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RESEARCH ARTICLE

Investigation of Harmful Substances to Health Using Electronic Nose and Weight Elimination Algorithm With Correlative Gaussian Function

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ABSTRACT Humans can be exposed to various substances that could either contribute, cause, or catalyze illness. Electronic Nose can be used to detect presence of such elements in excess in human body, through smelling of human breath, skin, or body fluid samples. The objective of this project is to implement a simple, low cost, and portable E-Nose that can be used to detect substances, such as, acetone, ammonia, alcohol, which contribute to Diabetes and Kidney Failure, among other elements, which could cause illness, or support further effect of the illness on human daily life. The main feature of the presented nose in this work, which uses Arduino hardware, is the intelligent Neural Networks software with Correlative Gaussian interpolation function. This function is used together with the Weight Elimination Algorithm (WEA) to enable smart classification of detected substances. The WEA works similar to genetic algorithm in the way it eliminates weak weights and links. Together with Correlative Gaussian, a Correlative Weight Elimination Algorithm is produces (CWEA). Such intelligent discrimination technique allowed not only to detect and classify chemicals in a single substance, but also, to detect and classify the same element and its overall effect in multiple substances. The obtained results are promising, with better results, and possibility of covering more substances, is applicable using higher level and integrated sensors.

INDEX TERMS E-nose, signal processing, Arduino, neural networks, Gaussian interpolation, illness, discrimination, classification.

I. INTRODUCTION

There many studies being done to better understand human sensory systems. These initiatives have resulted in important developments that make it possible to utilize chemical sensors in different designs to imitate these mechanisms. It is now possible to digitize human complex sensory systems, including the olfactory system [1], [2].

The senses of taste and smell are mostly utilized to identify flavors. However, a key element in identifying and differentiating the flavors of various items is the olfactory sense. Hundreds of other chemicals, including as the combustion byproducts nitrogen dioxide (NO2), sulfur dioxide (SO2), carbon monoxide (CO), and a number of volatile organic compounds (VOCs), are also commonly present inside. Some of these substances, like NO2 and CO, are extremely harmful even at very low quantities. Additionally, formaldehyde (CH2O) and benzene (C6H6) are thought to be carcinogenic. Therefore, keeping the conditions safe and healthy depends on regular monitoring of such substances. A biomimetic olfactory system known as artificial olfaction can safeguard people and enhance quality of life by identifying illnesses [3], [4].

Now that artificial sensing technology has advanced, it is conceivable to simulate some of the functions of human olfaction. Electronic noses (E-Noses) are particularly interesting since they have the ability to identify chemical alterations in the composition of chemicals, air or gases. The E-nose technology is based on the identification of gases, volatile organic compounds (VOCs), or their mixes based on their chemical characteristics [5], [6], [7].

Electronic nose devices have received a lot of attention from sensor technology during the past twenty years, in part due to the discovery of several applications as a

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result of research in various applied sciences. Electronic nose technologies are now being used as a result of recent developments in advanced sensor design and material technology together with software innovation and electronic circuitry developments [8], [9].

The term ''E-nose'' refers to a device that consists of a number of cross-reactive gas sensors and pattern identification software. It relies on the individuality of each sensor in the array, which makes each sensor's response to an odor unique within the array. The pattern recognition software is then taught the sensor responses related to a certain fragrance source. This operating principle aims to mimic the function of organic olfactory receptors by identifying a complex pattern [10], [11].

Electronic nose systems can be used in a wide range of applications such as agriculture [12], [13], [14], [15], [16], [17], environmental monitoring [18], [19], [20], food [21], [22], [23], [24], [25], [26], quality control [27], [28], [29], [30], [31], military [24], [32], [33], and medical applications [34], [35], [36], [37], [38], [39], [40], [41] like pharmaceutical, biomedical, disease and illness early detection, cosmetics, and numerous scientific research domains.

