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IDENTIFICATION OF FOREST FIRE SMOKE BASED ON ELECTRONIC NOSE USING ARTIFICIAL NEURAL NETWORK

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Abstract. *Forest fires are still being carried out manually using monitoring posts, binoculars and human labor. There are still many problems related to early warning. The smoke detectors are limited and cannot distinguish between types of fire smoke that have complex gas compositions. Therefore, an intelligent instrument is required. The electronic nose (e-nose) based on the gas sensor array and pattern recognition has the ability to identify samples based on their characteristics. In this research, we identified fire smoke types using the e-nose and artificial neural network (ANN). Peat (140 g), wood (12 g) and grass (10 g) each were burned and repeated 10 times through sniffing process. Periodic sensor response wave formed in preprocessing using the difference is used to eliminate unnecessary information to get a sharp and scalable sensor response. Feature extraction using an integral method is applied to finding unique information contained in the sensor response. Data (210 $\times$ 12) was subsequently used by ANN (12-20-1) for learning (60%) and testing (40%). The results of ANN can clearly identify each sample. The network is optimized, stable and the pattern of each sample is unique and consistent. So, the e-nose can be used for forest fire smoke detection.*
Keywords: Forest fire smoke, E-nose, Sensor response, ANN, Identification

1. **Introduction.** Early detection of forest fires still uses human observation, satellite systems, infrared cameras, wireless sensor networks, visuals/images, etc. [1]. Generally, detectors are non-contact, such as cameras, temperature, humidity and gas sensors. Therefore, fire smoke is formed from many volatile gaseous elements/compounds and only certain gases can be detected by gas sensors [2]. This is due to the limited number and types of gas sensors, so the information provided is incomplete. In fact, if the number of gas sensors used is too small, it is possible that a large error will occur in identifying the sample. In addition, false alarms can also occur when it is difficult for the detector to distinguish between types of forest fire smoke, wood smoke, cigarette smoke and vehicle smoke [3]. For example, smoke from forest fires is a complex mixture of various gases with particulate matter (PM2.5) [4], and wood smoke produces pollutant gases such as CO, CO_2, aldehydes, PAHs, PM and other gases [5]. Meanwhile, to distinguish the types of smoke required chemical analysis and sophisticated instruments such as gas chromatography-mass spectrometry, and Fourier-transform infrared spectroscopy. Gas detectors are limited,

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not real-time and expensive, making it difficult to implement a cheap and practical forest fire detection system.

Electronic nose (E-nose), the intelligent instrument, can be used as an alternative [6] to detect and distinguish fire smoke. This instrument is based on a gas sensor array [7] made of metal oxide semiconductor (MOS) and pattern recognition machine for data analysis [8]. The unselected sensor detected not only specific gas contained in the smoke but also accumulation of several gases. Therefore, the output results in a qualitative and overlapping value. Each gas sensor converts fire smoke to electrical signal (mV) for a certain period. After the data acquisition is carried out, the results are in the form of a digital signal from each sensor or called the sensor response [9]. In the initial stage, preprocessing is carried out on the sensor response so that unwanted signals can be separated, sharper and more scalable [10]. Furthermore, feature extraction is used to retrieve the specific features of each sensor that have been manifested in the sensor response [11]. In the final stage, a pattern recognition machine is used to classify gases to identify the type of fire smoke. Implementation of e-nose has been carried out in various fields [12] such as medicine [13], agriculture [14], food and beverage [15], pharmacy [16], and military [16]. In the environment, e-nose is implemented for air quality monitoring [17], fire alarm, forest fire, etc.

This research focuses on the steps to identify types of fire smoke using e-nose. In general, the e-nose hardware will convert the smoke into a patterned electrical signal, and the software based on artificial neural network (ANN) will identify the samples. Based on the results, it shows that the e-nose instrument based on a gas sensor array that is practical, efficient, inexpensive, real-time and online can be used for early detection of forest fires. Therefore, e-nose can overcome the limitations of detector systems that previously used a quantitative approach through qualitative measurements. The research has also proven that the limitations of gas sensors in quantitatively identifying forest fires can be corrected by qualitative measurements and pattern recognition methods.

2. Research Methodology.

The sensor response (Figure 1) must be processed in order for the sample to be identified. The difference method [18] is used to sharpen and clean the signals in the early stages of processing. To obtain specific features, the signal curve for each sensor is calculated by the integral method [11]. Artificial neural networks will identify smoke from peat or non-peat fires. Initially set up ANN with twelve gas sensors (MQ-3, MQ-4, MQ-9, MQ-136, TGS 813, TGS 822, TGS 2600, TGS 2602, TGS 2610, TGS 2611, TGS 2612 and TGS 2620) as inputs [19]. Twenty neurons are used for one hidden layer and one output neuron for sample identification, namely peat (value 0) or non-peat (value 1).

