Development of an Electronic Nose for Smell Categorization Using Artificial Neural Network

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***Abstract*—Electronic Nose employs an array of gas sensors and has been widely used in many specific applications for the analysis of gas composition. In this study, electronic nose, integrating ten MQ gas sensors, is intended to model olfactory system which generally classifies smells based on ten basic categories namely: fragrant, sweet, woody/resinous, pungent, peppermint, decaying, chemical, citrus, fruity, and popcorn using artificial neural network as its pattern recognition algorithm. Initial results suggest that four (Pungent, Chemical, Peppermint, and Decaying) among the ten classifications are detectable by the sensors commercially available today while technology for classifying the remaining six is still under development. Meanwhile, results provided by this study affirm that electronic nose indeed displays a potential of modelling olfactory system.**

***Index Terms*—electronic nose, MQ gas sensors, artificial neural network, pattern recognition**

I. Introduction

The olfactory system is one of the most important sensory systems. It includes one of the most primal parts of the brain. In fact, among all senses, the sense of taste and smell display a distinctive property as they are referred to as “chemical sensors” because the messages they send to the brain come in the form of chemicals found in the surrounding environment. Unique as they are, the senses of taste and smell are nonetheless intimately entwined. But smells, unlike tastes, can be detected from a distance which provide signals or even advanced warnings to the brain about a particular matter being sensed before we actually put it into our bodies.

Olfaction manifests an innate sophistication that it exhibits both high sensitivity for odors and high discrimination between them. The sense of smell has always been considered as one of the most intelligent sense humans and other living things have but it remains vague even up to this modern time. As the most volatile sense, it is not surprising that there is as yet no proper understanding of how smell perception works [1]. The mechanism for olfactory system has not been widely studied [2]. This subject opens a room for work which is connecting distinct biological attributes with hardware, as well as capturing the odor fingerprint using pattern recognition algorithm and integrating multi-sensor array therefore creating an artificial olfactory system which we technically refer to as electronic nose [3].

Artificial olfaction had its beginnings with the invention of the first gas multi-sensor array in 1982 [4]. From this, several works have been done in the past attempting to mimic the mammalian olfactory system employing different methods. J. White *et al.* (1998) used an array of fiber-optic chemosensors and sent the outputs of the sensors to an olfactory bulb [5]. They then used a delay line neural network to perform recognition. In the year 2000, a study conducted by S Schiffman *et al.* shows that an electronic nose consisting of 15 metal-oxide sensors can be used to detect and classify bacteria and fungi by measuring odor in air samples [6]. The aforementioned ability of this device to categorize bacteria and fungi is made possible because all of the sensor response patterns are digitized and recorded using a National Instruments® Data Acquisition Card controlled by LabVIEW®. Another successful study, this time concerning a significantly different application, was conducted by Mahdi Ghasemi-Varnamkhasti *et al.* (2009) describing the applications of electronic nose systems for meat quality assessment using sensor array technology and artificial neural network [7]. The technology of artificial olfactory system has continuously been advancing up to present. In fact, recent studies include a bioinspired neural network that contains olfactory sensing neurons, mitral cells, and granule cells. Ya-Qi Jing *et al.* (2016) proposed a method that can directly use the raw data collected from sensors in the electronic nose without any signal preprocessing, feature selection, or reduction and it aims to replace the traditional data processing method in e-nose which have been designed in the past years. The said study is primarily focused on the classification of Chinese liquor [8].

Basically, incorporating ANN to electronic nose devices makes them intelligent. Analyzing complex data and recognizing patterns through Artificial Neural Networks (ANNs) shows promising results in chemical vapor recognition [9]. Due to the simplicity of its feed forward calculations, unknown chemical can be rapidly identified in the field. For this reason, many artificial neural network configurations and training algorithms have been used in electronic or artificial noses nowadays. [10], [11].

Manuscript received May 26, 2020; revised November 24, 2020.

doi: 10.12720/jait.12.1.36-44

Among those e-nose technologies with the application of ANN are intelligent gas-monitoring system used to detect the pollution at vehicle exhaust and later on informs the user about the concentration of carbon monoxide and hydrocarbons by Chote and Ugale (2012) and an electronic nose classifying fruits with four different aroma data (strawberry, lemon, cherry, and melon) using artificial bee colony algorithm others discussed above [12]. Electronic nose using ANN is also utilized in agriculture. The system, which focuses specifically on the classification of the odor of aromatic herbs, consists multi-sensor, five TGS-series sensors, gas array which detects gas through an increase in electrical conductivity when reducing gases are absorbed on the sensor's surface [13].