In contrast to the conventional molecular recognition approach to chemical sensing, the E-Nose's recognition principles are based on spread pattern processing, which is connected to the brain and olfactory bulb. Thus, an intelligent chemical sensing system with array of sensors that mimics the mammalian olfactory system, is the model to achieve. The essential parts of the e-nose are a chemical sensor array, electronic interface circuitry, and data processing and pattern recognition software [12], [13], [14], [15].

The e-nose is made up of a number of sensors, each of which reacts differently to the volatiles released. One processing system receives a pattern that is generated by this reaction. The sensors' attributes must be specific for each volatile substance. The chemiresistive sensors are used in an integrated e-nose because of their straightforward electrical characteristics and interface circuitry [16], [17].

Electronic nose systems can be used in a wide range of applications such as agriculture [18], [19], [20], [21], [22], [23], environmental monitoring [24], [25], [26], food [27], [28], [29], [30], [31], [32], quality control [24], [33], [34], [35], [36], military [37], [38], [39], and medical applications [40], [41], [42], [43], [44], [45], [46], [47] like pharmaceutical, biomedical, disease and illness early detection, cosmetics, and numerous scientific research domains.

Breath analysis is an important technique in medical examination and diagnosis, since it analyzes the composition of exhaled human breath and the levels of both organic and inorganic chemicals within the breath. It is possible to investigate processes and identify pathological conditions by evaluating a breath sample since there is a direct correlation between the makeup of exhaled air and a number of metabolic activities taking place in the human body [41], [48], [49], [50], [51], [52], [53], [54]

Changes in the molecules' concentration in volatile organic compounds may indicate a number of disorders, or alterations in metabolism. Several molecules, including nitric oxide, isoprene, pentane, benzene, acetone, and ammonia, may indicate specific diseases. Thus, smelling or sniffing chemical compounds either through breath or by smelling samples from within the human body can result in early diagnosis of illness and identification of diseases [20], [55], [56], [57], [58], [59], [60], [61].

In this work, a low cost Metal Oxide Semiconductor (MOS) chemical sensors system with Neural Networks recognition and classification system is designed and employed in correlating food substances to medical cases and illness. This pattern recognition and correlation is used to enable early warning of patients suffering from symptoms associated with increase in ammonia, acetone, and other chemicals, which could lead to cancer or diabetes. Therefore, the main objective of this research is to design a device that aids medical personnel in initial diagnostics of diseases related to food ingredients.

The rest of this paper is divided as follows:

Methodology: Where main objective and system components are described, together with the mathematical model for the correlative and intelligent classification system, **Results and Discussion**: presentation of numerical data and analytical analysis is presented in this section, with emphasis on illness discrimination and correlation to food substance. The clear effect of weight elimination algorithm and the marked effect of Gaussian interpolation are highlighted in the discussion. **Conclusion:** summary of the achieved development of an economic, effective E-Nose system, andfinally **references.**

II. METHODOLOGY

Ammonia can be found in various fast foods at restaurants as well as being an indication of some disorders in people. Additionally, since its presence in food might have an impact on human health, it needs to be investigated and those who consume these items should be made aware of its side effects if they consume large quantities at regular times. This is where the electronic nose can be used as a tool to test for the presence or absence of excess ammonia using a variety of sensors.

The electronic nose technology and system, can use gases exhaled from the mouth to identify the type of disease or illness. Ammonia, which can be associated to types of illnesses can trigger a specific response from chemical sensors. Also, Nitric oxide, which is associated to bronchiectasis, airway inflammation, and chronic obstructive pulmonary disease, can be detected using chemical sensors as well.

Detection and correlation of certain substances to specific illnesses is accomplished using a matrix of sensors, each of which is designed to detect a particular gas or gases as presented in Figure 1.

