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BPN BASED ENSEMBLE CLASSIFIER FOR GAS SENSOR ARRAY DRIFT DATASET

D. Arul Pon Daniel
Department of Computer Science
Periyar University
Salem – 636 011, India
apdaniel86@yahoo.com

K. Thangavel
Department of Computer Science
Periyar University
Salem – 636 011, India
drktvelu@yahoo.com

***Abstract*-Much work has been done on classification for the past fifteen years to develop adapted techniques and robust algorithms. The problem of data correction in presence of simultaneous sources of drift, other than sensor drift, should also be investigated, since it is often the case in practical situations. The classification systems, however, are not work on the gas sensor domain, where the benefit of correct classification of chemical components is also the cost of wrong classification is different for all pairs of predicted and actual classes. BPN is a competitive machine learning technique, which has been applied in different domains for classification. In this paper BPN have been implemented for Gas Sensor Array Drift Dataset. The experimental results show that the BPN classifies the drift dataset with an average accuracy of 97% than the other classifiers. The proposed method is compared with C4.5 and SVM.**

Keywords-C4.5, SVM, BPN, Ensembles, Gas sensor array Drift Dataset.

I. INTRODUCTION

The past decade has seen a significant increase in the application of multi-sensor arrays to gas classification and quantification. The idea to combine an array of sensors with a pattern recognition algorithm to improve the selectivity of the single gas sensor has been widely accepted and being used by researchers in this field. In fact, an array of different gas sensors is used to generate a unique signature for each gas [1]. A single sensor in the array should not be highly specific in its response but should respond to a broad range of compounds, so that different patterns are expected to be related to different odors [2]. Different methods have been suggested recently to compensate for sensor drift in experiments for gas identification [3]. Chemical sensor arrays combined with read-out electronics and a properly trained pattern recognition stage are considered to be the candidate instrument to detect and recognize odors as gas mixtures and volatiles [4].

After learning the features of the class, the SVM recognizes unknown samples as a member of a specific class. SVMs have been shown to perform especially well in multiple areas of biological analyses; especially functional class prediction from microarray Sensors produced data [5].

This paper has been organized into five sections. Section 2, presents the short note about the Dataset used. Section 3, describes the approach of Back Propagation Neural Network. Sections 4, experimental results of various classification tools are presented. Section 5, conclusions and further research scope are presented.

II. DATASET

The Drift Dataset contains 13910 measurements from 16 chemical sensors utilized in simulations for drift compensation in a discrimination task of 6 gases at various levels of concentrations. The resulting dataset comprises from six distinct pure gaseous substances, namely Ammonia, Acetaldehyde, Acetone, Ethylene, Ethanol, and Toluene, each dosed at a wide variety of concentration values ranging from 5 to 1000 ppm [6]. This dataset is available in http://archive.ics.uci.edu/ml/datasets/Gas+Sensor+Array+Drift+Dataset

III. BACK PROPAGATION NEURAL NETWORK

There are different kinds of pattern recognition methods available in the literature. In this paper, Back Propagation Neural Network method is adopted and discussed in the subsequent section.

Apply the input vector to the input units. Let $X_p = (x_{p1}, x_{p2}, \ldots, x_{pN})^t$ is be an input vector.

Calculate the error terms for hidden units:

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$$\delta_{pj}^{h} = f_{j}^{h\prime}\left(net_{pj}^{h}\right) \sum_{k} \delta_{pk}^{o} w_{kj}^{o} \quad (1)$$

where δ_{pj}^{h} is the error at each hidden unit

Notice that the error terms on the hidden units are calculated before the connection weights to the output-layer units have been updated.

Update weights on the output layer:

$$w_{kj}^{o}(t+1) = w_{kj}^{o}(t) + \eta \delta_{pk}^{o} i_{pj} \quad (2)$$

Update weights on the hidden layer:

$$w_{ji}^{h}(t+1) = w_{ji}^{h}(t) + \eta \delta_{pj}^{h} x_{i} \quad (3)$$

where η is the learning rate parameter. The order of the weight updates on an individual layer is not important. Be sure to calculate the error term

$$E_p = \frac{1}{2} \sum_{k=1}^{M} \delta_{pk}^{2} \quad (4)$$

since this quantity is the measure of how well the network is learning. When the error is acceptably small for each of the training-vector pairs, training can be discontinued [7-12]. The Figure 1 illustrated the Neural Network structure of system.