All the above-mentioned developments in the electronic nose industry explicitly show that the room for improving this technology is still spacious. Having realized that present technologies are focused on specific applications such as analyzing the ripeness of fruits, classification of liquor, analysis of body fluids [14], [15], etc., this paper aims to develop a device that will classify odors of all types into ten basic categorizations presented by the study conducted by Castro *et al.* (2013) [16]. This device shall incorporate Artificial Neural Network as its pattern recognition algorithm to meet the objective of creating a device that is learned to identify odor into most basic classifications.

This ten largest- valued adjective descriptor for odors includes fragrant, woody/ resinous, fruity (non-citrus), chemical, minty/peppermint, sweet, popcorn, lemon, pungent, and decayed. The group applies Stochastic Neighboring Embedding (SNE) in order to obtain 8 discrete and non-overlapping clusters of the 146 descriptors. Similarly, applying SNE to the space of odorants, they obtained 10 discrete and non-overlapping clusters of the 144 odors shown in Fig. 1. A list of odorants present for all ten categories of smell is shown in Table I.

Cluster 1

Aldehyde C-16, Allyl Caproate, iso-Amyl Acetate, Amyl Butyrate, Dimethyl Benzyl Carbinyl Butyrate, Ethyl Butyrate. Ethyl Propionate, Fructone, Methyl Anthranilate, Undecylenic Acid, gamme-Valerolactone

Cluster 2

Amyl Phenyl Acetate, Auralva, iso-Bornyl Acetate, Cashmeran, Dimethyl Phenyl Ethyl Carbinol, Hydroxy Citronellal, Indolene, beta-Ionone, apha-Irone, Lyral, Methoxy-Naphthalene: 2-Methoxy, Naphthalene, Methyl Acetaldehyde Dimethyl Acetal, Musk Galaxolide, Musk Tonalid, Phenyl Ethanol, Sandiff, Santalol

Cluster 3

dl-Camphor, l-Carvone, p-Cresyl Acetate, Eucalyptol, l-Menthol, Methyl Salicylate, Safrole

Cluster 4

Amyl Cinnamic Aldehyde Diethyl, Acetal, Citral, Citralva, Floralozone, Hexyl Cinnamic Aldehyde, Linalool, d-Limonene, Melonal, Myracaldehyde

Cluster 5

Anisole, 1-Butanol, m-Cresol, p-Cresol, p-Cresyl-iso-Butyrate, p-Cresyl Methyl Ether, Cyclohexanol, 2,5-Dimethyl, Pyrazine, Diola, Diphenyl Oxide, 1-Heptanol, 1-Hexanol, 3-Hexanol, Iodoform, Methyl Furoate, para-Methyl Quinoline, Nonyl Acetate, 1-Octanol, Phenyl Acetylene, Terpineol, Tetraquinone, Thymol, Toluene

Cluster 6

Adoxal, Andrane, iso-Butyl Quinoline Chlorothymol, Iso-Cyclocitrall, Cyclotropal, Decahydro Naphthalene, Dibutyl Amine, Grisalva, Hexanal, Hydratropic Aldehyde Dimethyl Acetal, 2-Methyl-iso Borneol, Methyl iso-Nicotinate, Nootkatone, 1-Octen-3-OL, iso-Phorone, alpha-Pinene, iso-Propyl Quinaline, propyl Sulfide, gamma-Undecalactone

Cluster 7

Abhexone, Acetophenone, Aldehyde C-18, Anethole, Benzaldehyde, Dihydro Pyrone, Caryophyllene (beta and gamme Isoners), Celeriax, Cinnamic Aldehyde, Coumarin, Cuminic Aldehyde, Eugenol, Furfural, trans-1 Hexenal, ortho-Tolualdehyde, Vanillin

Cluster 8

Ortho-Acetyl Pyridinem Cyclotene, 2,4-trans-trans-Decadienal, 2,3-Dimethyl Pyrazine, 2,5-Dimethyl Pyrrole, 2-Ethyl Pyrazine, Furfuryl Mercaptan, Guaiacol, Heptanal, Thienopyrimidine, Zingerone

Cluster 9

Butyl Sulfide, Cyclodithalfarol, 2-Cyclohexanedione, Diethyl Sulfide, Dimethyl Trisufide, Hexyl Amine, Pyridine, Tetrahydro, Thiophene, Thioglycolic Acid, Thiophene

Cluster 10

Amyl Valerate, Butonic Acid, Hexanoic acid, Hexyl Amine, Indole, Maritima, Methyl Thiobutyrate, Pentanoic Acid, 4-Pentenoic Acid, Phenyl Acetic Acid, Propyl Butyrate, Skatole, Trimethyl Amine, iso-Valeraldehyde, iso-Valeric Acid

Figure 1. Two-dimensional embedding of the descriptor-space using ten clusters.