The designed and implemented E-Nose system comprises the following components:

A. GAS SENSORS

Gas sensors or gas detectors are electronic devices that detect different types of gasses. Figure 2 shows the employed gas sensor, where the MQ135 sensor series is used, as it is capable

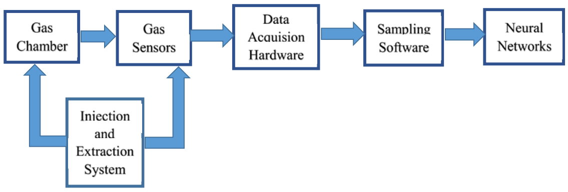

FIGURE 1. E-Nose System.

of detecting vapors from chemicals such as NH_3, NOx, Alcohol, Benzene, Smoke, and CO_2. The sensor has sensitivity from 10 ppm for Benzene and Alcohol to 100 ppm for NH_3 to a maximum of 300 ppm for Alcohol and NH_3, and 1000 ppm for Benzene. The MQ135 is a Metal Oxide Semiconductor (MOS) type Gas Sensor part of the chemiresistor family, since the detection is based upon change of resistance of the sensing material when the Gas interacts with sensor deposited film.

FIGURE 2. Chemical sensor on chip.

B. TEMPERATURE AND HUMIDITY SENSOR

The DHT11 shown in Figure 3 is used for temperature and humidity sensing, which is to be correlated to the value of detected gas or chemical, in order to obtain more accurate results. The sensor consists of two parts, capacitive humidity sensor and a thermistor. There is also a very basic chip inside that does some analog to digital conversion and outputs digital signals giving temperature and humidity data.

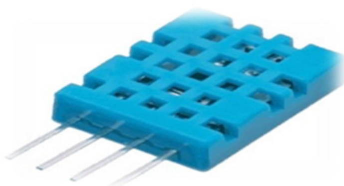

FIGURE 3. Humidity sensor.

C. DATA ACQUISITION HARDWARE

Figure 4 shows the interface hardware circuit (Arduino) used for data acquisition. Arduino is an open hardware development board that can be used to connect sensors to transfer sensor detected values into readable output signal. Arduino is a microcontroller board, It is connected to a computer or any mobile computing device. Arduino is a low-cost, flexible, and easy-to-use programmable open-source microcontroller board that can be integrated into a variety of electronic applications.

D. INJECTION AND EXTRACTION SYSTEM

Figures 5 to 7 show the components of the injection and extraction system used in the E-Nose testing system. The components are:

FIGURE 4. E-Nose hardware (arduino).

FIGURE 5. Nebulizer device.

FIGURE 6. Extraction fan.

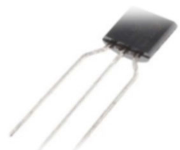

FIGURE 7. Switching transistor.

I. Nebulizer device: Coverts solvents to vapor. The Ross-Max nebulizer device, used to convert the solvent samples to vapor that flows and interacts with the surface of used sensors.
II. Fan: Used to extract gas out of the gas chamber so the sensor can recover faster and not saturate. The CAIZHU-FAN is 5V mini cooling brushless DC fan, used to prevent sensor overheating and to extract gas molecules, thus reducing sensor recovery time.
III. Switching Transistor: Used to switch the extraction system automatically

The designed system allows a combinations of different sensors together with integrated information processing. Each sensor will produce and signal as it is exposed to a certain chemical. The obtained signal is converted to a code that is used as one of the key elements to enable identification of food substance contributing to a certain illness, through the following four steps process.

1. Chemical interaction with the material of the sensing device
2. Signal generation and data acquisition.
3. Signal Processing
4. Chemical identification, and possible illness classification.

As it is extremely difficult, if not impossible, to achieve perfect selectivity in gas sensors purely through hardware modification. Most of the time, many gases will interact with gas sensors in some way, adding to the overall signal.

In addition, the target chemicals are frequently mixes of several compounds rather than single compounds, as in applications involving breath analysis. Therefore, it may not be possible to acquire selectivity just from a chemical or physical perspective.

To achieve the extraordinary selectivity to the surrounding gases and further discriminate them, mammals rely on a complex recognition mechanism in the brain and a large number of olfactory receptors. As a result, scientists develop the idea for E-Nose, an artificial olfaction system that functions similarly to the olfaction system of mammals and consists of a variety of gas sensors and a pattern recognition algorithm, as a way to improve the selectivity of gas sensors.

