off disease. Early detection can help to take action to reduce the loss of regeneration material due to the negative effects of the pathogens.

FIGURE 1. Experimental setup of Petri dish with the measured sample and the low-cost electronic nose inside the laminar flow cabinet, connected to the laptop controlling the operation and collecting data.

III. ELECTRONIC NOSE

A. GAS DETECTION USING MOX SENSORS

Let us briefly recall the main components of a MOX-type gas sensor and its operation principle. The sensing material, typically tin dioxide, is heated by the built-in electric heater, usually made of platinum, up to the temperature of a few hundred Celsius degrees. In the conditions of clear air, oxygen is absorbed on the surface of the sensing element and attracts donor electrons, which prevents electric current flow. In the presence of reducing gases, oxygen reacts with the gas molecules and that reaction decreases the surface density of adsorbed oxygen. Electrons are released from the surface into the sensing material and that allows the electric current to flow. That means that the sensor temperature significantly influences the physical processes responsible for the sensor operating principle. A MOX gas sensor operating at different temperatures may have different response characteristics to measured gases [15] and exhibits different sensitivity and selectivity to various chemical components.

A physical property measured in MOX sensors is their resistance in the presence of the considered gas sample. However, the absolute value of the measured resistance is not used, but its value in proportion to the resistance in the clean air conditions. It is a known property of this type of sensor that the measured magnitude of the sensor response exhibits drifts over time and that requires that the sensor baseline resistance (resistance in clear air) should be measured just before each measurement of the studied odor sample. As an output value from the electronic nose sensor array, one can use the stationary value of sensors resistance obtained after a sufficiently transient response after a change of gas conditions. However, more sensitivity and selectivity can be achieved, when one uses the whole sensor response characteristics captured during changes in the measured gas condition: firstly from clean air to the measured odor sample (adsorption) and then back to the clear air (desorption). That approach exploits transient sensors response regions and allow odors discrimination using responses of even one sensor [23], [39], [40], [41], [42]. However, that approach also requires that the changes in the measured gas conditions should be abrupt and repeatable [43]. That requires advanced designs of sensor array chamber [44] and precise pneumatic gas supply.

Another approach is to capture sensor resistance characteristics while sensor temperature is modulated. That approach allows the construction of a simpler low-cost electronic nose as it doesn't require as precise and advanced pneumatic modulation of the supplied gas. Modulation of the sensor temperature with the required time profile is much easier to achieve by a relatively simple electronic circuit. The modulation is performed when the sensor already reached the stationary state in the presence of the measured gas conditions.

An important aspect of the construction of the electronic nose based on heater temperature modulation is the choice of the modulation profile. Various approaches were proposed in this domain. As we reviewed in the Introduction section, patterns or modulation such as sinusoidal, stair-like, or rectangular were demonstrated. Furthermore, most researchers investigated cases when the sensors heater voltage explores a wide range. Also in most cases, it was demonstrated that multiple periods of modulation were used to collect data required for sample classification. In some cases also variation or tuning of modulation frequency was required.

B. ELECTRONIC NOSE CONSTRUCTION

The described in this manuscript electronic nose device (PW7) is an improved version of previously used and described devices PW4 [14] and PW6 [15]. The whole experimental setup is presented in Fig. 1.

The PW7 electronic nose is designed as low-cost equipment to detect smells emitted by various types of fungus. Each construction of an electronic nose consists of two main parts: the sensors probe and the main electronic unit connected to the computer. The probe is the round aluminum block in which the sensors are placed. Similar to earlier devices we used various types of metal oxide sensors made by Figaro co., Japan. The sensor types are listed in Table 1. Additionally, there were also placed HIH 4031 humidity sensor (Honeywell, Charlotte, NC, USA) and LM35 temperature sensor (Texas Instruments, Austin, TX, USA).

The improvement of the PW7 device, compared to our previous constructions, is the ability to modulate the sensors' heater voltage. This leads to modulation of the operation temperature of the sensors. The changes could be made in every single sensor reading cycle from 0 to 7 V with a step of 30 mV. The main unit has wires to connect with the sensors probe, a USB cable to connect with the computer, and a 12 V DC power supply. The complete schema of the device can be seen in Fig. 2. As one can see, it can be made at a relatively low cost as the most expensive parts of the device are the sensors themselves. This voltage is divided into two separate circuits. One of them is stabilized 5 V, which provides energy for most electronic parts and the sensors' readings. The other is adjustable and stabilized voltage that powers up sensors' heaters. The core of the PW7 enose device is the ATmega 328P-PU microcontroller. It controls all the communication between the computer and sensors. The measurements from the sensors are read using a multiplexer one by one with a delay of a few milliseconds, so we can assume that they are in the same moment. All readings are sent to a computer and archived in a text file that can be easily worked out.

Additionally to the electronic nose, we prepared simple equipment to clean reference air during baseline measurements and between measurements. This simple construction consists of a rotary vane pump (Thomas G6/01-K-LCL, Gardner Denver), a 5 V DC power supply, a self-made active charcoal filter, and a set of tubes with a diffuser. It helps to clean up sensors quicker and provide more stable baseline readings.

C. SENSOR HEATER VOLTAGE MODULATION PROFILE

In Section III-A we reviewed several proposed patterns of sensor heater modulation. In many cases, they rely on significant changes in voltage allowing them to exploit a wide range of sensor response characteristics in various temperatures. Also, often the exploited response relies on voltage increase from a very low voltage base level. That leads to heater conditions, which are usually far from the nominal operating temperature, for which the sensors were originally designed. When the sensors are operating at low temperatures, the gas molecules are adsorbed at the porous gas sensing layer. Their presence cannot be used to gas identified by the measurements of average electrical characteristics such as resistance, but only by the application of the fluctuation enhance sensing methods [45], [46]. That may suggest, that rather operation and modulation at higher heater voltages could give better results of gas recognition. In our approach, we decided to use relatively shallow heater voltage modulation in conditions close to the ones recommended by the sensors' manufacturer. The profile of the modulation is presented in Fig. 3(a).