TABLE I. LIST OF COMPOUNDS IN EVERY CLUSTER IDENTIFIED FROM NON-MATRIX FACTORIZATION (NMF)

Cluster 1	Cluster 2	Cluster 3
1. Isoamylphenylacetate, 2. Aurantiol, 3. 6,7-dihydro-1,1,2,3,3-pentamethyl-4-(5H)indanone, 4. Indol-hydroxycitronellal, 5. beta-ionone (low concentration), 6. beta-ionone (high concentration), 7. N'-[(E)-3-(5-methoxy-2, 3-dihydro-1,4-benzodioxin-7-yl) prop-2-enoyl]-2,3-dihydro-1,4-benzodioxine-3-carbohydrazide, 8. hydroxyisohexyl 3-cyclohexene carboxaldehyde, 9. 2-methoxynaphthalene, 10. Diethoxymethane, 11. Galaxolide, 12. ethylenebrassylate, 13. Phenylethyl Alcohol (low concentration) 14. Phenylethyl Alcohol (high concentration)	15. Cedrene epoxide, 16. bornyl acetate, 17. 8-sec-Butylquinoline, 18. 2,4,6-trimethylcyclohex-3-ene-1-carbaldehyde, 19. decalin, 20. dibutylamine, 21. Synthetic amber, 22. 1,1-Dimethoxy-2-phenylpropane, 23. Methyl isonicotinate, 24. Nootkatone, 25. 1-octen-3-ol, 26. isophorone (low concentration), 27. isophorone (high concentration), 28. Isopropyl quinolone, 29. Argeol, 30. Gamma-undecalactone, 31. 10-undecenoic acid	32. ethylmethylphenylglycidate (low concentration) 33. ethylmethylphenylglycidate (high concentration) 34. allylcaproate, 35. isoamyl acetate, 36. n-amyl butyrate, 37. Dmbc butyrate, 38. ethyl butyrate, 39. ethyl propionate, 40. Fructone, 41. methylanthranilate, 42. Pentylvalerate

Cluster 4	Cluster 5	Cluster 6	Cluster 7
43. Butyric Acid 44. hexanoic acid 45. indole 46. methylthiolbutyrate 47. n-pentanoic acid 48. 4-pentenoic acid 49. 50. . phenylacetic acid 51. Propyl butyrate 52. Skatole (3-Methyl-1H-indole) 53. Isovalerylaldehyde 54. isovaleric acid	55. Acetophenone 56. Anisole 57. 1-Butanol 58. 4-cresol 59. p-Tolylisobutyrate 60. 4-methyl anisole 61. cyclohexanol 62. 2,5-dimethylpyrazine 63. methyl hexyl ether 64. 1-hexanol 65. 3-hexanol 66. iodoform 67. methyl furan-3-carboxylate 68. 4-methylquinoline 69. phenylacetylene 70. alpha-terpineol 71. 6-methyl-1,2,3,4-tetrahydroquinoline 72. Thymol 73. Toluene 74. 3-Methyl-1H-indole	1. Anethole 2. 8-sec-Butylquinoline 3. carvone 4. caryophyllene 5. 4-cresyl acetate 6. eucalyptol 7. Eugenol 8. Menthol 9. methyl salicylate 10. Safrole	11. Abhexon 12. Gamma-nonalactone 13. Benzaldehyde 14. 3,4-dihydrocoumarin 15. 3-Propylidene phthalide 16. cinnamic aldehyde 17. coumarin 18. cyclotene 19. Furaldehyde 20. 2-hexenal 21. 2-methylbenzaldehyde 22. gamma-valerolactone

Cluster 8	Cluster 9	Cluster 10
23. Vanillin 24. 2-acetylpyridine 25. 2,4-decadienal 26. Pyrazine 27. methyl hexyl ether 28. 2,5-dimethylpyrrole 29. Ethylpyrazine 30. Ethylpyrazine 31. Heptanal 32. n-hexanal 33. 1-Octanol 34. 2-methyl-5,7-dihydrothieno[3,4-d]pyrimidine	35. Zingherone 36. dibutyl sulfide 37. Chlorothymol 38. 2-Mercaptopropanone 39. 1,2-cyclohexanedione 40. diethyl sulfide 41. dimethyltrisulfide 42. furfurylmercaptan 43. Guaiacol 44. Hexylamine 45. Hexylamine 46. AC1L18DS	47. polythiophene 48. Adoxal 49. Amyl cinnamic aldehyde diethyl acetal 50. Citral 51. Geranonitrile 52. Cuminaldehyde 53. 4-Methyl-2-(1-phenylethyl)-1,3-dioxolan 54. 2-Methyl-4-phenylbutan-2-ol 55. phenyl ether 56. Floralozone 57. Heptanol 58. hexylcinnamic aldehyde 59. hydroxycitronellal 60. linalool 61. limonene 62. Melonal 63. Myrac aldehyde 64. n-Nonyl acetate

This figure shows the clustering of smell using the two-dimensional embedding of the descriptor-space of odor. Ten clusters of odor and type of chemicals falling under these categories are presented in the figure.