To enable intelligent database formation and pattern recognition and both food substance and illness identification, Neural Networks is used in this work. The designed neural system is utilized to allow for the following:

1. Learning patterns of different chemicals associated with food substances and illnesses.
2. Identification of different food substances patterns
3. Correlation between food substance and illness

Figure 8 represents the used Neural Network architecture.

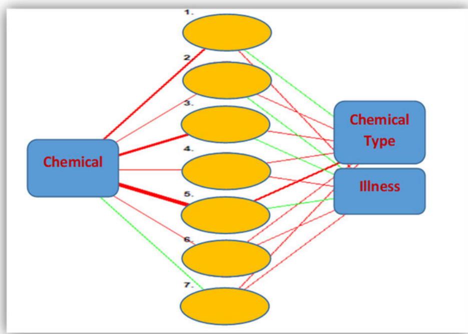

FIGURE 8. **Neural networks architecture.**

The neural networks in this work is based on Weight Elimination Technique (WET). The WET algorithme uses accountability functions to modify weights between neurons, with the weakest weight and link eliminated. This enables faster and more optimized convergence. Equation (1) shows the overall error function, which comprises of two parts as a function of weights, the overhead error cost and the accountability part.

$$\boldsymbol{Error}\,(\boldsymbol{w})_{\boldsymbol{overall}} = \boldsymbol{Error}\,(\boldsymbol{w})_{\boldsymbol{overhead\ cost}} + \boldsymbol{Error}\,(\boldsymbol{w})_{\boldsymbol{accountability}} \tag{1}$$

w: weights.

The overhead error cost is given by equation (2).

$$\boldsymbol{Error}\,(\boldsymbol{w})_{\boldsymbol{overhead\ cost}} = \left(\frac{\mathbf{1}}{\mathbf{2}}\right) * \sum\nolimits_{j} \left(\boldsymbol{R_j} - \boldsymbol{A_j}\right)^{\mathbf{2}} \tag{2}$$

R_j: Required output

O_j: Actual output

Accountability is given by equation (3)

$$\boldsymbol{Error}\,(\boldsymbol{w})_{\boldsymbol{accountability}} = \boldsymbol{\theta} * \left(\sum_{ij} \frac{\left(\frac{\boldsymbol{w_{ij}}}{\boldsymbol{w_{cycles-l}}}\right)^{\mathbf{2}}}{\mathbf{1}\mathcal{C}\left(\frac{\boldsymbol{w_{ij}}}{\boldsymbol{w_{cycles-l}}}\right)^{\mathbf{2}}}\right) \tag{3}$$

The weight change during as neural engine is learning is given by equation (4).

$$\boldsymbol{\Delta w_{ij}} = \left(-\boldsymbol{\phi} * \frac{\boldsymbol{\partial Error_{overhead\ cost}}}{\boldsymbol{\partial w_{ij}}}\right) - \left(\boldsymbol{\theta} * \frac{\boldsymbol{\partial Error_{accountability}}}{\boldsymbol{\partial w_{ij}}}\right) \tag{4}$$

where:

φ: Learning Rate (between 0 and 1)

w represents the weight vector, θ is the weight-optimization factor through reduction, and w_{ij} represents individual weights in the neural network engine.

$W_{cycle-l}$: Scale parameter computed by the weight elimination algorithm, and chosen to be the smallest weigh from the last cycle or set of cycles to enable small weights to converge to zero, thus apply weight elimination function.

θ is computed from previous works [ ] by the expression in equation (5).

$$\boldsymbol{\theta} = \boldsymbol{\theta_i exp}\left(-\boldsymbol{\varepsilon}\left(\frac{\boldsymbol{Patterns_{all}} - \boldsymbol{Patterns_{correctlyclassified}}}{\boldsymbol{Patterns_{all}}}\right)\right) \tag{5}$$

where:

ε: Scaling factor

θ_i: Initial Weight-reduction value.