IV. MEASURED SAMPLES

A. SAMPLES PREPARATION

Strains of both pathogens were isolated in a forest nursery from pedunculate oaks (*Quercus robur*) with visible symptoms of damping-off. The isolated organisms were stored in the Forest Protection Department of the Forest Research Institute in Sękocin Stary (Poland). Two organisms *Phytophthora plurivora* and *Fusarium oxysporum* as the most frequently responsible for the occurrence of damping-off symptoms in Polish forest nurseries were selected for detailed analysis [33]. The pathogen isolates were cultured on classical PDA agar media (20 g dextrose, 15 g agar, 4 g potato starch, and 1 L distilled water) in 9 cm Petri dishes. They were kept at room temperature until the mycelium completely covered the surface of the dishes.

TABLE 1. List of sensor models used in the PW7 electronic nose device and target odors and gases.

Sensor	Target gas detection
TGS 2600	Has a high sensitivity to low concentrations of gaseous air contaminants such as hydrogen and carbon monoxide, which exist in cigarette smoke. The sensor can detect hydrogen at a level of several ppm.
TGS 2602	Has high sensitivity to low concentrations of odorous gases such as ammonia and H_2S generated from waste materials in office and home environments. The sensor also has a high sensitivity to low concentrations of VOCs such as toluene emitted from wood finishing and construction products.
TGS 2603	Has high sensitivity to low concentrations of odorous gases such as amine-series and sulfurous odors generated from waste materials or spoiled foods such as fish.
TGS 2610	Uses filter material in its housing, eliminating the influence of interference gases such as alcohol, resulting in a highly selective response to LP gas.
TGS 2611	Uses filter material in its housing which eliminates the influence of interference gases such as alcohol, resulting in a highly selective response to methane gas.
TGS 2612	Has high sensitivity to methane, propane and butane, making it ideal for LNG and LPG monitoring. Due to its low sensitivity to alcohol vapors (a typical interference gas in the residential environment), the sensor is ideal for consumer market gas alarms.
TGS 2620	Has high sensitivity to organic solvents and other volatile vapors, making it suitable for organic vapor detectors/alarms.
TGS 2630	Has high sensitivity to low GWP (Global Warming Potential), low-flammable refrigerant gases such as R-32 and R-1234yf, as well as to R-404a and R-410a which are commonly used in air conditioning and refrigeration systems. Uses filter material in its housing to eliminate the influence of interference gases such as alcohol, resulting in highly selective response to low-flammable refrigerant gases.

B. MEASUREMENT PROCEDURES

From the point of view of the person making the measurements, the procedure for the odor measurements was very similar to that used in our previous experiments [14], [15].

The whole experiment lasted two weeks, and during this time we had 7 days of measurements. In total, we prepared six Petri dishes for each category of samples. One set of three dishes of each category was used during the first week of the experiment. Since the samples could be contaminated by other species, another set of dishes was used in the second week of the experiment. Each Petri dish was measured only once per day. Since the fungal and oomycete samples were

