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DEVELOPMENT OF E-NOSE FOR DETECTION OF HAZARDOUS GASES USING MACHINE LEARNING APPROACH

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Abstract

This paper presents the development of an e-nose for detection of hazardous gases using a machine learning approach. The aim was to develop an intelligent system for accurate detection of harmful gases contained in the atmosphere of mining sites, which are majorly Carbon (ii) Oxide (CO) and Methane (MH_4), mostly released into the atmosphere during mining activities and have resulted to the death of many workers at the mining site over the years. This issue was solved using machine learning approach. The methodology employed data collection of hazardous gasses using MQ-7 and MQ-2 sensors, feature extraction using dynamic moment technique. Feed-Forward Neural Network (FFNN) developed with the tanh activation function and back-propagation training algorithm was adopted and used to train the features to generate the gas detection algorithm. The gas detection algorithm was implemented with Simulink and evaluated. The mean square error and the regression results were obtained, analyzed and validated via tenfold cross-validation. The MSE and regression values were 2.5113e-07Mu and 0.9944 which implies that the system developed was reliable and efficient for the detection of said hazardous gas found in mining sites.

Keywords: Hazardous Gasses, Machine Learning, Mining Site, Neural Network, Regression

I. INTRODUCTION

Mining is the removal of minerals and metals from the ground, such as copper, coal, and gold. it could also be said to be the extraction of valuable materials or other geological materials from the Earth (Mero et al. 2017). Mining has proved its importance to the national economy by providing raw materials which promote employment, impact wages, and increases the GDP of the nation (Marcela et al. 2017). However, this mining process also has its disadvantages which include environmental pollution, and exposure of miners to dangerous gasses among others. Furthermore, accidents occur in the mines which can result in loss of life. For instance, in Reuters (2020), 58 South African workers were victims of a mining disaster; Retzer (2010) reported another death of over 1500 people as a result of the mining disaster.

According to Wang et al. (2013), harsh working conditions in underground mines due to dangerous gas exposures have led to the listing of the mining industry as one of the most dangerous professions in the world. Some of the gases present in the underground mines are flammable gas (CH_4), Carbon Monoxide (CO), and Carbon Dioxide (CO_2). Hydrogen Sulphide (H_2S), Sulphur Dioxide (SO_2). Some of the effects of the gases on the human body include: CO when largely exposed to the body can lead to CO poisoning, Methane CH_4 which is responsible for the majority of the underground mine explosion (Mohd et al. 2017) among many other hazardous gases.

The production of hazardous gas detectors, E-nose (Electronic nose), has contributed to the solution of the problem to an extent, the E-nose system is sent into the mine to detect the concentration level of the hazardous gases in the mine and inform the workers on the safety level of the site. Mohd et al. (2017), in the work on gas monitoring and testing in underground mines using wireless technology, a gas detection system was proposed that made use of the MQ4 and MQ7 sensors to detect CH_4 and CO respectively, then communicated the concentration level over ZigBee network to an Liquid Crystal Display (LCD). Kun et al, (2018) designed and implemented a toxic gas concentration monitoring system for indoor decoration based on odor sensor technology. the system made use of a highly sensitive formaldehyde sensor with which the gases were monitored and communicated through a highly stable Wi-Fi tech. But despite their success, there is still room for improvement because the systems lacked intelligence (learning abilities).

Recently Hernandez et al. (2016), Hernandez et al. (2016), in the research on Predictive Model for Detecting MQ2 Gases Using Fuzzy Logic on IoT Devices, designed a system using the fuzzy logic approach to detect hazardous gasses, using an MQ2 sensor. Khalaf et al. (2008) in their work on gas detection via machine learning, adopted the Support Vector Machine (SVM) approach to training the system to differentiate between different gases. This improves the accuracy and correlation coefficient. The intelligent approach proved to produce a more reliable and efficient result compared to the traditional approach, hence my Artificial Neural Network (ANN) approach. ANN in comparison to its counterpart is an approach best suited for a pattern recognition problem like ours, to solve the issues of Cross-Sensitivity in the detection of the gases, Cross-Sensitivity is when a gas is interrupted by other gases with similar features, ANN takes a deeper look at the gases to make sure that one gas does not disguise as the other and interfere with the result. The use of ANN produces a reliable and accurate result.