Equation (5) follows a Gaussian interpolation form, with the spread of classification covered by the parameter ε. The expression removes small weights based on the assumption that small weights are noise and allows support and reinforcement of larger weights on the basis on such weights representing data or signal.

The expression in equation (5) will affect the overall calculated error, as it dynamically affects $Error\,(w)_{accountability}$, and affects small weights, causing elimination and large weights, resulting in re-enforcement. It is important to choose an optimum value for φ (equation (4)) in order to timely prune the network and avoid early weight elimination, through early application of equation (5).

Learning rate (φ) is related through the previous equations to the weights-reduction parameter (θ), as it depends on the stage and values of weights to speed up or slow learning process, thus reaching convergence. This is achieved through its relationship with overhead cost error. φ is also related to the overall error of the network as in equation (6).

$$\varphi = \boldsymbol{\rho Error}\,(\boldsymbol{w})_{\boldsymbol{total}} \tag{6}$$

where:

ρ: Learning rate scaling factor, and should be maintained at minimum of twice the network error.

Considering equations (4) and (6), results in equation (7).

$\boldsymbol{\Delta w_{ij}}$

TABLE 1. Neural networks training data sample.

Sample Sequence	Ammonia Chemical Sample (ppm)	Alcohol Chemical Sample (ppm)	Diluted Acetone Chemical Sample (ppm)
1	240	770	380
2	245	800	390
3	250	830	400
4	255	860	410
5	260	890	420
6	265	920	430
7	270	950	440
8	275	980	450
9	280	1010	460
10	285	1040	470
11	290	1070	480
12	295	1100	490
13	300	1130	500
14		1160	510
15		1190	520
16			530
17			540
18			550
19			560

$$= \left(-\rho Error\,(w)_{total} * \frac{\partial Error_{overhead\ cost}}{\partial w_{ij}}\right) - \left(\theta_i exp\left(-\varepsilon\left(\frac{Patterns_{all} - Patterns_{correctly\ classified}}{Patterns_{all}}\right)\right) * \frac{\partial Error_{accountability}}{\partial w_{ij}}\right) \quad (7)$$

Considering equations (3) and (5), results in equation (8).

$$Error\,(w)_{accountability} = \theta_i exp\left(-\varepsilon\left(\frac{\left(Patterns_{all} - Patterns_{correctly\ classified}\right)}{Patterns_{all}}\right)\right) * \left(\sum_{ij} \frac{\left(\frac{w_{ij}}{w_{cycles-l}}\right)^2}{1C\left(\frac{w_{ij}}{w_{cycles-l}}\right)^2}\right) \quad (8)$$

WET concentrates on weights pruning, which helps to uncover dominant features in a similar way to genetic algorithms. The WET tracks weights decay through the error function and carry out pruning of lowest weights as they are not related to required features. This optimization and tuning process is similar to evolution, which depends on the position of the weight within the neural architecture.

III. RESULTS AND DISCUSSION

Table 1 shows part of the sample used to train the designed E-Nose.

The detected chemical substance, which could be found in foods and environment, have the following response characteristics.

Diluted Acetone (Related to Diabetes):

1- Substance detected at 18 seconds after exposure.
2- Response reaches maximum level at 36 seconds.
3- Response duration =18 seconds
4- Average response time =27 seconds
5- Average Concentration =470 ppm

Alcohol (Related to Diabetes):

1- Substance detected at 118 seconds after exposure.
2- Response reaches maximum level at 132 seconds.
3- Response duration =14 seconds
4- Average response time =125 seconds
5- Average Concentration = 980 ppm

Ammonia (Related to Kidney Failure):

1- Substance detected at 68 seconds after exposure.
2- Response reaches maximum level at 80 seconds.
3- Response duration =12 seconds
4- Average response time =74 seconds
5- Average Concentration = 270 ppm

From Table 1 and from Figure 9, it is evident the ability of the E-Nose to nose to detect the considered substances with no overlap between their values.