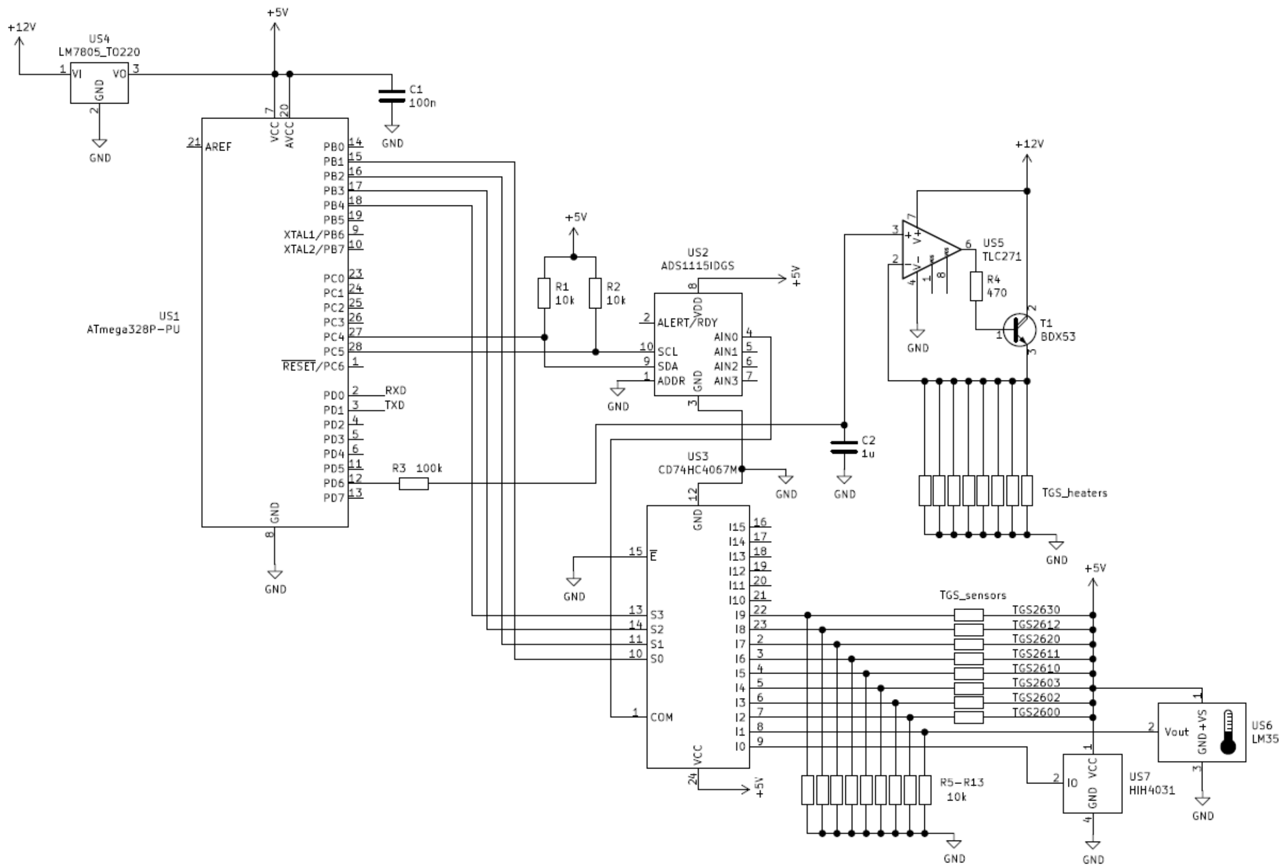


FIGURE 2. The electronic circuit diagram of the PW7 low-cost electronic nose.

living organisms, they varied daily and so did the composition of the volatiles emitted by the samples. The order of sample measurements was randomly selected at the beginning of each day.

The sensors were preheated in clean air at a nominal voltage of 5 V at least seven days before the experiment, as recommended by the manufacturer. During the two weeks of the experiment, they were kept in clean air with a power supply. During the experiment, controlled conditions were maintained with a constant temperature of 20 °C and humidity of 20%. The measurement was performed in a laminar flow cabin.

The operation of the electronic nose device was performed manually. One measurement procedure lasted 15 minutes and during this time 1200 readings of the sensor resistance were recorded. Fig. 3(a) shows an example of a sensor curve acquired during one cycle of sample measurement. The measured quantity is the voltage read from the resistor, which represents the sensor resistance. According to the sensor manufacturer's specification, the quantity that should be used is not the sensor resistance, but its magnitude relative to the resistance measured under clear air conditions. Thus, if voltage is the primary measurable it corresponds to U/U_0, where U is the voltage measured at the given time and U_0 is the base value. After starting the measurement, the electronic nose was still kept in clean air during the 200 sensor readings to ensure that the sensors response was flat, which means that they already recovered to the baseline and were not contaminated by residues from the previous measurement. Then, the sensor array was placed over a Petri dish containing the measured sample. It was waited for 100 measurements (1 minute 15 seconds) and during this time the resistance of the sensors reached a steady state. At this moment modulation the heating voltage of the sensors started, with three rectangular steps with a length of 50 sensor readings started and a different modulation depth, as schematically shown in Fig. 3(a). For the voltage modulation steps of voltage drop steps of –0.3, –0.6, and –0.9 V, each from the nominal heater voltage of 5 V were applied. After the temperature modulation, the sensor array was manually moved to clean air, where the residues of the measured gas could be desorbed, the sensors were cleaned and prepared for the next measurement process.

V. DATA ANALYSIS TECHNIQUES

The data preparation, statistical analysis, and machine learning models presented in this manuscript were performed using computer codes developed in the Python 3.8 language. The statsmodels package [47] was used for statistical tests and scikit-learn package [48] for machine learning modeling.

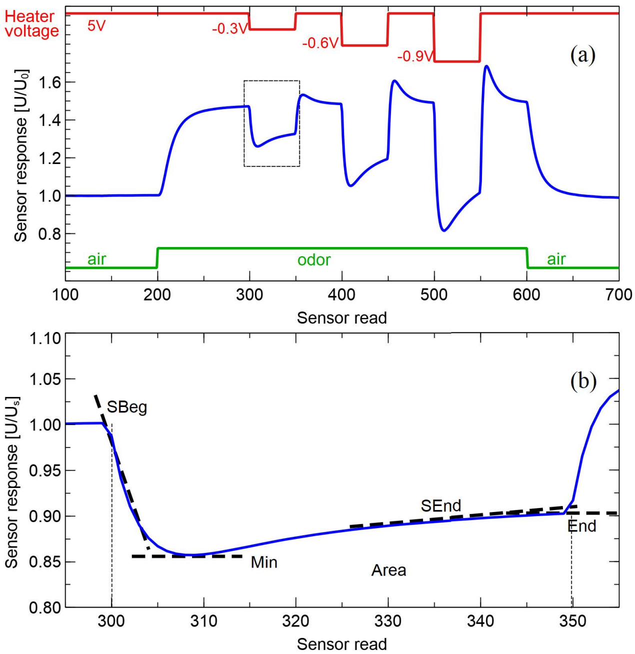


FIGURE 3. Schematic representation of the sensor response during measurement (a) and explanation of the extracted classification features (b). The dashed rectangular in Figure (a) represents the period presented in Figure (b). The time when sensors are placed in clear air and measured gas, and the pattern of sensor heater voltage characteristics are schematically represented in Figure (a). The x-axis is represented by sensor response read number, where one read takes 0.75 s.
In Figure (a) the y-axis is the measured voltage relative to the baseline voltage in clean air U/U_0, in Figure (b) the y-axis is represented the measured voltage relative to the voltage at the moment just before the heater voltage drop U/U_S. The definition of modeling features presented schematically in Figure (b) is described in Table 2.

A. FEATURES EXTRACTED FROM SENSOR RESPONSE CURVES

In Fig. 3(b), a portion of the sensor response curve taken during one step of the heater voltage drop is shown. The quantity used in the analysis is the voltage relative to its magnitude just before the voltage drop U/U_s. This means that the output voltage measured under clean air conditions is not needed for the analysis. The sensor response curve contains 100 data points, and only five features describing the curve are extracted for further analysis. This allows the dimensionality of the problem to be significantly reduced. The definition of these features is shown schematically in the figure and listed in Table 2. The selected types of features allow to capture the behavior of the response curve in the different time domains and to reduce the influence of the instantaneous data fluctuations.