The electronic nose system, an application-based prototype, must be capable of categorizing a given ambient smell through the use gas sensors employing artificial neural network, integrate ten MQ gas sensors in a compact electronic nose prototype that will mimic the mammalian olfaction system, classify the odor of a given sample object under the ten basic smell categorization (Chemical, Citrus, Decaying, Fragrant, Fruity, Peppermint, Popcorn, Pungent, Sweet, Woody/Resinous), assess the working performance of the electronic nose prototype in smell categorization using MATLAB embedded application for artificial neural network that includes obtaining the cross-entropy error during the training period, computing for the confusion matrix in the validation period and measuring precision, recall and F-measure during the testing period.

This table shows the compounds presents in each ten clusters of smells: Fragrant, Sweet, Woody/Resinous, Pungent, Peppermint, Decaying, Chemical, Citrus, Fruity, and Popcorn.

II. Artificial Neural Network

An Artificial Neuron Network (ANN) is a computational model based on the structure and functions of biological neural networks. Information that flows through the network affects the structure of the ANN because a neural network changes - or learns, in a sense - based on that input and output. A common type of artificial neural network consists of three groups, or layers, of units: a layer of input units is connected to a layer of hidden units, which is connected to a layer of output units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weight on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units. In this type of network, the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents [17].

An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward neural network that has been trained accordingly.

During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern [18], [19].

III. Methodology

The study focuses on the development of a portable olfactory system modeling employing an ANN algorithm for pattern recognition and modeling. Fig. 2 shows the conceptual framework summarizes the input parameters, the processes done in the study and the expected output of the system. The input of the project is gathered from the different gas sensors sensitive for a range of gasses at room temperature. The data is telemetered to a server via short-range wireless communication where it is processed by the artificial neural network for pattern recognition. The output of the system is a categorization of the smell of the sample input to the system.

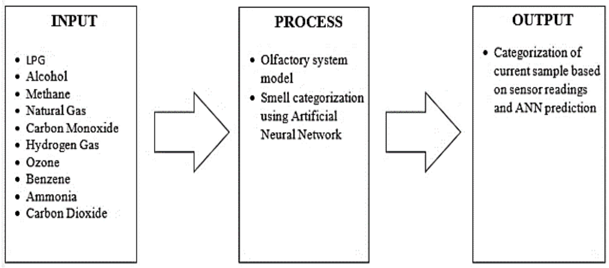

Figure 2. Conceptual framework of the study.

The figure shown is divided into three parts: input, process and output.

The overall system block diagram is shown in the Fig. 3. The electronic nose, consisting of different sensors will measure gas concentration of input sample. The sensors send the readings through a radio frequency transmitter module. The radio frequency transmitter and receiver module are in-charge of the short-range wireless communication between the electronic nose and the personal computer. The output category of smell will be displayed in a graphical user interface.

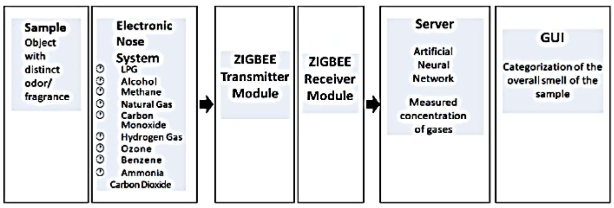

Figure 3. Overall block diagram of the system.

The block diagram is distributed into three main parts.

The electronic nose prototype, as shown in Fig. 4, consists of an enclosure box to encase and protect the electronic parts of the prototype which includes the microprocessors and the built-in sensors and is intended to hold all the peripherals together, flask port for placing and holding an Erlenmeyer flask, with which the different substances are contained, touch panel to serve as an input transducer and a visual output display for the users, and sensors for the proper implementation of the prototype.

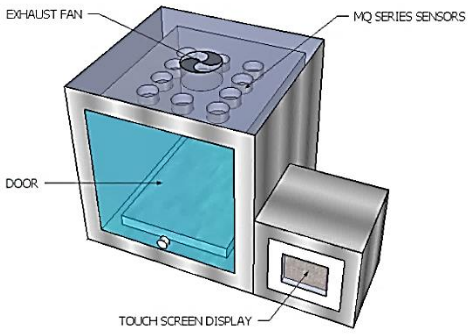

Figure 4. Electronic nose prototype.

This figure presents the proposed electronic nose with its main parts: gas sensors, door, touch screen display and exhaust fan

Table II shows the 10 MQ Gas sensors used in the system, carefully calibrated to accurately detect smells based on the designed categories.

