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An Empirical Investigation on Hazardous Gas Detection

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Abstract

Human fatalities in the sewer have been reported due to higher proportion of toxic gases in the manhole. The toxic gases like methane, carbon monoxide, nitrogen dioxide etc. can cause intense damage to human parts even leading to death. Hence predetermination of these gases is of vital importance. Analyzing the toxicity of gases is a crucial task and it has to take place with minimum time which can save a life. A machine learning based sensor system is designed to prevent such fatalities. A collection of gas sensors are being used to sense the manhole gases. The dataset is trained using different algorithms. A predictive model is designed to classify the state (safe/unsafe) of the manhole. To design such a prediction model, different algorithms were used and their performances were compared over the collected dataset. In present chapter the performance of various algorithms on such a real world problem was studied. From the comprehensive study the algorithm which produces higher accuracy and lesser error rate is chosen for the application.

Keywords: Gas detection, Gas sensors, Back propagation algorithm, Genetic algorithm, Naive Bayesian classification.

INTRODUCTION

As the days go by there is constant increase in human population that attributes to vast consumption of food and fuel in order to live. New methods are deployed through automation and hybrid growths to ensure the constant supply of needs in the modern world. This article is about providing a solution for a real world problem through computational intelligence. Computational intelligence solves many real world problems. Detection of manhole gas mixture is considered as a prediction problem which is implemented using a sensor system. In the past few years, artificial intelligence and machine learning has been proved as an efficient technique to solve complex problems. The central theme of the chapter is to present a comparative study of various algorithms to predict the hazardousness of the manhole gas mixture for designing such a sensor system.

We extract energy from various resources like wind, water, chemicals etc. there is one inevitable outcome we fail to encounter is waste by-products. Decomposition of waste into sewage leads to formation of toxic gases. In recent days human fatalities have increased due to higher proportion of noxious gases formed in the sewage. In the recent survey from department of urban development and housing it has been reported that the deaths due to manhole gases has been increased in 2017 than the previous year. Several municipality laborers have lost their life in cleaning and sanitation works [20, 21, 22, 23, and 24]. Environment and pollution are the major concerns in today's world. Toxic gases are one of the major threats to the society. Sewer gas is a complex mixture of toxic and non-toxic gases. The sewage gas is produced in the sewer by the decomposition of organic, household and industrial waste. The toxic gases in the sewer include methane, nitogendioxide, and carbonmonooxide, hydrogen sulphide [17, 18, and 19]. They pose a significant health hazard. So, there is a need of a portable instrument which can assist a sewage worker that may predict the safeness of a manhole. It is a complex problem to find the proportion of noxious gases. To serve this purpose, a sensor system is designed to detect multiple gases. It has been found that the commercially available gas detectors are not sufficient to detect all the aforementioned gases. Thereby a system of sensors is used to sense multiple gases. The objective of this work is to find the hazardousness of a manhole gas mixture. Algorithms like back propagation, genetic and naive bayesian are used and their performances were studied. The algorithm associated with higher accuracy is chosen for this application.

The related works is provided in section 2 followed by the methodology and algorithms in section 3. Readers may find the design of the proposed sensor system in the section 3.1.A discussion about the data acquisition mechanisms and the normalization process is given in the section 3.2. A detailed explanation about the backpropagation algorithm and the cross sensitivity issue is given in the section 3.3 followed by the genetic algorithm in section 3.4. Section 3.5 provides a brief discussion about the naïve bayesian classification for classifying the manhole gases. Section 4 provides the performance study of backpropagation, genetic and naïve bayesian algorithm by tuning their parameters like epochs, hidden nodes, and dataset size. Finally the results and conclusion is offered in section 5 and 6.