II. LITERATURE REVIEW

ByungWan et al. (2018), researched the internet of things system for underground mine air quality pollutant prediction based on an azure machine, the work introduced an efficient, and cost-effective Internet of Things (IoT) system for quality air monitoring using the Principle Context Analysis (PCA) based (ANN) for my Environment Index (MEI). This system is comprised of Arduino-based sensor modules for gas detection, communication protocols (ZigBee), and an Azure Machine Learning (AML) base station.

Khalaf et al. (2008), worked on gas detection via machine learning, this work adopted a training model using the SVM approach to train the system to discriminate among different gases. This system made use of 8 sensors, 5 of the sensors being gas sensors and the remaining 3 being a temperature, humidity, and pressure sensor. After testing, the system was 96.61% correct and had a 0.979 and 0.964 correlation coefficient.

Mohd et al. (2017), in the research on Gas Monitoring and Testing in Underground Mines Using Wireless Technology, proposed a system that made used of two sensors, the MQ4 and MQ7 used to detect CH_4 and CO respectively, connected to an Arduino board for programmability, an LCD for display, and a wireless ZigBee network used for communication.

Junhua et al. (2001), in the research on cross-sensitivity reduction of gas sensors using genetic algorithm neural network, the problem of cross-sensitivity was observed, this problem was solved using the intelligent hybrid approach known as the genetic neural network algorithm to solve the pattern recognition problem, this proposed system made use of an infrared gas sensor, and the combination of genetic algorithm and neural network, to reduce cross-sensitivity between gases**.**

Mohd et al. (2012), in his work on performance analysis of neuro genetic algorithm applied on detecting proportion of components in manhole gas mixtures, proposed a system that solved the problem of hazardous gas mixtures in the manhole, by training a neural network using genetic algorithm, the aim was to reduce the cross-sensitivity issue between gases of closely related features, this system made use of the neuro genetic algorithm approach and a semiconductor gas sensor array for the detection of manhole gases.

Jambi, R. et al. (2019), researched Pollutant Gases Detection using the Machine learning on Benchmark Research Datasets, this work aimed at designing an E-nose using the ANN approach to increase the sensitivity, specificity, and accuracy, of the system in comparison to SVM and Naïve Bayes approach.

Deepak et al. (2016), worked on Artificial Neural Network for Automated Gas Sensor Calibration, and designed a gas sensor system with the ANN approach, which learns from a dataset and provides an accurate result, the system aimed to solve pattern recognition problem by using an ANN approach.

III. METHODS

Problem Formulation: In the underground mine dangerous gases like CO and CH_4 are formed during the mining activities, like the explosion of mine beds which can lead to the incomplete combustion of carbon, incomplete combustion of carbon is when the oxygen in the atmosphere is a deficit to properly combine with the carbon produced from the mining activities, hence the production of a lethal gas called CO as in equation 1 (Pandey et. al 2017);

$$CO_2 + C \rightarrow 2\,CO \qquad 1.0$$

CH_4 is also a hazardous gas formed during the mining operation, it is emitted as a result of coal extraction from the earth, it is a tetrahedral bonding of carbon with four molecules of hydrogen. Methane is one carbon atom attached to 4 hydrogen atoms by single bonds (Pandey et. al 2017).

$$C + H_4 \rightarrow CH_4 \qquad 2.0$$

Data Collection: 3000kg/cm^3 gas samples were collected from the engineering lab in Enugu State University of Science and Technology (ESUT). The gases were synthesized by mixing the gas molecules in different concentration, which was then stored for training the system.