TABLE II. MQ GAS SENSORS USED IN THE PROTOTYPE

Sensor	Gas detected
MQ2	LPG, i-butane, propane, methane, alcohol, Hydrogen, smoke
MQ3	Alcohol
MQ4	CH4, Natural gas
MQ5	LPG, Natural gas, town gas
MQ6	LPG, iso-butane, propane
MQ7	Carbon Monoxide
MQ8	Hydrogen
MQ9	Carbon Monoxide and CH_4
MQ135	NH3,NOx, alcohol, Benzene, smoke,CO2
MQ138	n-Hexane, Benzene, NH3, alcohol, ,smoke, CO

Fig. 5 basically shows the sequence of events during the training mode. Therefore, this explains how the neural network is trained to identify the classification of smell.

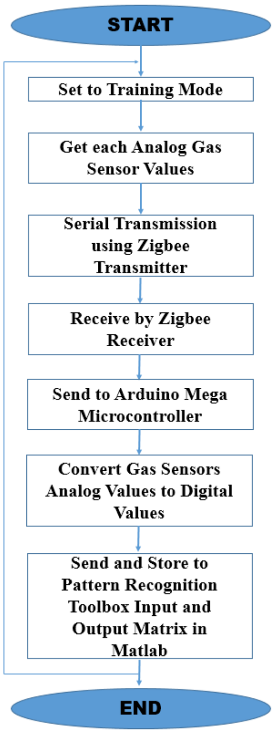

Figure 5. Software flowchart: Training mode.

This figure shows the flow of events during the training mode

IV. TESTING AND RESULTS

The data sets involved in classifying the smell into ten categories has 753 samples. The categorical attributes such as the concentration of different gases detected by each gas sensors are considered for classification. Gases detected includes Smoke, Hexane, Alcohol, LPG, Propane, Carbon Monoxide, Hydrogen, Methane, Ammonia and Benzene. The neural network for the classification of smell into ten categories using the electronic nose is shown in Fig. 6.

There are ten inputs in the electronic nose suggesting that there are ten different gases obtained by different gas sensors that serves as input to the electronic nose. The number of hidden layers and output layers are ten, default number of hidden layers of the MatLab software. The ten outputs represent the ten classifications of smell namely Chemical, Citrus, Decaying, Fragrant, Fruity, Peppermint, Popcorn, Pungent, Sweet, and Woody.

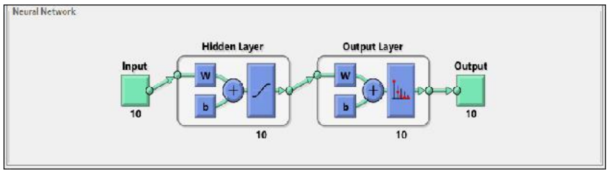

Figure 6. Neural network for classifying the smell into ten categories.

This figure presents the neural network and the number of inputs, hidden layers, output layers and outputs which are 10, 10, 10, and 10 respectively.

Samples in the training, validation and testing are in the ratio of 70:15:15 as shown in Fig. 7. The number of samples in the training, validation and testing are 527, 113 and 113, respectively. The lowest value of cross entropy obtained during the training period is 2.26% as presented in Fig. 7. A cross-entropy error of less than one percent is proposed to serve as a stopping condition in training the electronic nose.

It is noted in the study that if %CE of the training is greater than one percent, the system will be retrained, adding more samples, until the required cross entropy error is reached. Yet, during the training period, the cross entropy error heavily penalizes outputs that are extremely inaccurate with very little penalty for fairly correct classifications and since the difference in the output analog voltage of the gas sensors are very little, this cross entropy error tends to allow very small errors to change weights even when nodes saturate and thus the proposed one percent cross entropy error is hard to obtain if ten classifications of smell are to be trained.

Fig. 8 shows the confusion matrix for the classification of smells into ten categories and Table III presents the standard metrics values of accuracy, precision, recall and F-measure computed on confusion matrix for the classification of smell into ten categories with predictive parameters. Based on the matrix, four classifications of smell have always the highest number of samples that are correctly categorized namely Chemical (10.4% of the total samples), Peppermint (7.8% of the total samples), Decaying (9.4% of the total samples) and Pungent (9.2% of the total samples).

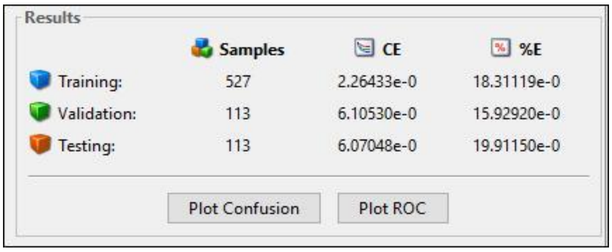

Figure 7. Number of samples in categorizing smell into ten classifications.