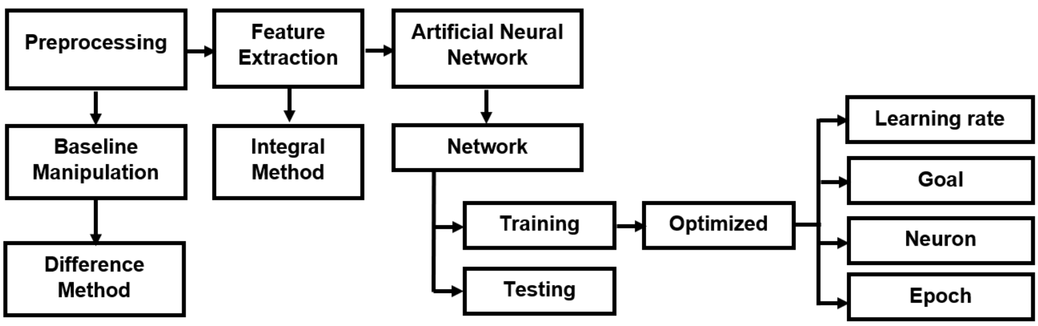


FIGURE 1. Signal analysis for smoke identification with artificial neural network

Based on the data that has been collected, network optimization is carried out during training for learning rate, goals, neurons and epochs. During the training, several variations of the learning rate (0.1-1.0, increments of 0.001), goal (0.1-1.0, increments of 0.0001), neurons in the hidden layer (2-26, increments of 2), and epoch (100-1000, increments of 100) were also carried out. While the activation function used is a linear function, where the output is the same as the input value.

The basic principle of the ANN algorithm is to improve network weights in a direction that makes network performance drop rapidly. There are two processes of training and testing, where, during the training process the weights are arranged iteratively to minimize network performance with the mean square error (MSE). This function uses the average of the squared error between the output and the target. Besides that, training on this network is to produce a balance between the ability of the network to respond correctly to input patterns and output patterns. Many activation functions can be used, but in this study a linear activation function is applied, where the input is the same as the output [20]. The network is used for testing if it can be used to recognize the pattern at training.

Based on the description above, we can conclude that the smoke from a fire is a collection of various volatile gas compounds/elements captured by the gas sensor array. Each sensor has its own ability to convert the smoke into a sensor response with a specific pattern. Based on the pattern data, ANN optimizes its network in order to identify samples. Of course, to get this feature, the sensor response must be pre-processed and feature extracted. Furthermore, samples to be identified by the e-nose are described in the next section.

3. **Material and Method.**

3.1. **Material.** Peat samples were taken from Rantau Karya Village, Geragai District, Tanjung Abung Timur Regency, Jambi, Indonesia. Non-peat samples in the form of dry grass and wood were taken from Sleman, Jogjakarta, Indonesia. Three samples (peat, wood, grass) were prepared, where, total number of samples that have been provided is 21 pieces, each consisting of seven pieces of peat (140 g), wood (12 g) and grass (10 g).

3.2. **Experimental setup.** The e-nose used for measurement is shown in Figure 2. Experiments are carried out by placing one of the three samples into the sample chamber. After the furnace is turned on, the combustion process has occurred. Then the smoke from the combustion is channeled to the chamber sensor via the air flow system (AFS). A compressor is used to compress the air, so that air can flow through the AFS carrying the sample smoke. Twelve gas sensors capture the smoke which is then converted into an electrical signal with their respective characteristics.

Each sample was measured ten period of sniffing process using e-nose. One period sniffing process consists of flushing (300 s), collecting (120 s), and purging (100 s). After one period of sample measurement is carried out, the next measurement period only

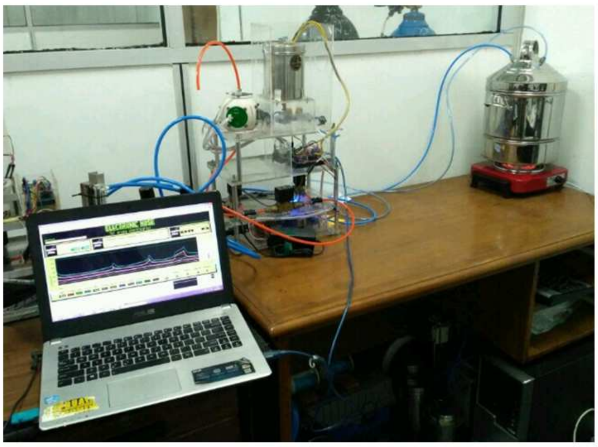


Figure 2. Dynamic electronic nose with air flow system used in this research

involves collecting and purging process with nine repetitions. The sniffing process is formed by controlling the solenoid valve in the AFS system [7].