Sensors: MQ 2 is a metal oxide semiconductor type gas sensor that has a high sensitivity to CH_4, with low power consumption, long power life, wide range, and cost-effective. Figure 1 shows a block diagram of an MQ-2 sensor. MQ 7 is a metal oxide semiconductor type gas sensor that has a high sensitivity to CO, with low power consumption, long power life, fast response time, wide range, and cost-effective. Figure 2 shows a pictorial diagram of an MQ-7 sensor

Figure 1: MQ-2 (Pandey et. al 2017).

Figure 2: MQ-7 (Pandey et. al 2017)

Feature Extraction: Many feature extraction techniques have been used in gas sensor applications such as curve Fitting Parameters, Parallel Factor (PARAFAC), Power Density Spectrum (PSD), and Moving Window Time Slicing (MWTS), but the sue of PS and Dynamic Moments (DM) approach was adopted (Martinelli et al, 2004; Padilla 2006; Lee et al, 2014; Vergara et al, 2007), because of the dynamic nature of gases, thereby increasing the accuracy of the gas detection despite the dynamic nature of gases.

Development of the ANN algorithm

Many other approaches have been taken to solve the problem of gas detection but the use ANN approach has shown over time to be superior in accuracy and reliability for classification problems such as gas detection classification (Deepak et .al 2016). The artificial neuron takes the features $X_1 + X_2 + \ldots + X_n$ extracted from the gas compound, and then multiplies it with a specific weight $w_1 + w_2 + \ldots + w_n$, the product of the input and the weight is summed together to produce the net input of the neuron as in equation 3 (Babs 2018);

$$z = \sum_{i=1}^{n} x_i w_i + b \qquad 3.0$$

Where x_i = extracted features; w_i = weight; b = bias. The net input (z) in equation (3) is then passed through a hyperbolic tangent function g(z) (activation function) in equation 4 (Babs 2018) ;

$$g(z) = tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \qquad 4.0$$

Where $g(z)$ is the activation function model.

The use of the Hyperbolic Tangent function (Tanh) was employed because it is a smoother, zero-centered function having a range between -1 to 1. The tanh function is much more extensively used than the sigmoid function since it delivers better training performance for multilayer neural networks. The biggest advantage of the tanh function is that it produces a zero-centered output, thereby supporting the back-propagation process.

The equation 3 which is the model of the neuron without an activation function and the equation 2 the activation function, were combined to develop the model of the neuron in equation 5.

$$a = g(z) = g\left(\sum_{i=1}^{n} x_i w_i + b\right) \qquad 5.0$$

The neurons are now interconnected to create a neural network with two imputes, 10 hidden layers and an output layer in figure 3.

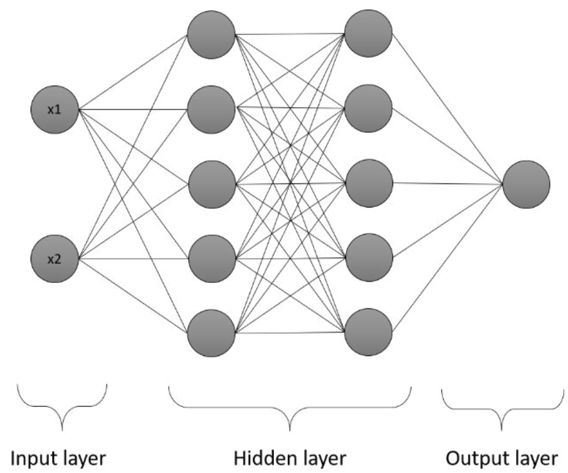

Figure 3 Artificial Neural Networks

The input of the neural network are the attributes of the natural gas to be detected which were extracted from the natural gases using the dynamic moment feature extraction method. The ANN made use of ten hidden layers to enhance computation and increase accuracy in the detection of hazardous gases. The ANN was trained using the back-propagation algorithm in figure 3 and the training parameters in table 1;