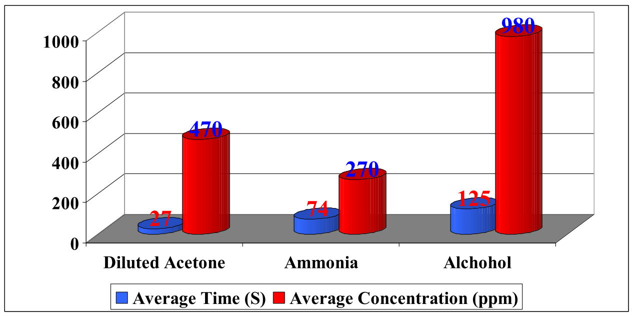

FIGURE 9. E-Nose average response to substances that could cause illness.

The correlative weight elimination algorithm (CWEA), uses Gaussian algorithm as a final stage to guarantee correct classification and correlation to possible illness. The CWEA, also enables correlation between different chemical substances and their response values to enable multi-substance and correlative diagnostics.

Equation (9), presents the proposed Gaussian single substance discrimination function, where the center value is the average values for the training data of any substance. Such average values represent average detected concertation of a substance and average response time. The exponent in the modified Gaussian interpolation, allows for sensitivity adjustment for the discriminating algorithm.

$$C_i = exp\left(-\left(\frac{(S_a - S_i)^n}{S_a}\right)\right), \quad (9)$$

where;

S_a: Average of sampled values by E-Nose.
S_i: Testing sample values by E-Nose.
n: Discrimination related exponent.

Equation (10), presents a correlative version of the Gaussian interpolation function, used for discrimination and classification after training the WEA algorithm, with a summation and weight added to the original function, which enables to establish collective effect of different levels of the same substance within different and manufactured products.

This will enable better decision making regarding patient health.

$$C_i\,(\boldsymbol{correlative}) = \sum_{j\mathcal{D}1}^{M} \boldsymbol{\Psi_j exp}\left(-\left(\frac{(S_a - S_i)^n}{S_a}\right)\right) \quad (10)$$

where;

Ψ: weight or contribution of each tested substance.

Figures 10 and 11 show the result of applying equation (9) to testing data. The testing data covered same time duration and constraint as the training data. The plot as shown in Figure 10 reveals the presence of excess acetone and alcohol in separate samples, which are a contributor to diabetes illness. The plot shows clearly that some samples contains acetone above normal or accepted limits.

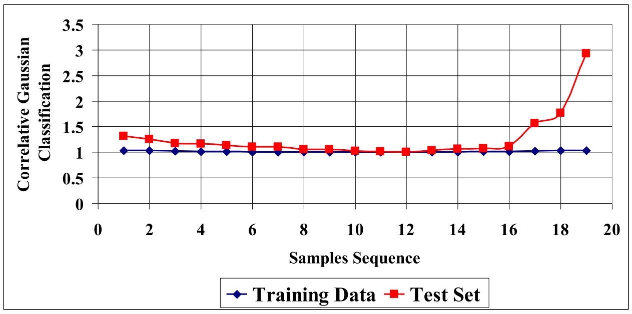

FIGURE 10. E-Nose testing results for the presence of Acetone in same substance.

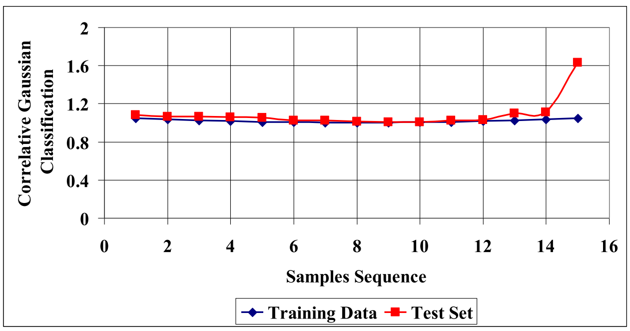

FIGURE 11. E-Nose testing Results for the presence of Alcohol.