Signal analysis begins with preprocessing all recorded sample data. By eliminating all phases of flushing, the only remaining data are collecting and purging in each period. Baseline manipulation with the difference method is used to equalize the baseline of all sensor signals. Then in each period, the features are extracted using the integral method to get a unique pattern from each sample. The results of feature extraction obtained 210 data from 3 types of samples for 12 sensors. This information is stored in the form of a high order matrix (210×12) which is ready to be processed with ANN.

The training process on the network was carried out using 60% of the sample to optimize the network. The purpose of this training is to get the best network performance with parameters such as epoch, learning rate, goals, and the optimal number of neurons in the hidden layer. Furthermore, the optimal network is then used for the testing to identify peat or non-peat smoke by using the remaining 40% of data.

Varied sampled smoke was measured using an e-nose based twelve gas sensors. Measurements were made repeatedly to obtain data for each sample. In order to get a specific signal pattern, a snifting process is carried out at a certain time and periodically. The sensor response resulting from the measurement is converted to digital for further analysis. The next section will present the results of measuring forest fire smoke with the e-nose.

4. **Results and Discussion.**

4.1. **Sensor response.** The sensor response is an interpretation of the response of each sensor (12 sensors) to peat or non-peat (wood, grass) smoke. Smoke is converted into an electrical signal (mV) due to the compound gas attached to the sensor surface to change its conductivity. Waves were formed periodically with collecting (120 sec) and purging (100 sec) processes which were carried out to get the pattern from the sample.

The sensor responses of peat smoke sample are shown in Figure 3. Almost each sensor responds to peat smoke and looks like sharp waves. The average response time for each sensor is fast and has not reached saturation point. It indicates sensor surface was briefly covered by dense smoke, because peat smoke contains a lot of dust particles.