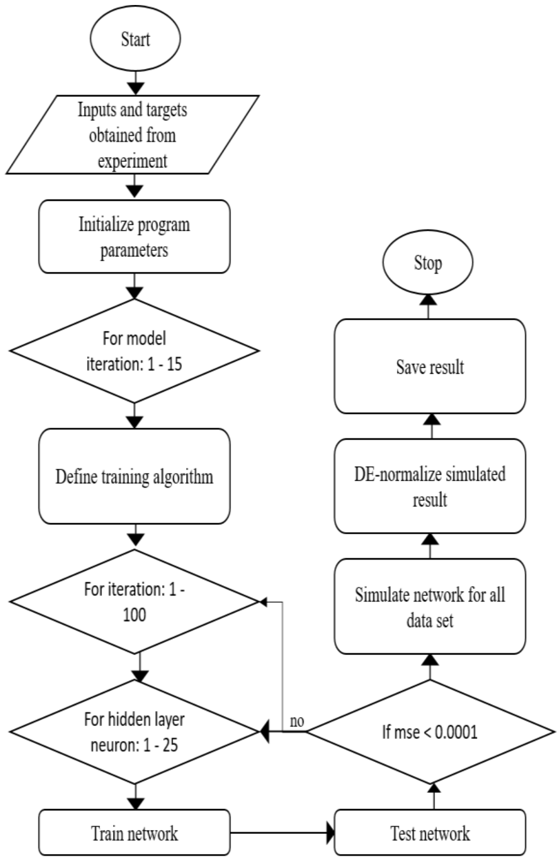

Figure 4: Back-propagation (Salem 2022)

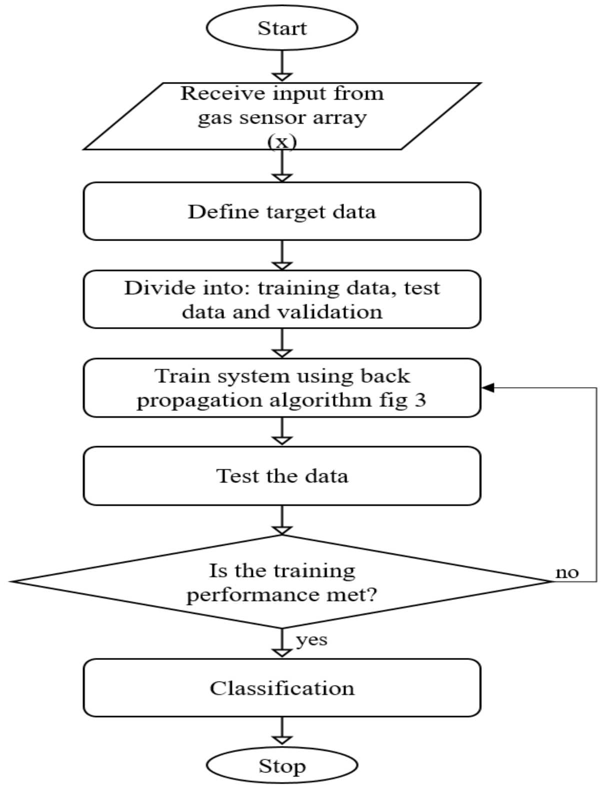

Figure 5: Gas detection algorithm

Figure 4 shows the algorithm of an ANN network, the first layer is responsible for the collection of the features extracted from the gas compounds detected by the sensor arrays, the target data or threshold is then defined with which to compare the trained data with. The data is then divided into training data set, used to train the system; test data used to test the data that was trained; validation used to find the mean value of a couple of conducted tests. The system is trained using a learning algorithm called the back-propagation algorithm in figure 3, after this phase the data is tested with the trained data, and the error is calculated and compared to the target data, if the error didn't converge then the training process is repeated till the error converges, then the data is classified.

Table 1: the ANN Training parameters

Parameters	**Values**
Training epochs	20
Size of hidden layers	10
Training segments	6
No. delayed reference input	23
Maximum feature output	1
Maximum feature input	23
Number of non hidden layers	12
Maximum interval per sec	2
No. delayed output	1
No. delayed feature output	2
Minimum reference value	-0.7
Maximum reference value	0.7
Time	0.05sec

IV. IMPLEMENTATION

This system was implemented using the toolbox available in Matlab: the Data acquisition toolbox was used to get the data from the sensors; the Statistical and machine learning toolbox were used for extracting gas features from the sensor; the Neural network toolbox was used to train the gas detection system to classify gasses according to their similarities in features.