B. PRINCIPAL COMPONENT ANALYSIS

A common practice in analyzing multidimensional data is to project it into a low-dimensional space. Such transformed data can be used as input for further analysis or for visualization purposes to understand patterns in the distribution of data points for the case under study. The Principal Component Analysis (PCA) the commonly used statistical technique was used for this task. One of the advantages of the PCA

TABLE 2. The list of types of modeling features extracted from the sensor response curve, for each step of the sensor heating voltage drop.

Feature	Definition
`Area`	Area under the response curve.
`End`	Final value of the collected response.
`Min`	Minimum value of the response.
`SBeg`	Slope at the beginning of the response.
`SEnd`	Slope at the end of the response.

transformation is an intuitive interpretation, as the rotation of the coordinate system, which gives the new coordinates in order of the amount of variability captured from the data set. We used as input for the PCA transformation all features extracted from the response curves of the sensors. Since the input features represent non-comparable quantities expressed in different units and have different ranges of values, we used initial normalization of the input dataset to equal variance. In our analysis, the PCA method was used only to visualize the patterns of the data points in the two-dimensional space of the two main principal components.

C. RANDOM FOREST MACHINE LEARNING MODELS

One goal of the electronic nose measurements is to apply the collected data to create classification models that are able to discriminate between the samples studied. Different types of machine learning models have been applied to the data collected by the sensors, and in the present work we have chosen the Random Forest model [49]. This method has been successfully used by other authors for classification tasks of electronic noses [50], [51], [52], [53], [54] or in other sensor array data [55], [56].

Random Forest is one of the most popular machine learning algorithms used for classification tasks and belongs to the ensemble model group. It is based on the creation of a large number of decision tree models, each of them trained on a subset of the dataset and a subset of modeling features. These individual decision tree models are trained independently and the average of their results is used as the output of the Random Forest model. The ensemble estimator usually results in much better model performance than any of the individual models because its variance is reduced. Prediction accuracy is improved and the Random Forest model is less prone to overfitting.

The Random Forest models used in this analysis offer several important advantages. Since during Random Forest training the individual decision tree models are fit using a subset of the entire training data set, the remaining portion of the data can be used to estimate model performance. The so-called out-of-bag score (OOB) can be calculated as the model classification accuracy based on the observations that were not used to fit the decision tree. The score calculated from each tree is then averaged and used as a fair estimate of model performance. The advantage of such an approach is that fewer computations are required and the model can be tested while it is trained. The OOB score is similar to the commonly used cross-validation method for estimating the performance of classification models. The OOB score converges to the leave-one-out cross-validation score [57].

An interesting output of the random forest model is the ranking of the predictive performance of the modeling features [58]. In this context, the measure of mean decrease in impurity [49] can be used. This measure is defined for a given feature as the sum of the weighted impurity decreases for all decision tree nodes where the feature is used in a split, averaged over all trees in the forest.

VI. RESULTS AND DISCUSSION

A. SENSOR RESPONSE

As described earlier, the electronic nose is based on analyzing the response of the sensors to the voltage drop across the sensor heater, when the sensor is placed in the environment of the measured gas. In Fig. 4 we plot the collected data, where the voltage measured for each sensor is normalized by the voltage measured a moment before the voltage drop. The measurements for the different sample categories are shown in different colors. There are distinct patterns in the response of the sensors that can be used to distinguish between the volatiles emitted in the three cases studied. It is also interesting to note that among the patterns in the six types of sensors used, only the TGS 2612 and TGS 2630 sensors behave almost identically in all measurements. The results acquired by these two sensors were not analyzed further, since they cannot be used for the classification and detection of the samples studied.

At the end of the measurement period, when the heating voltage was decreased, only the response of sensors TGS 2602 and TGS 2611 was close to a stable value. For these and the other sensors, the response was still in the transition region, and as can be seen, the slope of the last part of the recorded response shows a linear behavior that can be used for a reliable calculation of the response slope. Variability between responses of the same sample category was observed, which is related to the variability of biological samples, variations in external measurement conditions such as temperature or humidity, and measurement errors.

B. MODELLING FEATURES

As described in Section V-A, we extracted several features from each sensor response curve acquired during the measurement of a sample. These features sufficiently represent the collected data and should allow us to find patterns that distinguish the categories of samples. In Fig. 5 we show in the form of a box-plot diagram the distribution of features grouped by three categories of samples. The presented features were extracted from the first step of the sensor heating voltage drop (–0.3 V). However, features from two other steps were also used for the analysis, as described in the following sections.

As one can see, different features allow discrimination between samples. To avoid relying solely on visual inspection and to confirm that these patterns were statistically significant, we calculated the p value using Tukey's HSD (honestly significant difference) test. The pairs of groups for which the p value is < 0.05 are marked in the figure.