RELATED WORKS

In the past few years many works have been proposed for analyzing the toxic sewer gases using various algorithms. V.K.Ojha et al. [1] proposed an intelligent sensory system to detect the proportion of toxic gases and its hazardousness in the manhole. Classification methods have been used to find which classifier produces the highest accuracy to classify the gases. K.R.Katole et al. [2] designed a hazardous gas detection system using Arduino. This system will be able to detect the gases like methane, carbon-mono-oxide, LPG using the sensors. This device can be used in houses and workplaces. V.S.Velladurai et al. [3] illustrated the use of gas sensors and GSM module to detect the noxious gases in the garbage and unused wells. If the gas level exceeds the threshold then a message is sent to the concerned person. GSM and wireless networks are used for communication between the user and the device. Eungyeong Kim et al. [4] described the process of finding the gases by its odor. Genetic algorithm and Artificial Neural Network is used to determine the pattern of the gas. The gases in the sample mixture are identified by comparing it with the pattern derived from the neural network. V.K.Ojha et al. [5] proposed a hybrid model for analyzing the safety level of a manhole. A hybrid model of a neural network and genetic algorithm has been used here. This paper presents the performance analysis of neuro-genetic algorithm applied for multiple gas detection. Meng Xiaomin [6] compared the methods of back propagation (BP) and Self Organizing Feature Map (SOM) for recognizing the toxic gases in power plant. A qualitative analysis has been made on the three gases (CO, SO_2, NO_2) using both methods and proved that SOM is better than BP in terms of study time, training epochs in entirety. V.K.Ojha et al. [7] on the topic of designing an intelligent sensory system for manhole gases used back propagation algorithm for training the neural network. The back propagation algorithm has been employed to handle the issue of cross sensitivity. A comprehensive study has made, compared with other hybrid intelligent methods statistically and theoretically. D.E.Rumelhart et al. [8] explained about back propagating the errors and updating the internal weights of the hidden nodes. Back propagating the errors takes place when the observed output vector does not match the expected output. This algorithm minimizes the error between the expected and the observed output. J.Liu et al. [9] explained about the cross sensitivity issue using genetic algorithm. This paper handles the issue of cross sensitivity in the infrared gas sensors by applying the genetic algorithm on the pattern of gases. Paramartha Dutta et al. [10] used the concurrent neurosimulated annealing algorithm for training the neural network to detect the proportion of gas components in the manhole. The training of neural network is supplemented by the parallel version of simulated annealing (SA) algorithm which is Concurrent Neurosimulated Annealing algorithm (CNSA). The performance analysis of CNSA is made based on various parameters like search space, step length, annealing temperature, network configuration etc.

METHODOLOGY AND ALGORITHMS

Design

The system used her is embedded to a learned predictor model with the sensor system. The system model is shown in Fig.1. The system designed in this chapter comprises of three constituents sensor unit, classifier unit and output unit. The sensor unit consists of a gas pumping chamber, a set of sensors and a data collection block. Classifier unit receives the data from sensor unit and stores it in a database. The learning and prediction of algorithms are applied to the stored data. The output unit presents the level of gases and safeness of a manhole in a user friendly form. Gas mixture collected in a gas pumping chamber is allowed to pass over a sensor system. Data collection unit receives sensed data values from the sensor system. The gas data values are normalized before feeding it into classifier block. The output unit generated an alarm if any of the noxious gases exceeds the safety level.

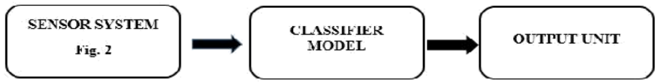

Figure 1. Overall Design

N number of distinct sensors is used to keep track of M number of gases. The sensors used here are MQ-2, MQ-136 and MICS 2714. The sensors are integrated into a single system to function as a unit. The working of sensors is based on the concept of resistance. The resistance of the sensors changes when there is a change in resistance is given as $\Delta R/R$ where ΔR is the change in the resistance of the sensor and R is the base resistance [11, 12]. The gas sensors are not only sensitive to the target gases but also for the nontarget gases. Hence the cross sensitivity issue is confirmed [9]. The sensor responses were noisy. The noisy data is recorded as a instance in the dataset. Hence a non-intelligent use of raw value will mislead the prediction of hazardousness of a manhole. The gases are measured in Ppm (parts per million). Ppm is a unit of measuring concentration of gases in air. One volume of gas in 10^6 volume of air is measured as one Ppm. In the real world the sensor responses may not be able to use directly for predicting the safety level of a sewer. Therefore, there is a need of the prediction system to predetermine the concentration of toxic gases in the manhole, we proposed an intelligent system that will detect the concentration of gases above the threshold and report the worker in the manhole through an alarm.