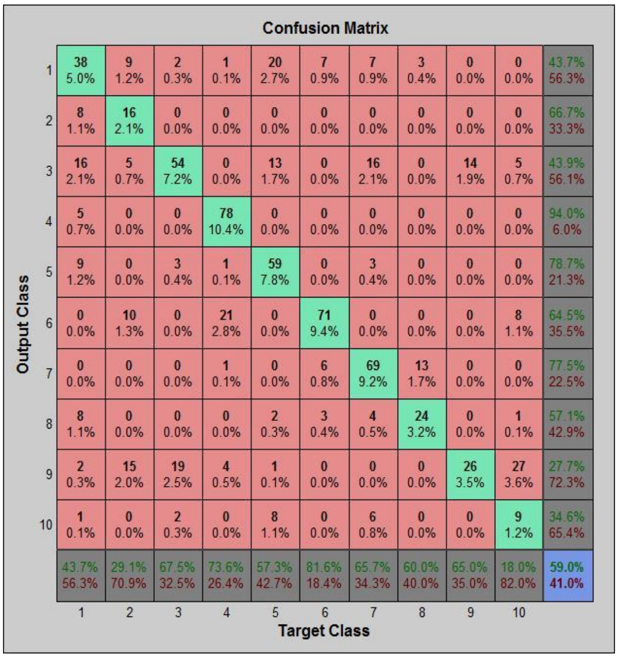

Figure 8. Confusion matrix for the classification of smell into ten categories.

The classification recalls of these four categories are respectively 94.0%, 78.7%, 64.5%, and 77.5% while their precision percentage are respectively 73.6%, 57.3%, 81.6%, and 65.7%. Using the precision and recall percentage values shown in the gray cells in the last row and rightmost column of the matrix respectively, the computed F-measure of these four categories are respectively 82.54%, 66.29%, 72.08% and 71.13%. Despite Precision and Recall are valid metrics in their own right, one can be optimized at the expense of the other and therefore, F-Measure was used.

The prediction failed in six cases. This includes Fragrant (5% of the total samples), Woody (2.1% of the total samples), Fruity (7.2% of the total samples), Citrus (3.2% of the total samples), Popcorn (3.5% of the total samples), and Sweet (1.2% of the total samples). The prediction of the device is unsuccessful in six classifications of smell, particularly, Fragrant and Sweet were predicted as Peppermint, while Woody, Fruity and Citrus were expected as Fragrant. Concerning the classification of smell prediction, in most of experimental proofs the electronic nose was able to correctly associate the data in input with the actual concentrations in input.

Results show that the overall accuracy of the electronic nose when it is used in classifying the smells into ten categories is only 59.0 %, very low enough to categorize the ten classifications. Table III suggests that the four classifications of smell: Chemical, Peppermint, Decaying and Pungent which have the highest number of samples that are correctly categorized also registers high values of F-measure. With this, the proposed electronic nose is only adequate and limited to classify only the four categories of smell: Chemical, Peppermint, Decaying and Pungent.

TABLE III. STANDARD METRICS VALUES OF ACCURACY, PRECISION, RECALL AND F-MEASURE COMPUTED ON CONFUSION MATRIX IN FIG. 8 PREDICTIVE PARAMETERS

Class Test	TP	TN	FP	FN	Recall (%)	Precision (%)	F-Measure (%)
1 Fragrant	38	406	49	49	43.68	43.68	43.68
2 Woody	16	428	8	39	66.67	29.09	40.51
3 Fruity	54	390	69	26	43.9	67.5	53.2
4 Chemical	78	366	5	28	93.98	73.58	**82.54**
5 Peppermint	59	385	16	44	78.67	57.28	**66.29**
6 Decaying	71	373	39	16	64.55	81.61	**72.08**
7 Pungent	69	375	20	36	77.53	65.71	**71.13**
8 Citrus	24	420	18	16	57.14	60	58.54
9 Popcorn	26	418	68	14	27.66	65	38.81
10 Sweet	9	435	17	41	34.62	18	23.69
						ACCURACY:	**59.0%**

Another test was then conducted and the electronic nose will only classify the four classifications of smell that have the highest F-measure. The neural network for the classification of smell into ten categories using the electronic nose is shown in Fig. 9. There are ten inputs in the electronic nose since there are ten different gases to be obtained by different gas sensors. The number of hidden layers and output layers are ten and four respectively, default number of hidden layers of the MatLab software. The ten outputs represent the four classifications of smell namely Chemical, Peppermint, Decaying and Pungent.

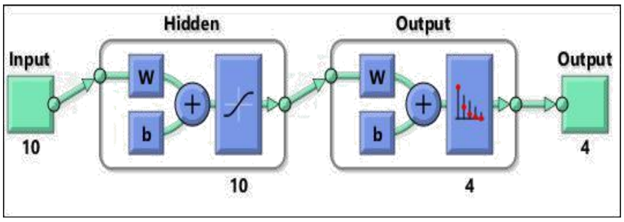

Figure 9. Neural network for classifying the smell into four categories.