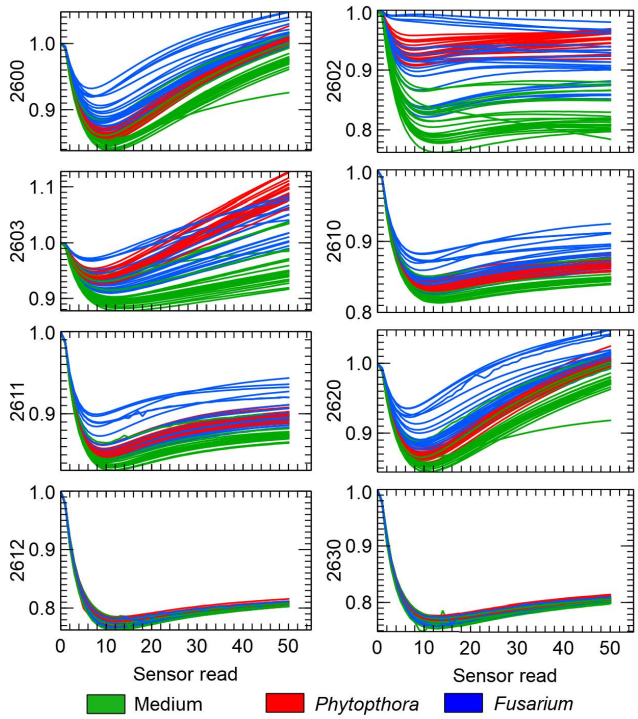


FIGURE 4. The sensor responses during the first step of the heater voltage modulation are shown as normalized U/U_S, where the normalization is due to the sensor response at the time just before the heater voltage drops. The sensor type is indicated on the Y-axis in the subfigures. The different types of samples measured are indicated by the line color. The x-axis is shown in read events of the sensor response, counted from the beginning of the voltage modulation step, with events lasting 0.75 s.

Interestingly, different patterns can be observed when looking at Fig. 5. For example, looking at the features extracted from the TGS 2610 sensor data, it is possible to distinguish between *Fusarium* and two other categories if we use the feature `SEnd`, but this feature does not allow us to distinguish between *Phytophthora* and medium samples. Other features extracted from this sensor allow us to distinguish between medium and other samples, but not between infested samples. This results in the ability to distinguish between all sample categories by extracting at least two features from the data collected by this sensor. We mention here the example of the TGS 2610 sensor because, as we will show in the following sections, the data acquired by this sensor exhibited the best performance in terms of classification accuracy.

C. PRINCIPAL COMPONENT ANALYSIS

As shown in the previous section, the distributions of the extracted modeling features differ significantly among the three categories of samples considered. The data presented above also show very similar behavior for different features either extracted using different techniques or obtained from data collected by different sensors. Further insight can be gained by using more advanced data visualization techniques and plotting the data after transforming the modeling features

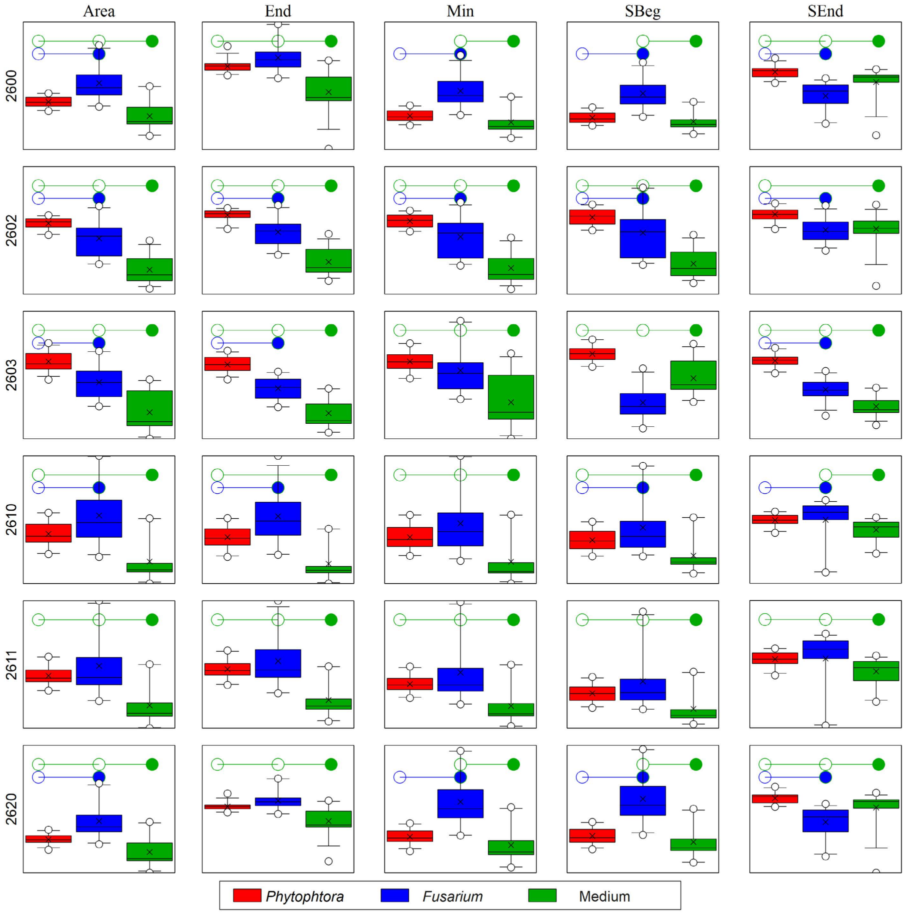


FIGURE 5. Distribution of classification features extracted from sensor response curves, starting with the first stage of heater voltage drop (−0.3 V). The definition of the feature types given above the subimages can be found in the Table 2. The different categories of samples are indicated by colors: ***Fusarium*** (blue), ***Phytophthora*** (red), medium (green). The size of the feature is not important, only the relative differences in the distribution are important, so the values on the y-axis are shown without units. Category pairs where the difference is significant at the < 0.05 level are marked above the bars.

into a lower dimensional space using the Principal Component Analysis method.

Fig. 6 shows the distribution of data points in the coordinate system of the two principal components resulting from the transformation of all features extracted from the three applied levels of heater sensor voltage drops. Notice that, as it can be observed, these principal components together contain 86% of the total variability in the data. What can be also noticed, there is no perfect linear separation of the clusters, even when the different categories of samples are clustered together. The clusters overlap, especially in the case where we consider the separation between the Medium and *Fusarium* categories. However, it should be noted that a clearer separation of categories is possible when more dimensions of the data are included. Also, more flexible machine learning classification models can perform better than linear separation.