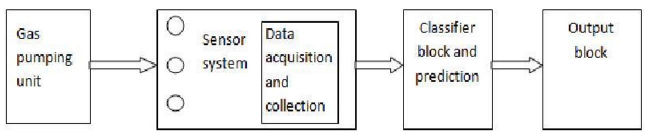

Figure 2. Sensor System

Data Acquisition and Normalization

Data acquisition involves several steps. Datasheets, literatures, laboratory tests of the manhole gases are collected as data samples initially. The data about the safety limits of each manhole gas is collected. The gas samples were prepared by mixing several gas mixtures in different concentrations. As an example, if there are three gases, its maximum and minimum level is found. The concentration of gases is varied in between these levels and 2500 data samples are obtained. Our designed sensor system consists of three gas sensors for sensing three different gases. They include carbonmonooxide,

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nitogendioxide, and methane. The gas sensors used here are MQ-2, MQ-136, and MICS-2174. The concentration range of the gases in ppm are [0.25-5], [20-1000], [300-10000] for NO_2, CO, CH_4 respectively. The data sample values may vary for different gases. There is a need of normalization to scale up the unequal values. Normalization is a technique that scales the values to a certain range say 0 and 1. One of the normalization used here is the Min Max normalization. Min max normalization transforms a value R to S that lies in the range of [U, V]. The mathematical representation is given below

$$S = (((R - MinimumvalueofR)/(MaximumvalueofR - MinimumvalueofR)) * (V - U)) + U \quad (1)$$

Table 1. Sensor responses and their normalized values

#	sensor responses			normalized sensor responses		
	NO2	CO	CH4	NO2	CO	CH4
1	0.5	100	2000	0	0	0.25
2	0.5	200	5000	0	0.5	1
3	2	100	1000	0.6	0	0
4	3	200	2000	1	0.5	0.25
5	1	300	5000	0.2	1	1

Back Propagation

Back propagation is a form of supervised learning for multilayer feed forward neural network. The principle of back propagation algorithm is to design a given function by modifying the internal weights of an input function to produce an expected output. Here the output of one layer is given as input to the following layer. Each layer is fully connected to the following layer. The input presented to the first layer is processed through the following layer and the output is compared with expected output. If both the results are not matched and there occurs an error, the algorithm back propagates to the previous layer. In the process of back propagation to the previous layer. In the process of back propagation, the weights of the internal layer are updated such that the errors are minimized [8]. The issue of cross sensitivity is handled easily by the back propagation algorithm [9]. As the non-target gases are not captured, the cross sensitivity problem occurs.

The cross sensitivity problem can be handled in two modes

a. Batch mode

b. Sequence mode

In batch mode, the synaptic weights are constant while calculating the error in each input sample and then the weights are updated once in an epoch, whereas in sequence mode, each time when an error occurs, the weights are updated frequently [25]. So, the error calculation uses different weights for each input sample. Batch mode updates for each epoch but sequence mode updates for each sample [7]. The number of weight updates differs for both the modes. Batch mode performs efficiently as it updates once in an epoch and has lesser number of weights updates.

In forward propagation, the input is given to the input layer and it is processed in the internal hidden layer and the output at the output layer. After forward propagation, the error at the output layer is found. Then the back propagation step follows. In back propagation, the error signal of the output layer is passed onto the hidden layer. This step propagates backward through each layer along with the error signal and the weight of the current layer. The error signals of all the hidden layer neurons are found. Once the error for each neuron is calculated, their weights are updated using the following formulas.

$$weight = weight + (learningrate * error * input) \quad (2)$$

The errors were accumulated across an epoch before updating its weights, thus it is batch learning.

Thus the dataset is trained using back propagation algorithm. Then a sample dataset is used for prediction. The sample data is set to forward propagation and their results are compared with the expected output.