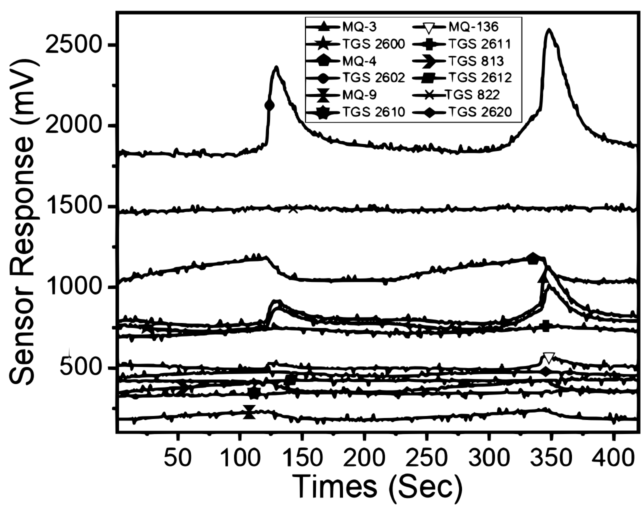


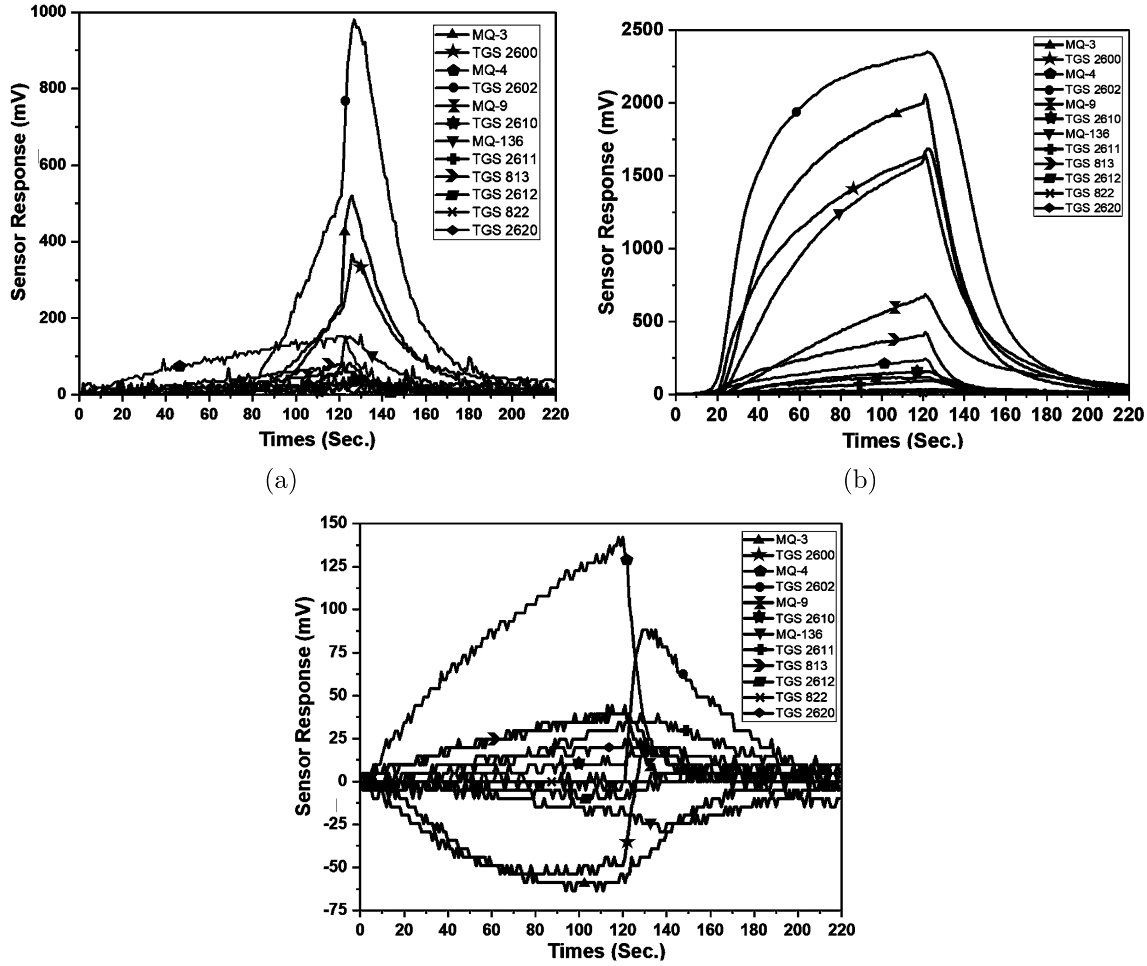
Figure 3. Sensor responses of peat smoke sample

4.2. **Preprocessing.** By using difference method, the response signal from each measured sensor is subtracted from the baseline. This process can make signal of each sensor clear, sharp and scalable. The preprocessing samples smoke describes one period of the response signal from the sniffing process. The graph is representative of the previous 10 sensor response periods.

In Figure 4(a), TGS 2602, TGS 2600 and MQ-3 sensors respond to peat smoke with a large and fast response signal, even though there is a delay of 80 seconds. It denotes that the smoke contains sensitive gases with high concentrations. MQ-4 sensor has slow response time with large enough sensor response. This indicates smoke contains a high gas concentration but the sensor is less sensitive to respond the gas.

Figure 4(b) shows the sensor response for wood smoke. Wood smoke has a different sensor response from peat, where the response of each sensor was almost saturated during the collecting process. The average response time for wood is longer than peat smoke. Meanwhile, the amplitude of signal response for wood is greater than peat smoke. Based on these two parameters, the two samples have different patterns. For another observation, the density of wood smoke is lower than peat smoke. Therefore, wood smoke dust particles are less than peat smoke. This prevents the sensor surface from being quickly covered by dust particles. So, the sensor can still catch the gases contained in wood smoke. The sensor response for grass smoke is shown in Figure 4(c). Some sensors are less responsive to this sample. Overall, response time is longer and signal amplitude is relatively small compared to peat and wood smoke. In general, it can be shown that each sample has a unique pattern.

In general, the response signal of each sample has more different pattern. This difference is due to the influence of the response signal from each sensor in detecting each sample



(a) (b)

(c)

FIGURE 4. Sensor response for (a) peat, (b) wood and (c) grass smoke after preprocessing

smoke. For example, response signal generated by TGS 2602 for peat is different from non-peat smoke. Similarly, sensor with the maximum amplitude can be known. TGS 2602 sensor has a maximum amplitude for peat and wood smoke, but not for grass. Meanwhile, sensors that are less responsive may be less sensitive to one sample but sensitive to another sample. Thus, response conditions have a meaningful role in pattern formation. Likewise, MQ-136 has strong response to wood smoke, but less strong on peat and no response to grass. Therefore, feature extraction of each sensor can be carried out after preprocessing.