Performance Evaluation models

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \qquad 6.0$$

MSE = mean squared error; n = number of data points; Y_i = observed values; $\hat{Y}_i$ = predicted values.

Regression analysis

$$Y_i = f(X_i, \beta) + e_i \qquad 7.0$$

Y_i = Dependent variable; f = function; X_i = independent variable; β = unknown parameters; e_i = error terms.

V. RESULTS AND DISCUSSION

The performance of the system was evaluated using Mean Square Error (MSE) model in equation 6. The aim was to measure the amount of error that occurred in the neural network during the training process. The result achieved was presented in figure 6;

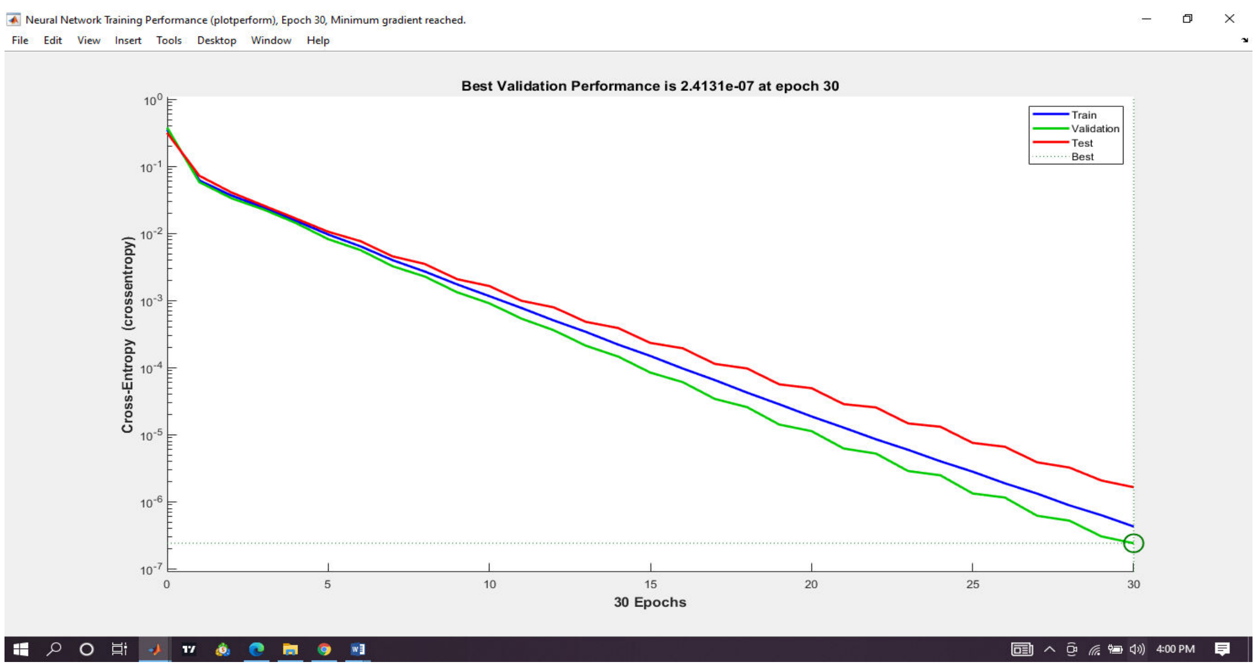

Figure 6: Training performance (MSE)

From figure 6, the MSE value is 2.4131e-07 at epoch 30, this result implies that the value achieved was an excellent achievement for its convergence to the ideal MSE value zero (0).