Genetic Algorithm

A supervised mode of training algorithms is used for training the neural network. This problem needs to optimize the weights of neural network. It is hard to optimize weights for such a complex problem. The conventional back propagation algorithm used is of error. It is a partial searching algorithm and its calculation rate is relatively slow [9]. To such a problem, the traditional optimization methods are not efficient. The genetic algorithm is a global optimization method. It is a higher level procedure which involves natural selection. They generate a good high quality results for optimization and search problems. Genetic Algorithm is dependent on the features like crossover, mutation, selection etc. It modifies the population repeatedly for each solution. The neural network applied with genetic algorithm is shown in Fig.3.

The steps of genetic algorithm are as follows:

1. Defining the members of the network: Define the number of units in the input layer (i), hidden layer (h) and output layer (o). Each member of the input layer is assigned a synaptic weight w_{ij} randomly.
2. Training of neural network: The learning network consists of an input specimen X_i and the output which is the expected specimen C_i. Each member is scored by a fitness function.
3. Fitness of a member: the fitness function determines the ability of a member to compete with others. It gives the probability that the member will be selected for reproduction.
4. Selecting the seed: This step involves selecting the members to produce offspring. The ability of a member to produce offspring is chosen according to its fitness value.
5. Crossover and mutation: The members are allowed to

breed among themselves to produce a new generation according to the crossover probability P_c. Some genes of the members are randomly changed according to the mutation probability P_m.

6. Simulated annealing: Simulated annealing is used for locating a good approximation on global optimum. The new individuals created by the crossover and mutation are accepted by the simulated annealing. Both top performing members and the inferior ones are accepted. The probability of accepting the inferior ones decreases when the annealing temperature decreases [10].

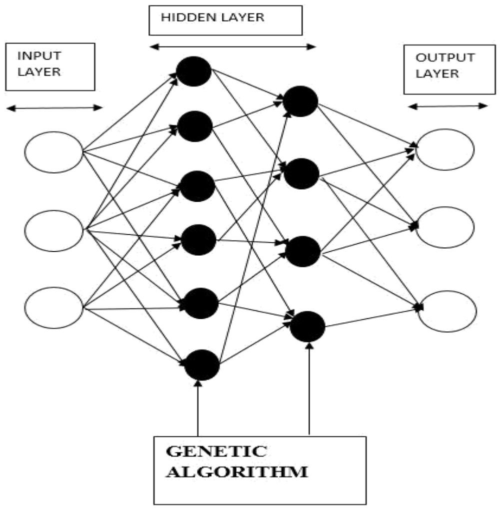

Figure 3. Structure a neural network applied with Genetic algorithm

The above procedure is repeated from step 2 until a convergence condition is found, that is until a fittest individual is found. The dataset is applied to this neural network and trained. The above procedure is repeated until a safer gas sample (fittest) is obtained and it is compared with the give test set to predict its safety level.

Naive Bayesian Algorithm

Naive Bayes Classifier is a probabilistic classifier. It classifies the given tuples based on the probability to which class they belong to. It is an intuitive method where the probabilities of every attribute belonging to each class are used for making prediction. It is a supervised learning with a predictive model probabilistically. Here the probability of each class attribute belonging to a class value is independent of all other attributes i.e. every attribute is independent of each other. The classifier is based on the Bayes' Theorem. Bayes' Theorem assumes that there is an independency among predictors. The presence of particular feature in a class is independent to the presence of any other feature. Naive Bayesian model is easy to design for large datasets because of its simplicity. Bayes' Theorem states that "the probability of an event, based on prior knowledge of conditions that might be related to the event". It can be expressed mathematically as,

$$P(C|X) = (P(X|C) * P(C))/P(X) \tag{3}$$

Let C_1, C_2 be the largest classes and X_1, X_2, X_3 are the feature (gases) to be classified to the class C_k (k=1, 2). P (C_k | X_i) is the posterior probability which gives the probability that X_i belongs to C_k.

P (X_i|C_k) is the likelihood.

P(C_k) be the prior probability of class C_k.

P(X_i) be the prior probability of feature X_i.