4.3. **Feature extraction.** The extraction feature is carried out to select important information contained in the three smoke samples. The selected information should be unique and consistent so that the pattern recognition engine can easily discriminate the samples. The selection of information for each sample is done by observing more deeply the uniqueness of each sensor in response to the sample.

The unique sensor response of each sample can be used to characterize it. For example, the response of TGS 2602 (Figure 4) in peat, wood and grass has different curved shapes. Thus, the characteristics of the sample can be determined based on these criteria. This can be done by calculating the area of the response signal curve for each sensor in one period using the integral method. Figure 5 shows results of the calculation of the area for the TGS 2602 signal response with different samples for 10 periods. The area is different for each sample; besides that the value obtained for one sample is relatively constant over the 10 measurement periods. Furthermore, the two samples (peat and non-peat) can be identified based on the predetermined characteristics, and the ANN method is used.

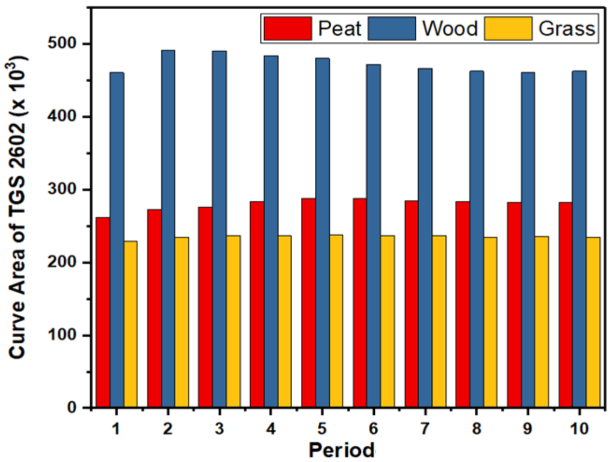


FIGURE 5. Curve area for the TGS 2602 signal response

4.4. **Training of artificial neural network.** Peat and non-peat smoke identification was carried out using the ANN. The initial network formed before training was 12-20-1. Network optimization is carried out during the training by improving the epoch, learning rate and the number of neurons in the hidden layer. The best value is taken based on the smallest mean square error (MSE).

Learning rate variation. In order for training, effectiveness and speed of network convergence to be achieved, it is necessary to optimize the learning rate (LR). Figure 6(a) shows the greater the LR, the more decrease in accuracy and an increase in MSE. Meanwhile, determine the optimal LR based on the smallest MSE and the greatest accuracy. From the graph, it can be seen that the first data is for optimal LR (1.00×10^{-2}) because the MSE is the smallest (2.90×10^{-2}) and the greatest accuracy is (100.00×10^{-2}).

Variation of the goal. Goal is a parameter used to determine the limit value of MSE. Meanwhile, the MSE value is used to determine iteration. The last iteration value is shown