D. MACHINE LEARNING MODELING

As shown in section VI-B, the features extracted from the sensor response curves differ significantly for different categories of samples studied. However, the statistical test checks the difference in the mean and is calculated for a single feature. In this section, we present the results of the multivariable analysis using the Random Forest classification technique.

1) CLASSIFICATION ACCURACY

In Fig. 7, we compared the performance of several classification models trained on different sets of modeling features, with the goal of assessing whether there are ways to reduce the sensor array to a smaller number of sensors or reduce the time of data collection without significantly decreasing the classification accuracy.

Fig. 7(a) shows the comparison of the classification performance for the case when the models were trained with the data from only one sensor and for the case when the modeling features were extracted from the data from all sensors. The results in this figure show that the models trained with the data from all sensors gave the best classification performance, while the models trained with the data from only one sensor

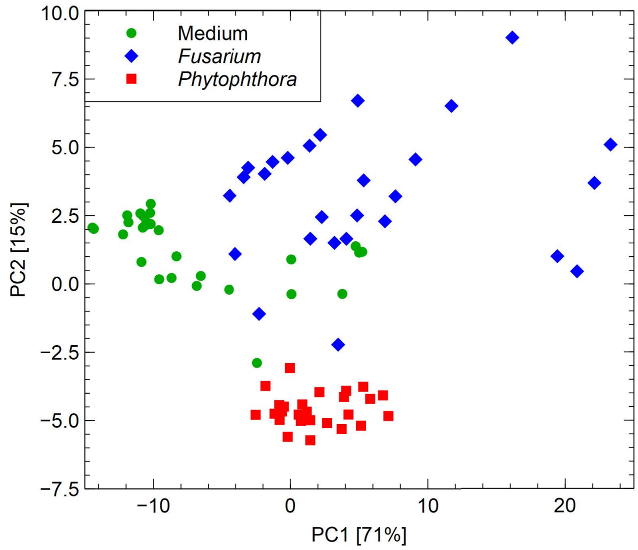
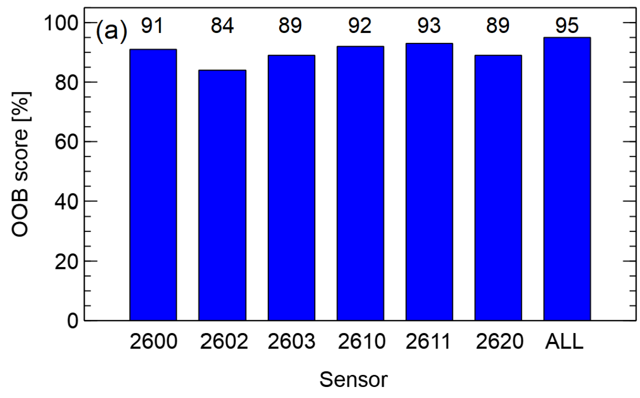


FIGURE 6. Distribution of data points in a coordinate system of the two principal components. PCA analysis transformed all features extracted from the sensor response curves of the three levels of heater voltage drop. The fraction of variance captured by the principal component is indicated in the axis labels. Three types of sample categories are indicated by colors and symbols.

TGS 2610 and TGS 2611 showed almost the same performance. This suggests that reducing the number of sensors used is feasible. We will return to the task of selection of sensors in Section VI-D3.

In Fig. 7, we compared the performance results of the classification models to test the hypothesis of whether it is possible to reduce the data collection time by using features extracted from less than three steps of the heating sensor drop. Notice that, as it can be observed the performance is very similar when we use data from only one step compared to the performance the model achieves with all data collected. In these calculations, we used data from all sensors. This result may indicate that we can only use data from one step of the heater voltage drop.

Another analysis we would like to present is to examine which step of the voltage drop should be chosen preferentially. In Fig. 8, we show a comparison of the performance of the models when they were trained only with features obtained from a single sensor data, and during a single voltage drop of the heating power. The performance of the models trained with single sensor data and features obtained from three steps of the heater voltage drop is also shown in the same subfigures. As it can be observed, the best performance was obtained for models trained with data extracted from the −0.3 V heater voltage drop response. This pattern is consistent for all sensors except the TGS 2611, but even in this case the difference in model performance between the −0.3 and −0.6 voltage drop cases is very small. The best model performance was also obtained for the cases modeling data from the TGS 2603 and TGS 2610 sensors. In these cases, the models with data collected during the –0.3 V voltage drop achieved performance close to that of the models based on data from the three heating voltage drops considered.



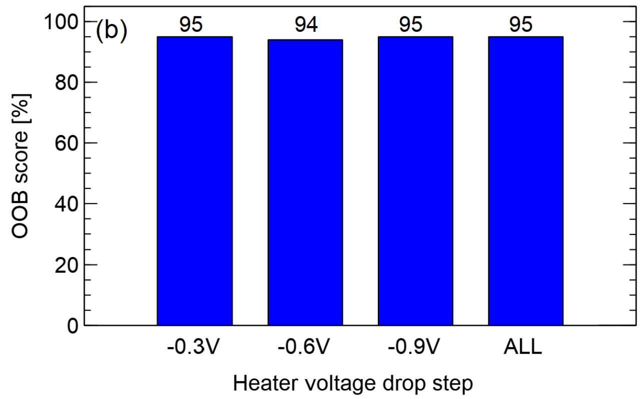


FIGURE 7. Out of bag score (accuracy) of Random Forest classification models. (a) - Models using data from a single sensor compared to the model using data from all sensors. Features are extracted from three levels of heater voltage drop. (b) - Models with features extracted from a single stage of heater voltage drop compared to the model using all features. Data from all sensors were used for modeling.