The value can be applied to the below equation to find to which class the given feature belongs to,

$$P(Ck|Xi) = (P(Xi|Ck) * P(Ck))/P(Xi)$$

This above equation gives the probabilities of each class to which the sample can be classified. The higher probability can be selected for classification.

Here the Gaussian Naive Bayes' model is implemented. As this dataset has continuous values they follow a normal distribution (Gaussian distribution). Gaussian data classification model is easy to work because only the mean and standard deviation of the training dataset is calculated. The probabilities of each input values for each class is calculated using a frequency with real valued inputs. Then the mean and standard deviation of input values(x) for each class to summarize the distribution is calculated.

The mean and standard deviation of each input value(x) for each class value is computed using following equation,

$$Mean(X) = 1/(n * sum(X)) \tag{4}$$

$$StandardDeviation(X) = \sqrt{1/(n * sum(Xi - (mean(X))^2))} \tag{5}$$

The inputs are summarized by the mean and standard deviation found based on the class value (0, 1). For each class value 0 and 1, the mean and standard deviation of each input is found.

Now the probability that the input x belongs to a class C is found using the Gaussian Probability Density Function (PDF)

The PDF is represented mathematically as,

$$PDF(X, mean, SD) = (1/(\sqrt{2 * \pi} * SD)) * exp(-((X - mean^2)/(2 * SD^2))) \tag{6}$$

Finally, each input value gets the probability of each class value to which it belongs to.

This Gaussian model is simple and easy to calculate the probabilities. It is an efficient method which increases the performance of the classifier. It outperforms the other classifier in terms of performance and accuracy.

Performance Study

The Back propagation algorithm has been implemented using Python, Forward and Backward propagation methods are implemented in the batch mode. The accuracy has been measured in terms of the number of hidden nodes and the number of epoch in Fig.4 and Fig.5. From the Fig.4 it is clear that the accuracy of the training network reaches the maximum of 70% when the numbers of nodes in the hidden layer are 12 and 14.

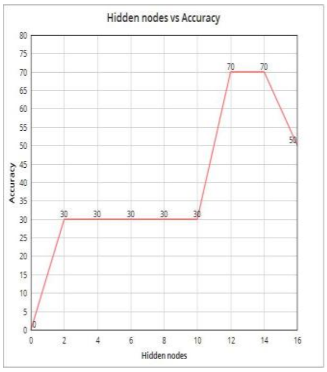

Figure 4. Accuracy of back propagation algorithm with respect to number of hidden nodes