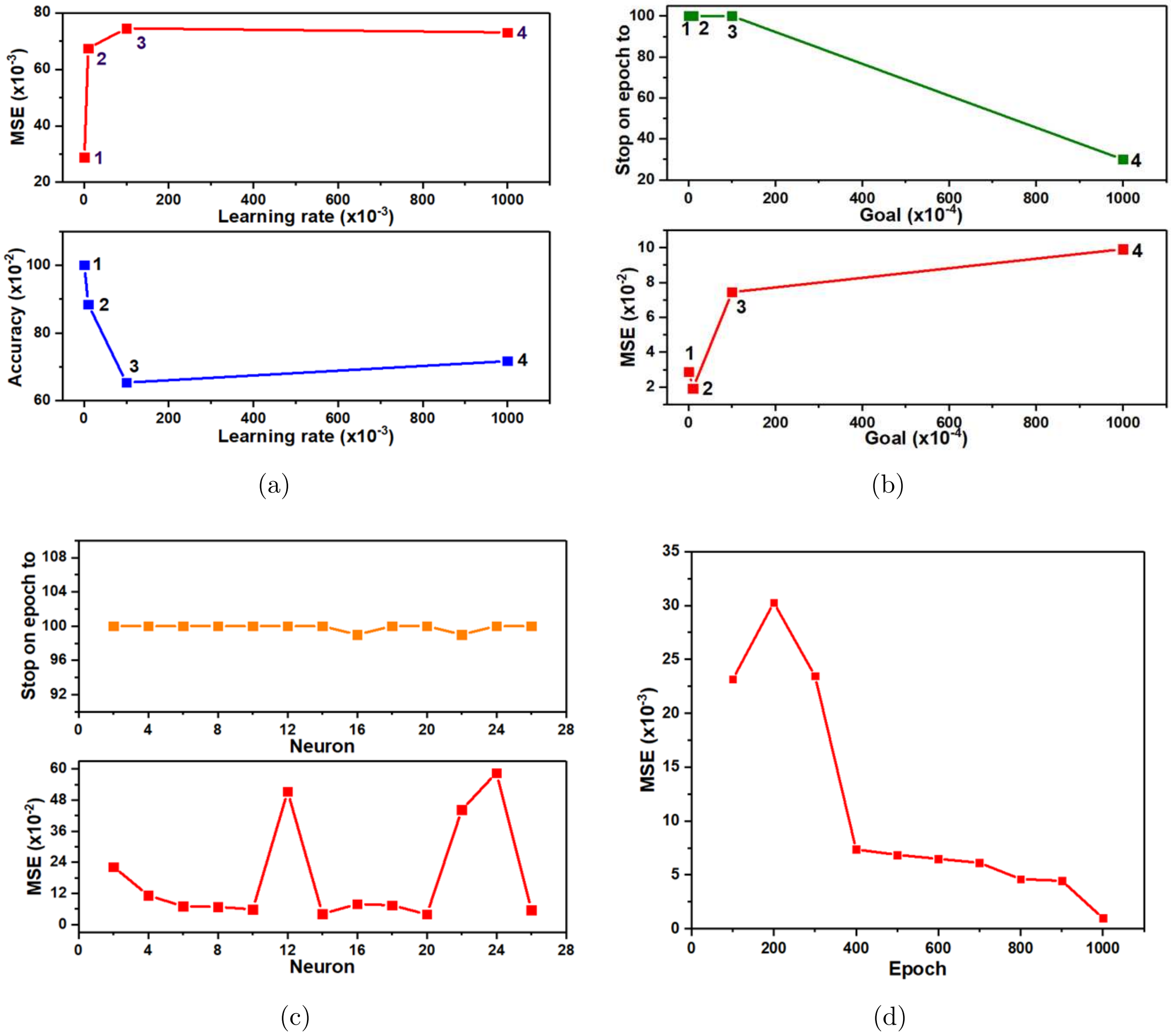


FIGURE 6. Variation of (a) learning rate, (b) goal, (c) neuron and (d) epoch at training process

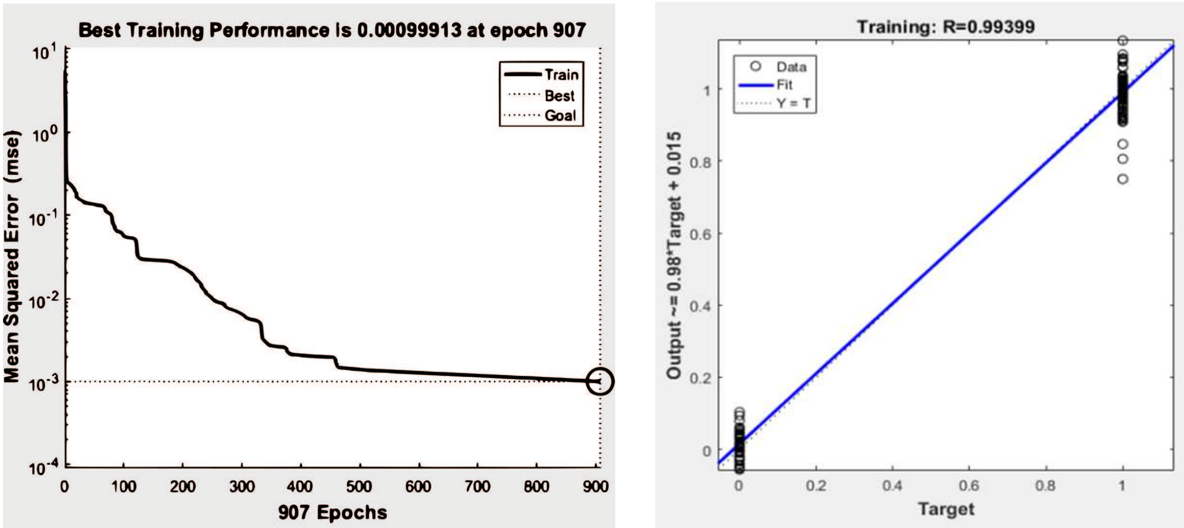
in epoch. Variations of objectives were carried out to obtain the smallest MSE value. If the MSE value gets smaller, the network performance will get better. Figure 6(b) shows, for a goal under 200.00×10^{-4}, the MSE is below 8.00×10^{-2} with the iteration stopping at epoch 100. However, the optimal goal is at 1.00×10^{-3} because it has the smallest MSE value (1.90×10^{-2}). This proves that the optimal value (1.00×10^{-3}) does not always come from the smallest or the largest goal.