In our opinion, there is an additional argument for choosing the stage with the lowest heater voltage drop (–0.3 V). This depth of modulation results in the least disturbance in the operation of the sensors and should be preferred since the time to reach a steady state should be the shortest. Also, that allows for avoiding sensor operation at low heater temperature, at which gas composition does not influence the electrical resistance.

2) RELATIVE IMPORTANCE OF MODELING FEATURES

An interesting output of the Random Forest classification model is the ranking of the importance of the modeling features. Fig. 9 shows such data for the models based on features extracted from data from a single sensor and the –0.3 V voltage drop of the sensor heater. An interesting observation for the TGS 2610 sensor is that the most important feature is `SEnd` (the slope of the sensor response curve at the end of the observation range). For other sensors, `SEnd` is also often the most important feature identified by the Random Forest model. This may indicate that the observation time necessary to differentiate between the studied sample categories cannot be reduced to a much shorter period, as it is necessary to achieve the region of the sensor response where the linear slope is detected after the minimum value is reached.

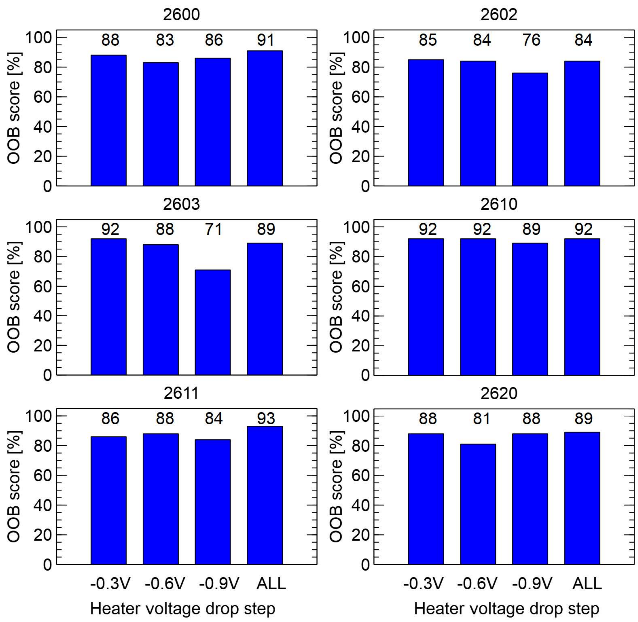


FIGURE 8. **Out of bag score (accuracy) of Random Forest classification models. Models that use data from a single stage of heater voltage drop compared to models that use features from all stages. Model uses data from a single sensor, sensor type is specified in the subframes.**

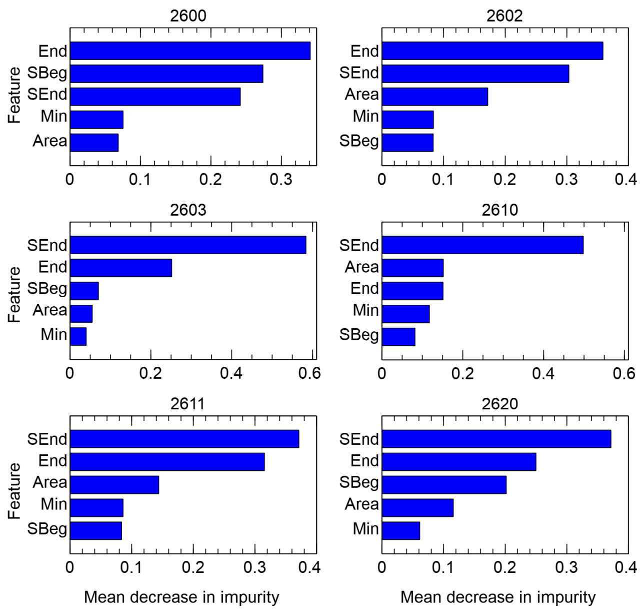


FIGURE 9. **Ranking of importance of modeling features expressed as mean decrease in contamination extracted by the Random Forest model. The classification models were trained using features extracted from data from a single sensor from the first stage of the heater voltage drop (−0.3 V). The sensor type is specified in the subframes.**

3) SENSOR ARRAY SELECTION

As can be seen in Fig. 8, the best performing classification model achieved 92% accuracy using data collected with a single sensor (TGS 2610) and a single heater voltage drop (−0.3 V). Moreover, we can see in this figure that the addition of other features extracted from the data collected by this sensor did not improve the classification performance. On the other hand, the results presented in Fig. 7 show that by fusing

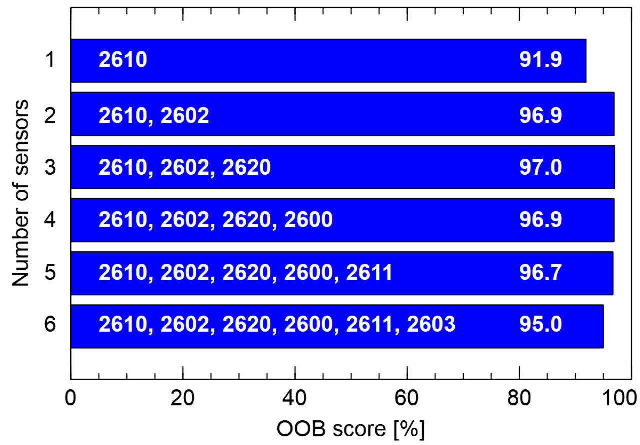


FIGURE 10. **Out of bag score (accuracy) of Random Forest classification models. Comparison of models trained with data from different number of sensors. The best model with the given number of sensors was selected. The data were extracted from the response curves of the sensors during the first stage of the heater voltage drop (–0.3 V). The lists of sensors are given in the bars.**

the data from multiple sensors, we were able to improve the classification accuracy up to 95%.