Fig. 10 shows the number of samples in the training, validation and testing stage while Fig. 11 shows the result confusion matrix for the classification of smells into only four categories. Samples in the training, validation and testing are in the ratio of 70:15:15 as shown in Fig. 7. The number of samples in the training, validation and testing are respectively, 678, 146 and 146.

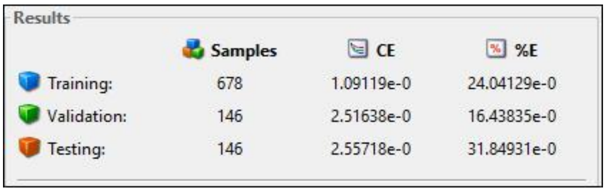

Figure 10. Number of samples used in the training, validation and testing of electronic nose in categorizing smell into four classifications.

When the number of classifications of the electronic nose is reduced from ten classifications to only four classifications, the value of cross entropy obtained during the training period was reduced from 2.26% to 1.09%. A cross-entropy error of less than one percent is proposed to serve as a stopping condition in training the electronic nose. It is noted that the %CE of the training is near one percent and thus the expected value for cross entropy error in training period is obtained.

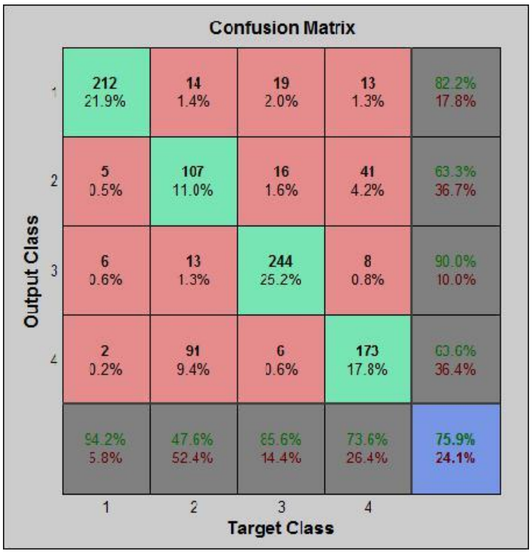

Figure 11. Confusion matrix for the classification of smell into four categories with predictive parameters.

The classification recalls of Chemical, Peppermint, Decaying and Pungent are respectively, 82.2%, 63.3%, 90% and 63.6% while the classification precision metric value percentage are respectively, 94.2%, 47.6%, 85.6% and 73.6%. Using the precision and recall percentage values shown in the gray cells in the last row and rightmost column of the matrix respectively, the computed F-measure of these four categories, shown in Table IV, are respectively 87.78%, 54.32%, 87.77% and 68.24%. Despite Precision and Recall are valid metrics in their own right, one can be optimized at the expense of the other and therefore, F-Measure was used.

Results show that the overall accuracy of the device when it is used in classifying odor into four categories increased to 75.9%, good enough to categorize the four classifications of smells. It is noted that the Chemical and Decaying smell have both high recall (82.17% and 94.22% respectively) and high precision (94.22% and 85.61% respectively) in classifying the smells as shown in Fig. 11 and in Fig. 12.

TABLE IV. STANDARD METRICS VALUES OF ACCURACY, PRECISION, RECALL AND F-MEASURE COMPUTED ON CONFUSION MATRIX IN FIG. 11 PREDICTIVE PARAMETERS. THE FIGURE SHOWS THAT CHEMICAL AND DECAYING SMELL HAVE BOTH HIGH RECALL (82.17% AND 94.22% RESPECTIVELY) AND HIGH PRECISION (94.22% AND 85.61% RESPECTIVELY)

Class Test	TP	TN	FP	FN	Recall (%)	Precision (%)	F-Measure (%)
1 **Chemical**	212	524	46	13	82.17	94.22	**87.78**
2 Peppermint	107	629	62	118	63.31	47.56	54.32
3 **Decaying**	244	492	27	41	90.04	85.61	**87.77**
4 Pungent	173	563	99	62	63.6	73.62	68.24
						ACCURACY:	**75.9%**