Variation of the hidden layer. The optimal number of neurons in the hidden layer can be determined by varying neurons. Furthermore, the optimal value is selected based on the smallest MSE value. From the variation of these neurons (Figure 6(c)), the smallest MSE value (3.91×10^{-2}) was obtained with 20 neurons. Likewise the iteration was stopped at epoch 100. This value is almost the same as the previous iteration.

Variation of the epoch. Based on the previous training, the average iteration was stopped at epoch 100 by the network because it had exceeded the optimal goal value (10^{-3}). The epoch is not an optimal value, even though some of the parameters used are optimal parameters. Therefore, to get the optimal epoch value, the next step is to vary the epoch.

Figure 6(d) shows, the MSE value decreased sharply and thereafter decreased slowly to an epoch greater than 400. This indicates, when the iteration is above that value, the network conditions are better and more stable than before. Furthermore, get the best network performance by choosing the optimal epoch (1000) based on the smallest MSE (9.99×10^{-4}). Overall, the new configuration is shown with learning rate (0.001), goal (0.001), epoch (1000). Furthermore, network was reconfigured with optimal parameters and retrained with 60% of the available data from peat and non-peat smoke by forming a matrix (150×12).

Training for epoch (Figure 6(d)) below 300 shows that the error (MSE order 10^{-2}) is still quite large. However, the error decreased sharply (MSE order 10^{-3}) and was significant after the epoch reached 450. This indicates that the process towards goals can be carried out quickly by the network. Besides that, this error reduction is also proof of error correction. Based on graphic analysis, if the number of epochs increases, then the gradient decreases towards the target (goal). This shows that the weights continue to adjust until the MSE is smaller than the expected target. So, all samples of training data can be identified correctly. The results of retraining with the new network for peat and non-peat with smallest MSE (9.99×10^{-4}) and iteration was stopped at epoch 907 (Figure 7(a)). In other words, the network can be used for testing a given sample.



(a) (b)

Figure 7. (a) Training performance for the new configuration network; (b) linear regression analysis at testing for peat and non-peat

4.5. **Testing of artificial neural network.** Linear regression analysis for 20 peat data, 40 non-peat data (20 wood data and 20 grass data) using the optimized network is shown in Figure 7(b). The result of the analysis is a correlation coefficient of 0.99399. This shows the output of the network in accordance with the desired target.

5. **Conclusions.** Peat and non-peat smoke (wood, grass) was identified using an electronic nose. Twelve unselected gas sensors (4 MQ and 8 TGS) are capable of converting the specific characteristics of each smoke sample into a consistent and stable sensor response. Furthermore, feature extraction support with an integral method has succeeded in extracting the unique features of the sensor response of each sample into a consistent digital pattern. Finally, the ANN engine (12-20-1) can identify all samples clearly. In general, e-nose can be used for smoke detection of forest fires. For future research, feature selection can be carried out by reducing sensors that are not strong enough to give specific characteristics to fire smoke samples. Optimization of these sensors needs to be done in order to realize an efficient early warning system for forest fires.

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REFERENCES

[1] S. Wu and L. Zhang, Using popular object detection methods for real time forest fire detection, *Proc. of 2018 11th International Symposium on Computational Intelligence and Design (ISCID2018)*, pp.280-284, doi: 10.1109/ISCID.2018.00070, 2018.

[2] A. A. A. Alkhatib, A review on forest fire detection techniques, *Int. J. Distrib. Sens. Networks*, vol.2014, doi: 10.1155/2014/597368, 2014.

[3] W. Krüll, R. Tobera, I. Willms, H. Essen and N. Von Wahl, Early forest fire detection and verification using optical smoke, gas and microwave sensors, *Procedia Eng.*, vol.45, pp.584-594, doi: 10.1016/j.proeng.2012.08.208, 2012.

[4] W. Yuchi et al., Blending forest fire smoke forecasts with observed data can improve their utility for public health applications, *Atmos. Environ.*, vol.145, pp.308-317, doi: 10.1016/j.atmosenv.2016.09.049, 2016.