We trained a series of Random Forest models with the goal of the optimization of the electronic nose sensors. In this task we chose to use only data collected during the first step of the heater voltage drop (–0.3 V). In addition to the previously presented models based on data collected from a single sensor, we evaluated the models based on all combinations of two, three, etc. sensors evaluated. For each number of sensors, we selected the model with the best performance and the results are shown in Fig. 10. As it can be noticed, merging the data from the TGS 2610 and TGS 2602 sensors resulted in a much better classification accuracy of nearly 97%. Adding data from additional sensors may slightly improve the estimated performance, but in our opinion the electronic nose with two sensors is sufficient.

VII. COMPARISON WITH OTHER RESULTS

Our results can be compared to other reports for the cases when measurements and classification of similar types of samples were reported. Lebanska *et al.* [59] used PEN3 commercial electronic nose for detection of *Fusarium* basal rot infection in onions and shallots and reached classification accuracy up to 89.6%. In our previous research, we investigated the possibility of recognition of similar pathogenic fungi and oomycetes species. We reported [14] accuracy of classification between *Pythium intermedium* and *Phytophthora plurivora* of 90%. Previously reported [15] accuracy of recognition between medium, *Fusarium oxysporum* and *Rhizoctonia solani* reached 78%. These results were obtained employing low-cost electronic noses based on the same types of Figaro Inc. sensors but without applying dynamic heater temperature modulation.

Another comparison can be made with results of other research, in which electronic noses, based on the same operation principle of sensors heater temperature modulation, were used. Hosseini-Golgoo *et al.* [18] applied stairs-like modulation between 1 and 5 V and reported classification accuracy up to 96.27% for differentiation between samples of pure gases like methanol, ethanol, and other. Oates *et al.* [25] used sinusoidally heated sensors to differentiate between oil samples and reached accuracies up to 93.75%. Another application [26] of a similar device allowed to reach accuracy up to 94.43% for differentiation between various foodstuffs. He *et al.* [27] applied sensors temperature modulation with varying frequency to recognize gases such as hydrogen, methane, carbon monoxide, and benzene and obtained an accuracy of 84.5-98.5% depending on the machine learning model. Amini *et al.* [21] investigated recognition of various concentrations of methanol using rectangular modulation of various heights, starting from a relatively low voltage of 2 V and reaching an accuracy of 92%. Iwata *et al.* [31] used modulation with various frequencies and amplitude for recognition between acetone, ethanol, and butyl acetate and reported accuracy up to 98.8%.

These results demonstrate that when similar odor samples were measured with electronic noses, the reported devices showed less accurate performance without sensor heater voltage modulation. But with such modulation, the performance of classification may be improved. When we compare with other results obtained with devices applying various patterns of sensor temperature modulation, our results exhibit a similar level of classification performance.

VIII. SUMMARY

One of the most important seedling diseases in conifer nurseries is root rot, which causes seedlings to fall over and die. It is also known as "damping off." There are many pathogens, including *Phytophthora* oomycetes and *Fusarium* fungi, responsible for this disease. Distinguishing between oomycete and fungal infestation is very important in order to choose an appropriate treatment, as fungicides are often class specific, and can control certain groups of fungi and not oomycetes or vice-versa, and the application of inappropriate chemicals usually only masks disease symptoms.

A low-cost electronic nose with MOX sensors from Figaro Inc. TGS sensors was constructed. The proposed device is based on an analysis of the measurement of the resistance of the sensors (expressed as measured voltage) during the modulation of the heating voltage of the sensors. The choice of such a mode of operation could be suitable for the construction of low-cost electronic nose devices used for continuous monitoring, for example, in the storage of seeds when they are infested with pathogens. Such a design does not require a sophisticated pneumatic system to supply clean air to the sensors, and does not require a precise and abrupt change in the environment of the sensors from clean air to the gas being measured.

A rectangular profile of voltage modulation was applied, with voltage drop steps of –0.3, –0.6, and –0.9 V, starting from the level of nominal heater voltage of 5 V. Unlike in other reported constructions of electronic noses, we decided to use sensor modulation at the heater voltage range close to the sensor nominal operating conditions. We also used relatively shallow modulation magnitude, which shows faster operation and especially faster sensor accommodation to changes in environmental conditions. In addition, small change of the sensor's heater voltage, starting from the nominal one (shallow modulation) allows for avoiding sensor operation at lower temperatures, where their resistance does not depend on the composition of the gas in which the sensor is immersed.

Experiments with measurements were performed on samples of pathogenic fungi - *Fusarium oxysporum* and oomycetes - *Phytophthora plurivora* cultured on classical PDA agar media, with the aim of using the collected sensor responses to discriminate between sample categories.

Five types of features describing the obtained curves were extracted from the sensor responses and used for further analysis. The Principal Component Analysis method was used after transforming the modeling features for data visualization. Random Forest machine learning models were trained with the data and the out-of-bag score was used as a measure of the performance of the models, which corresponds to the accuracy of classification between three categories under study.

It was found that the rectangular step of the heater voltage drop by –0.3 V from the nominal voltage of 5 V allowed collection of data that gave the best classification performance. The analysis also allowed us to estimate the time (duration of the rectangular heater voltage modulation steps) necessary to collect the data required for sample classification.

The fusion of the data collected by the two sensors, TGS 2610 and TGS 2602, was the optimal configuration of the electronic nose sensor array, which allowed a classification accuracy of 97%. This result is very promising as the obtained accuracy is higher than in the case of our previous constructions of low-cost electronic noses without dynamic sensors temperature modulation.

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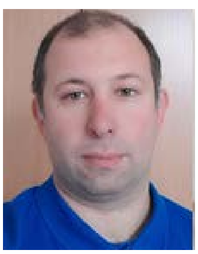

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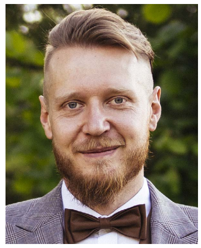

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