Another evaluation model was used, the Regression analysis model in equation 7, which was used in the system performance evaluation, which aimed at explaining the variability of the independent variable (Y) with respect to the dependent variable (X_i). The result achieved was presented in figure 7 as;

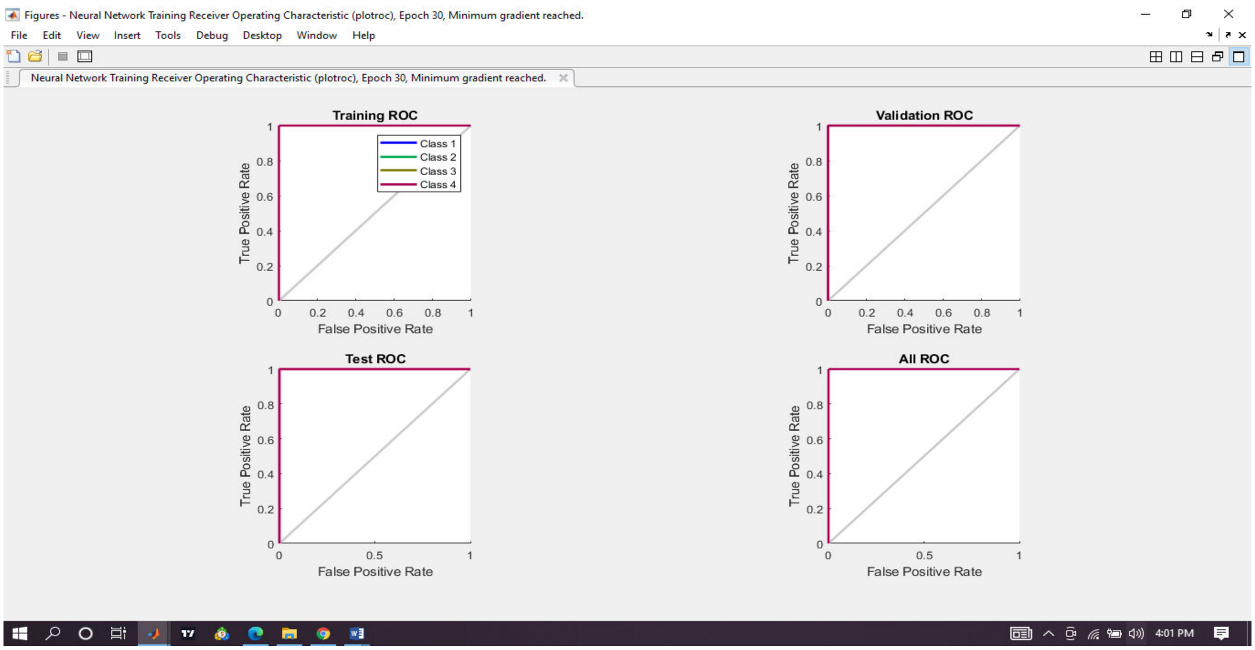

Figure 7: Regression Analysis

From the regression results in figure 7, the training ROC performance is 0.96, the validation ROC is 0.98, the test ROC is 0.97, the average ROC is 0.97, and this implied that the performance of the system is reliable due to its convergence towards the ideal ROC the value 1. For further validation, the tenfold model in equation 8 was adopted and table 2 displays the recorded data.

Tenfold validation formula (Mohd et al., 2017)

$$CVA = \frac{1}{10}\sum_{1}^{10} \mathrm{M}, R \qquad 8.0$$

Where;

M = Mean Square Error (MSE)

R = Regression

Table 2: Validation of Result

S/N	MSE	Regression
1	2.4131e-07	0.9786
2	2.3028e-07	0.9675
3	2.2417e-07	0.9876
4	2.1356e-07	0.9887
5	2.0245e-07	0.9889
6	2.7135e-07	0.9722
7	2.6024e-07	0.9816
8	2.5113e-07	0.9944

9	2.3262e-07	0.9861
10	2.1371e-07	0.9901
AVERAGE	2.3458e-07	0.9835

From Table 2, the MSE validation score is 2.3458e-07, the regression validation score is 0.9835. This implied that the system was reliable in the implementation field.