The parameter used in the Neural Network are listed below

- Number of Layers :1 (Input) +10 (Hidden) +1(Output)
- Data Division :Contiguous Blocks
- Performance function :Sum squared error
- Iteration :18
- Learning Rule :Levenberg-Marquardt

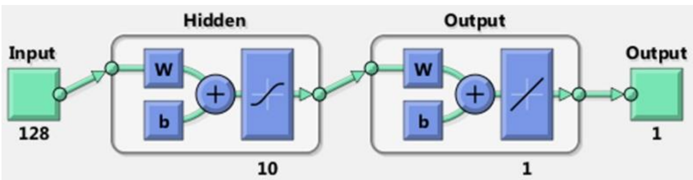

Figure 1. Neural Network structure

IV. EXPERIMENTAL RESULTS

In this experiment, the features in the training datasets are scaled appropriately to lie between −1 and +1. The kernel band-width parameter, the SVM parameter and BPN parameter were chosen using 10-fold cross validation by performing a grid search in the range $[2^{-10}, 2^{-9}, \ldots, 2^{4}, 2^{5}]$ and $[2^{-5}, 2^{-4}, \ldots, 2^{9}, 2^{10}]$ respectively. The performance of an SVM trained on batch 1 and tested on batches 2^{-10}. Note that this curve is estimated with the same SVM model used in Figure3 but tested on data from batches in-stead of months. It is found that the similar behaviors when we trained several SVMs on batches 2^{-5} and tested them on successive batches. These results are again shown in Figure 2,Figure 3, Figure 4. The complete set of results, i.e., the accuracy of classifiers trained on batches 1–9 and tested on successive batches, is given in Table 1, Table 2, Table 3 . The individual plots correspond to the performance of classifier trained with batch 1 and tested on batches at subsequent time points after applying the component correction method for every one of the six reference gases. In this analysis the BPN classifier achieves the best average accuracy of 96.94% rather than the C4.5 and SVM.

TABLE I. CLASSIFICATION ACCURACY OF THE C 4.5 CLASSIFIERS TRAINED ON BATCHES 1–9 AND TESTED ON SUCCESSIVE BATCHES.

Batch ID	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7	Batch 8	Batch 9	Batch 10
Batch1	82.71	68.41	60.24	35.03	56.04	27.87	32.65	34.26	26.06
Batch2		81.59	85.09	91.37	28.78	40.57	41.15	54.04	29.75
Batch3			63.97	45.17	4456	39.46	23.12	52.12	25.02
Batch4				76.14	21.17	24.68	10.2	23.61	25.77
Batch5					36.6	13.83	10.2	23.19	16.58
Batch6						61.25	36.39	17.23	28.8
Batch7							63.27	56.38	35.52
Batch8								56.59	36.38
Batch9									14.75

TABLE II. CLASSIFICATION ACCURACY OF THE SVM CLASSIFIERS WITH RBF KERNEL FUNCTION TRAINED ON BATCHES 1–9 AND TESTED ON SUCCESSIVE BATCHES.

Batch ID	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7	Batch 8	Batch 9	Batch 10
Batch1	98.18	98.78	99.28	88.01	98.62	98.96	98.88	98.46	99.4
Batch2		99.29	99.92	98.29	99.96	99.4	99.38	99.56	99.79
Batch3			99.38	97.3	99.26	99.79	99.49	99.78	99.85
Batch4				99.94	99.22	98.89	99.58	99.75	99.94
Batch5					99.94	99.95	99.75	99.68	99.86
Batch6						99.59	99.75	99.5	99.81
Batch7							99.2	99.7	99.76
Batch8								93.57	93.35
Batch9									84.3

TABLE III. CLASSIFICATION ACCURACY OF THE BPN CLASSIFIERS WITH RBF KERNEL FUNCTION TRAINED ON BATCHES 1–9 AND TESTED ON SUCCESSIVE BATCHES.

Batch ID	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7	Batch 8	Batch 9	Batch 10
Batch1	98.18	98.78	99.28	88.01	98.62	98.96	98.88	98.46	99.4
Batch2		99.29	99.92	98.29	99.96	99.4	99.38	99.56	99.79
Batch3			99.38	97.3	99.26	99.79	99.49	99.78	99.85
Batch4				99.94	99.22	98.89	99.58	99.75	99.94
Batch5					99.94	99.95	99.75	99.68	99.86
Batch6						99.59	99.75	99.5	99.81
Batch7							99.2	99.7	99.76
Batch8								93.57	93.35
Batch9									84.3