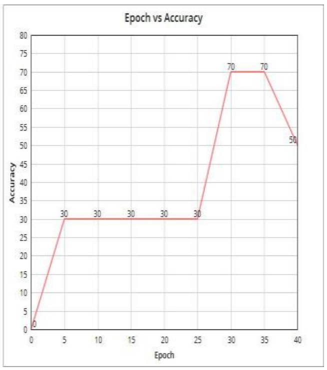

Figure 5. Accuracy of back propagation with respect to the number of epochs

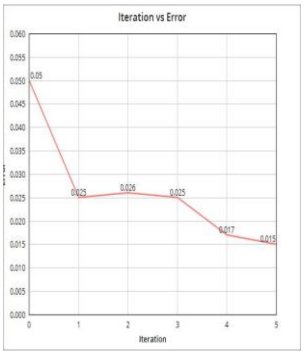

Figure 6. Error at each iteration

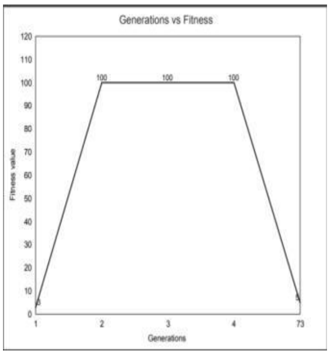

Figure 7. Generations taken to find various fitness valued genes

The error at each iteration is shown in the Fig.6. The error decreases at each iteration of back propagation. At the iteration 5 a minimum error of 0.015 is produced by back propagation. The function of genetic algorithms is to find the fittest gene by performing cross over and mutation operations. The Fig.7 shows the graph of generations versus the fittest gene. Fig.7 explains in how many generations a particular fittest gene can be found. A gene with a fitness value 5 takes 73 generations. It may take a long time for processing and other takes infinite number of generations to find other fitness value genes. From the graph Fig.7, it is observed that when a gene of higher fitness value is to be found, then it takes more number of generations. Fig.9 shows a clear graphical representation of Naive Bayes Algorithm implemented using Gaussian distribution. As the Gaussian distribution of Naive Bayes uses the mean and standard deviation it can generate a result of higher accuracy even with larger dataset when compared with other algorithm like back propagation and genetic. So, Naive Bayes algorithm gives an accuracy of 97%.

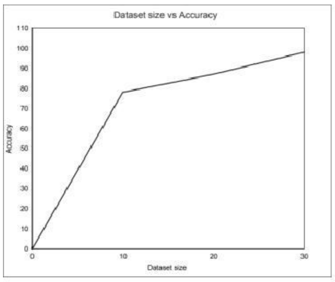

Figure 8. Performance of Naïve Bayes classifier for different size of datasets

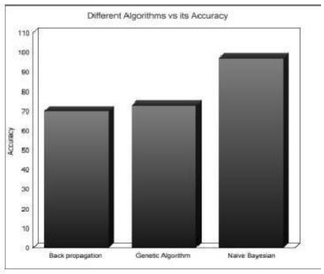

Figure 9. comparing the performance of three algorithms

RESULTS AND DISCUSSIONS

The aim of the experiment design is to obtain a highly accurate predictive model for identifying the hazardousness of the manhole gas mixture. The sewer pipeline gases were collected. The data samples are prepared as per the procedure mentioned in section 3.2. The collected dataset is partitioned into two parts. Seventy five percent of the collected dataset is used as training set and the remaining twenty five percent as the test set. The dataset is subjected to various training algorithms like backpropagation, genetic, naïve bayes. After training, the system is tested using the test set. The results of all the three algorithms were collected. The sensor values are normalized in order to obtain the results of same range and it is shown in Table 1. The number of epochs and hidden nodes are changed in the process of back propagation. The accuracy of it is plotted in the graphs Fig.4, 5. The results of genetic algorithm and the number of generations taken to find the fittest individual are shown in Fig.7. Accuracy of naïve bayes classification is shown in Fig.8 over the collected manhole gas data when there is an increase in dataset size. Note that the probability that each gas sample is safe (class 0) or unsafe (class 1) is predicted more accurately in the naïve bayes classification than the other two algorithms. The safeness of a manhole is predicted using the safety levels of each manhole gases. The safety level of NO_2 is in between 30 and 100 ppm [13, 14, and 15], H_2S is 50-100 ppm and CH_4 is 5000-10000 ppm [16].

Table 2. Safeness of the manhole gas mixture samples.

#	sensor responses			normalized sensor responses			class (safe/unsafe)
	NO2	CO	CH4	NO2	CO	CH4	
1	2	100	1000	0.6	0	0	safe
2	10	2000	12000	0.75	0.5	0.4	unsafe
3	12	10000	6000	1	1	0.25	unsafe
4	1	3000	5000	0.2	0.2	0.15	safe

CONCLUSION

The focus of this paper is to compare the performance of machine learning algorithms to find which suits better for the application of analyzing the sewage gases. The comparison of three algorithms is depicted in Fig.9. Naive Bayes classifier qualifies 97% accuracy, Back propagation and genetic algorithm 70% and 73% accuracy respectively. The accuracy of Back propagation is found using the number of hidden nodes, epochs and the error involved in the learning. Genetic algorithms accuracy is measured by the number of generations it took to find the fitness individual. The mean and standard deviation of each attribute belonging to each target class is used as the performance measure in Naive Bayes. So, it is clearly observed that Naive Bayes classifier implemented using Gaussian distribution is the best algorithm for classifying the mixture of gases according to their safety level. Therefore an interesting study of three algorithms to identify the hazardousness of a manhole gas mixture is presented in the chapter and the best appropriate method is chosen.

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