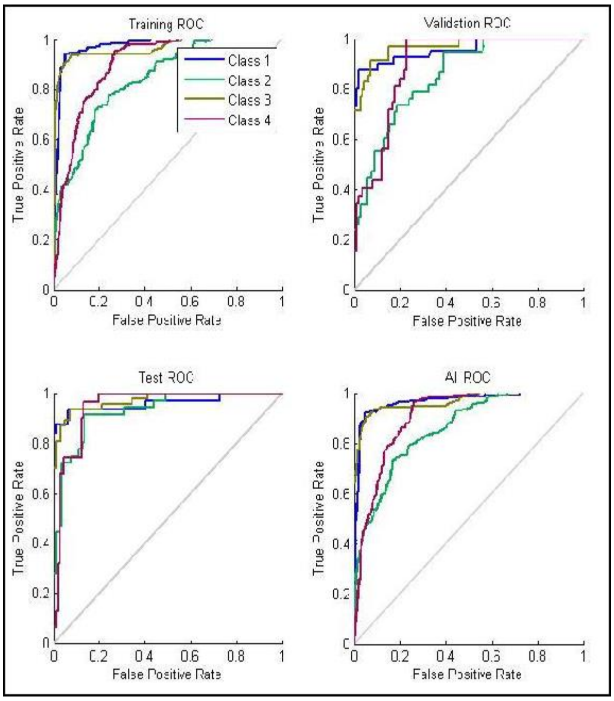

Figure 12. Receiver Operating Curve (ROC) for classification of smell into four categories using the electronic nose.

The figure presents the graph between precision and recall. Based on the graph, Chemical and Decaying smells have high area under the curve which means a high F-measure, a good indicator that e-nose can classify the chemical and decaying smells.

V. CONCLUSION

In this paper, the researcher proposed and presented a portable electronic nose for olfactory system modeling using artificial neural network. A prototype was made to test the feasibility and effectiveness of the proposed system. Amongst the past and already existing electronic nose, the researcher strived to integrate 10 MQ gas sensors and try to categorize smell according to its 10 basic classifications namely: Fragrant, Woody/Resinous, Fruity, Chemical, Minty/Peppermint, Sweet, Popcorn, Lemon, Pungent, and Decaying. It is also important to note that the system employs MatLab as its software tool for pattern recognition algorithm development.

The system has undergone intensive training in order to meet the objective of classifying smells into ten basic classifications. Several samples for each category were used to train and test the artificial neural network. Through repetitive training and testing, it has been apparent that the system was only able to categorize smell with strong and distinct odor specifically those belonging to the class under Pungent, Decaying, Peppermint and Chemical. The remaining six classifications: Sweet, Fragrant, Popcorn, Fruity, Citrus and Woody/Resinous, registered very small variations in the sensor's reading which resulted in ANN confusion and misclassification. Conclusively, this consideration is mainly due to the fact that today's exceedingly advanced sensors which will be of great help in the overall improvement of the prototype's working performance are not yet commercially available and are still in their earliest stage of development.

From this results, the researcher opted to focus the classification of smell according to whether the sample is Pungent, Decaying, Peppermint or Chemical. This adjustment in the prototype training and testing yielded a more acceptable classification and validation result with computed F-measure values of 68.24%, 87.77%, 54.32%, and 87.78%, respectively.

VI. Recommendation

The researcher of this study highly suggests the utilization and integration of the most advanced sensors available in the market to further enhance the ability of the prototype to classify odors with increased accuracy. The type of technology that the sensor will employ, along with the gases and chemical compositions that it will be able to detect, will allow for a more enhanced electronic nose model that can respond to a wider array of samples with varied scents.

For future researches of the same endeavor, it is of utmost importance to take into great consideration the ambient temperature of the room where the training and testing will be conducted. Electronic nose employing gas sensors performs more efficiently in a warmer environment.

In considering the creation of the portable electronic nose prototype of the same built, it is upon the researcher's recommendation that the materials to be used for the inside chamber where the samples will be tested and the exhaust fan for releasing the fumes should be of an odorless and smell-proof material. It is also recommended that an additional feature notifying the user that the system is ready to classify samples be made to prevent the user from prematurely instructing the system to classify which may then result in the misclassification of the sample.

In addition, implementing a software filtering method in the system program is expected to help future researchers in significantly improving their device's ability to classify smell by reducing the noise in the analog data sensor reading.

Lastly, the future researchers are highly encouraged to pursue further studies on technological advancement of electronic nose especially on the classification of the remaining six categories: Sweet, Fragrant, Popcorn, Fruity, Citrus and Woody/Resinous in the coming years as it was projected that the electronic nose industry will dramatically expand by 2020.

Conflict of Interest

The authors declare no conflict of interest.

Authors Contributions

D. D. Macasaet conceptualized the subject of the research, developed the prototype, performed the experiment, extracted and analyzed data, developed the algorithm, and wrote the research paper; A. A. Bandala, E. P. Dadios, and A. C. Illahi helped in the development of the research topic; S. C. Lauguico and J. D. Alejandrino performed data collection and analysis.

Acknowledgement

This study is supported by the Engineering Research and Development Technology (ERDT) of the Department of Science and Technology (DOST) of the Philippines and the De La Salle University (DLSU) Intelligent Systems Laboratory.

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