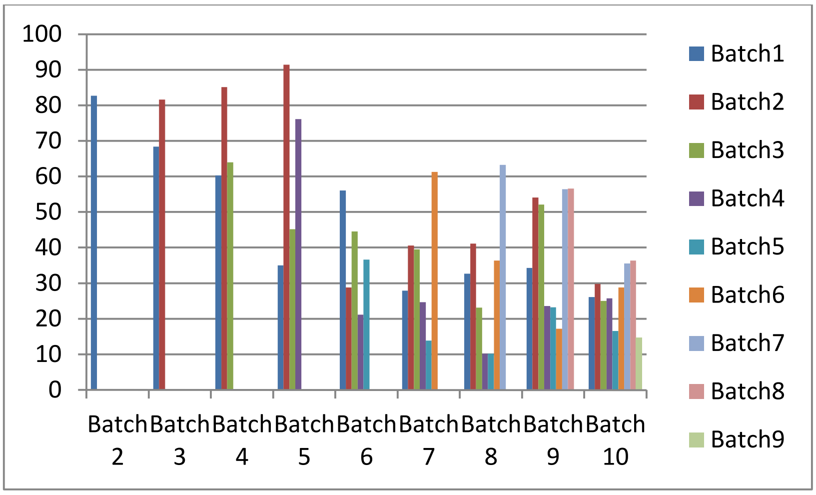

Figure 2. Classification accuracy of the C 4.5 classifiers

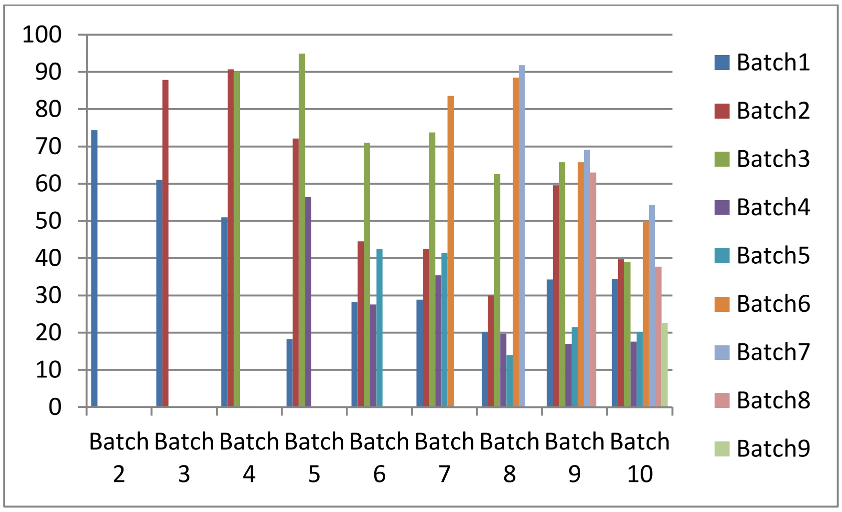

Figure 3. Classification accuracy of the SVM classifiers with RBF kernel Function

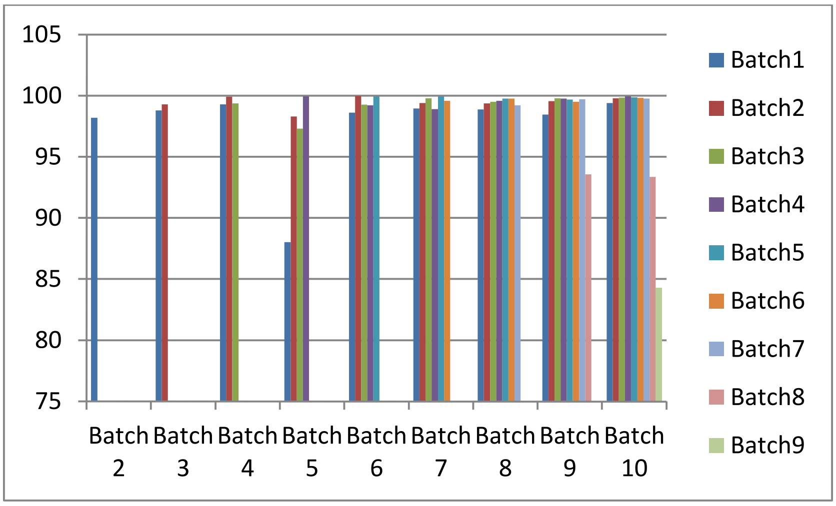

Figure 4. Classification accuracy of the BPN classifiers with RBF kernel Function

V. CONCLUSION

Gas sensor array drift dataset has been analyzed using C4.5, SVM and the proposed BPN classifiers. Six chemical components are used to acquire the drift data set with different time series. In this paper, BPN has been used for classification and compared with C4.5 and SVM. The proposed BPN classifier achieves the average accuracy of 96.94% when compared with other classifiers. This classification of chemical components may be used to train the system to detect the Non-communicable diseases from human exhaled breath in future.

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