Figure 12 shows applying equation (10) to real values of ammonia found in substances. The testing data covered same time duration and constraint as the training data. The plot as shown in Figure 12 reveals the presence of excess ammonia, correlated from different substance used by same human. Excess ammonia is known as a contributor to kidney failure illness. The plot shows clearly that some samples contains ammonia above normal or accepted limits.

The used weights in equation (10) are random to reflect real life activities. Table 2 lists, as an example, the ammonia content of substances that are consumed by people regularly.

Table 2: (Source: Grist, Jes Zimmerman).

The weight parameter in equation (10), can be used to tune human consumption in case of food materials, such that the total consumption does not exceed normal ammonia levels, especially for people who have problems in their kidneys.

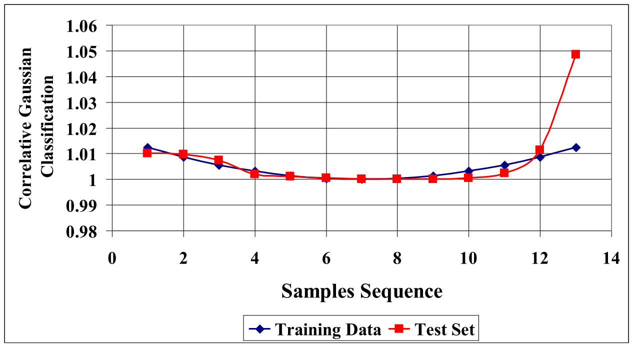

FIGURE 12. E-Nose testing Results for the presence of Ammonia within different substances.

TABLE 2. Ammonia presence in FOODS.

Food	Ammonia (ppm)
Cheddar cheese	110
American cheese	81
Salami	110
Peanut butter	49
Mayonnaise	41
Ketchup	35
Onions	27
Potato chips	24
Margarine	21

Further analysis of Figures 10 to 12 reveals that the maximum difference between tested samples values and training data after applying Correlative Gaussian classification are:

1. Acetone: {1.90}
2. Alcohol: {0.036}
3. Ammonia: {0.58}

These values show that the implemented E-Nose system is capable of clearly distinguish between different substances, and also able to provide indicators to how sever is the presence of a chemical in a human body.

Recently developed E-Nose sensing systems, are concentrating on high speed response sensors. These type of E-Noses focus on speed of response, by using nanotechnology, and 2-D materials, which has high efficiency and quick energy transfer, which is due to their huge surface-to-volume ratio and fast carrier mobility. However, the presented E-Nose in this work Focus its activities on providing reliable diagnosis and classification, using the new intelligent approach, which is based on the extra smartness provided by the inclusion of Gaussian function within the Neural Networks predictive and correlative structure.

IV. CONCLUSION

This work enables the investigation of substances that could cause harm to human health or accelerate illness within human body. The work looked at three different chemicals that could contribute to either diabetes or kidney failure or both, using a simple E-Nose with Correlative Weight Elimination Algorithm (CWEA), which is part of a higher level neural networks. The algorithm proved to be effective in classifying different samples of acetone, alcohol, ammonia, within the same substance, and correlating various contents of the same substance within different types of materials, such as food. The system showed promising results in both detecting, classifying, and correlating presence of chemicals, which could cause or support the progress of illness in humans. Mathematical model for the CWEA is presented within the work, which could be used in future work with higher accuracy sensors to enable better classification and threshold tuning of weights for correlation of chemicals present in substance used by human, in order to better control food consumption and environmental elements, which include meat processing.

After full approval of such a proposed approach to detection of illness through consideration of excess of chemical substances in foods, testing of humans should only be carried out after privacy and confidentiality considerations with full consent of participants, and the ability of any participant to withdraw permission at any moment or to stop participating in the study. In addition, the findings of any foods that could be a major contributor to illness, should not be disclosed without the proper procedures under the country norms.

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