[5] O. N. Avenbuan and J. T. Zelikoff, Review: Woodsmoke and emerging issues, *Curr. Opin. Toxicol.*, vol.22, pp.12-18, doi: 10.1016/j.cotox.2020.02.008, 2020.

[6] D. Lelono, M. Z. Abdillah, T. W. Widodo and M. Apandi, Clusterization of pure and formalin fresh noodles with electronic nose based on kernel principal component analysis, *Proc. of 2019 5th Int. Conf. Sci. Technol. (ICST2019)*, doi: 10.1109/ICST47872.2019.9166268, 2019.

[7] D. Lelono, K. Triyana, S. Hartati and J. E. Istiyanto, Development of electronic nose with highly stable sample heater to classify quality levels of local black tea, *Int. J. Adv. Sci. Eng. Inf. Technol.*, vol.7, no.2, doi: 10.18517/ijaseit.7.2.1659, 2017.

[8] H. R. Estakhroyeh, E. Rashedi and M. Mehran, Design and construction of electronic nose for multipurpose applications by sensor array arrangement using IBGSA, *J. Intell. Robot. Syst. Theory Appl.*, vol.92, no.2, pp.205-221, doi: 10.1007/s10846-017-0759-3, 2018.

[9] D. Lelono, R. P. Putri and C. Atmaji, Tofu shelf life using electronic nose based on curve fitting method, *Proc. of 2019 5th International Conference on Science and Technology (ICST)*, doi: 10.1109/ICST47872.2019.9166208, 2019.

[10] A. Sanaeifar, S. S. Mohtasebi, M. Ghasemi-Varnamkhasti and H. Ahmadi, Application of MOS based electronic nose for the prediction of banana quality properties, *Meas. J. Int. Meas. Confed.*, vol.82, pp.105-114, doi: 10.1016/j.measurement.2015.12.041, 2016.

[11] J. Yan, F. Tian, Q. He and Y. Shen, Feature extraction from sensor data for detection of wound pathogen based on electronic nose, *Sensors Mater.*, vol.24, no.2, pp.57-73, 2012.

[12] P. S. Laquintinie et al., An electronic nose prototype for the on-field detection of nerve agents, *Proc. of IEEE Sensors*, pp.1-4, doi: 10.1109/ICSENS.2018.8589517, 2018.

[13] X. Zhan, Z. Wang, M. Yang, Z. Luo, Y. Wang and G. Li, An electronic nose-based assistive diagnostic prototype for lung cancer detection with conformal prediction, *Measurement*, vol.158, 107588, doi: 10.1016/j.measurement.2020.107588, 2020.

[14] D. M. Martínez Gila, J. Gámez García, A. Bellincontro, F. Mencarelli and J. Gómez Ortega, Fast tool based on electronic nose to predict olive fruit quality after harvest, *Postharvest Biol. Technol.*, vol.160, 111058, doi: 10.1016/j.postharvbio.2019.111058, 2020.

[15] W. Dong et al., Comparative evaluation of the volatile profiles and taste properties of roasted coffee beans as affected by drying method and detected by electronic nose, electronic tongue, and HS-SPME-GC-MS, *Food Chem.*, vol.272, pp.723-731, doi: 10.1016/j.foodchem.2018.08.068, 2019.

[16] J. Li, Y. Shao, Y. Yao, Y. Yu, G. Cao and H. Zou, A novel quality evaluation method for magnolia bark using electronic nose and colorimeter data with multiple statistical algorithms, *J. Tradit. Chinese Med. Sci.*, vol.7, no.2, pp.221-227, doi: 10.1016/j.jtcms.2020.03.004, 2020.

[17] M. Rodríguez-Aguilar et al., Identification of breath-prints for the COPD detection associated with smoking and household air pollution by electronic nose, *Respir. Med.*, vol.163, no.550, doi: 10.1016/j.rmed.2020.105901, 2020.

[18] J. Yan et al., Electronic nose feature extraction methods: A review, *Sensors*, vol.15, no.11, pp.27804-27831, doi: 10.3390/s151127804, 2015.

[19] F. T. Windrasti, *Peat Fire Smoke Identification with Electronic Nose Based on ANN*, Undergraduate Thesis, Department of Computer Science and Electronics, Universitas Gadjah Mada, Yogyakarta, Indonesia, 2017.

[20] D. Karakaya, O. Ulucan and M. Turkan, Electronic nose and its applications: A survey, *Int. J. Autom. Comput.*, vol.17, pp.179-209, doi: 10.1007/s11633-019-1212-9, 2020.