Comparative analysis

This section gathered a few literature reviewed techniques and their regression value and displays them in table 3 for comparative analysis.

Table 3: Comparative Analysis

Authors	**Technique**	**Regression**
Parag et.al, (2021)	LSTM model	0.58
Parag et.al, (2021)	Early fusion model	0.92
New system.	New system	0.93

The data in table 3 presented some of the reviewed literature and their performances. The result was exported to excel software and then analyzed graphically as shown in figure 7;

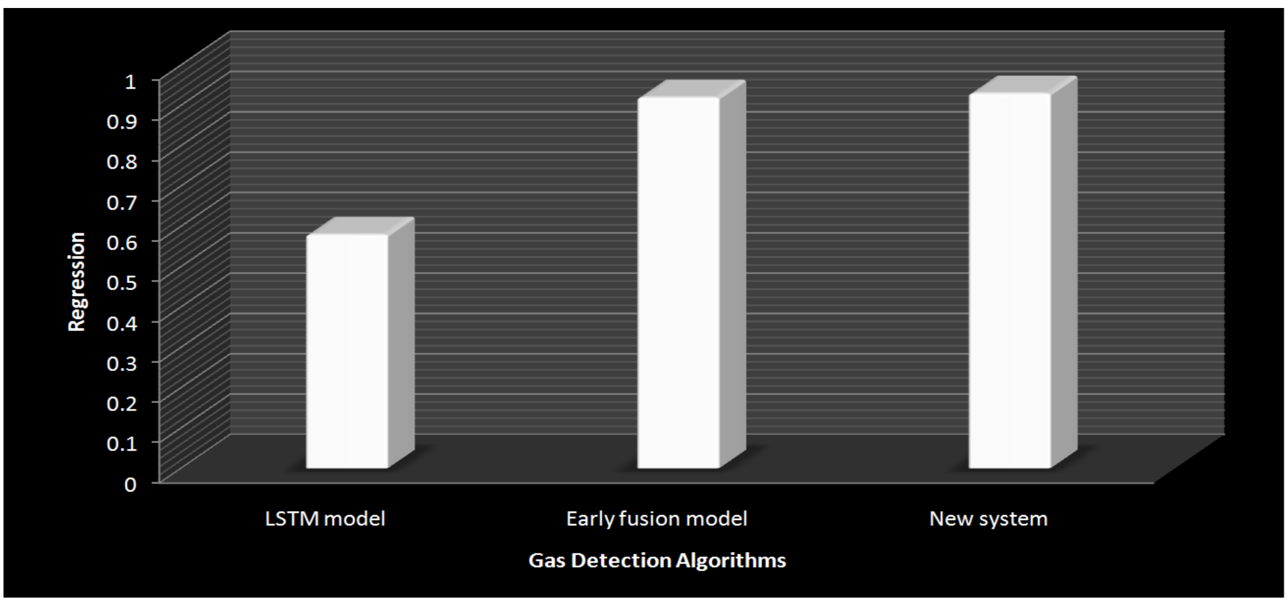

Figure 7: Comparative analysis

It was observed from the comparative analysis that the new neural network system performed better than the Long Short-Term Memory (LSTM) model and the early fusion model comparatively analyzed. This Neural Network performed better than the other models because this system developed using the dynamic moment feature extraction technique in collaboration with the Tanh activation function to increase accuracy in the detection of hazardous gases by the neurons.

VI. CONCLUSION

Over the years, dangerous gases such as CH_4 and CO have posed grave threats to the lives of man and animals, hence the need for gas detection devices. This work achieved the new intelligent system using the ANN algorithm to develop an intelligent system that detects CH_4 and CO. This gas detection system was tested and validated, and the results recorded showed that the gas detection system is highly efficient and reliable. The development of the new e-nose will reduced the number of fatalities drastically at mining and other environment prone to dangerous gas emission.

VII. CONTRIBUTION TO KNOWLEDGE

An intelligent system for CH_4 and CO detection in coal mining sites was developed using ANN.

VIII. ACKNOWLEDGEMENT

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