Mirror Mosaicking: A Novel Approach to Achieve High-performance Classification of Gases Leveraging Convolutional Neural Network

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Abstract: Limited dimensionality of the dataset obtained from an electronic nose (EN) is due to the number of elements in the sensor array used generally in the range of 4-8 elements only. Further, large number of sensor data can be generated by sampling the sensor responses both during the transient and steady states. The lower-dimensionality of sensor data prohibits the use of a convolutional neural network (CNN)-based pattern recognition techniques because the kernels of a CNN cannot be used on the obtained sample vectors to extract the features. In this paper, we have proposed a novel approach to enhance the data dimensionality keeping the sensor response characteristics absolutely unaltered. By leveraging the concept of mirror mosaicking technique, we have upscaled the input sample vectors into a 6×6 2-D input arrays to train the shallow CNN. Using the proposed approach, all the 16-unknown steady-state test samples classified accurately which are not used during the training. Moreover, the parameters of the classification report viz., Precision, Recall, and F1 score also obtained with a fraction value of 1.00. The proposed technique is a generic approach that can be used to classify various low-dimensional datasets obtained from various sensor arrays in various fields.

1 INTRODUCTION

In the current scenario, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and modern Pattern Recognition (PR) techniques are finding their applications in almost all the research areas; for delivering better results. An electronic nose (EN) is the mimicry of the olfactory system that is a popular topic of research as a multidisciplinary area. The word multidisciplinary represents the wide area of applications of EN related to different industries. Various traditional pattern recognition approaches have been used for the classification of gases or odors, as described by (Santos et al., 2017; Fujinaka et al., 2008; Hodgins and Simmonds, 1995; Tang et al., 2010; Keller et al., 1995; Rodrguez et al., 2010; Capelli et al., 2014; Kızıl et al., 2017; Chen et al., 2013). The EN is a system that contains a gas sensor array consisting of few sensors typically 4 to 16. Moreover, data pre-processing and pattern recognition modules are the main parts of any EN system (Arshak et al., 2004). The EN system can be made more selective for analytes under observation, using an array of sensors (Zhang et al., 2017). A gas sensor array logically has more than one sensor element to enhance the selectivity of the system. If there are fewer numbers of sensors in a gas sensor array, the resulting response dataset has a feature vector of limited size for each sample. A concept of mirror mosaicking technique is proposed in this work to broaden the applicability of deep learning pattern recognition techniques for automatic feature extraction and classification of small gas sensor array responses. Subsequently, any gas sensor array response can be analyzed using the convolutional neural network (CNN) at the sample level irrespective of the size of the gas sensor array. The feature vector of any sample is obtained from the respective gas sensor array response having the length equal to the number of the sensor elements. Each pattern recognition technique requires a specific input format or length of the feature vector. For example, various dimensional versions viz., 1-D, 2-D, and 3-D based on the type of operation of the convolution of CNN

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require a 1-D vector, 2-D array, and 3-D array (Eren, 2017; Yamashita et al., 2018). Therefore, each version has its limitation of input sample representation. A 2-D CNN has vast popularity in the area of computer vision and image processing. However, any of the versions of CNN can be used depending on the available dimension of the sample. In this work, data pre-processing and classification parts of an EN system has been demonstrated. The pre-processing has been used to obtain the mosaicked sample and later on the classification task is implemented using a convolutional neural network.

The rest content has been organized in the following sections. The proposed mirror mosaicking technique has been explained in Section 2. While Section 3 describes the designed convolutional neural network to generalize the proposed approach. Moreover, Section 4 and Section 5 are dedicated to the used material and obtained results, respectively. Lastly, the conclusions have been summed up in Section 6.

2 MIRROR MOSAICKING

2.1 Need of Mirror Mosaicking

As discussed in the previous section, the particular dimensional version of CNN requires a specific format of the input. The 1-D CNN requires input as a feature vector. The 1-D CNN significantly can be applied if the feature vector has sufficient length. The length of the feature vector proportionally depends on the number of sensor elements in the gas sensor array. As quoted earlier, a gas sensor array has more than one sensor element, then the least possible array must have two gas sensors elements. Let us suppose we have the smallest gas sensor array, then the feature vector of this array will have a length of 2 units. This length of the feature vector is insufficient to explore the significance of the 1-D CNN. Similarly, the 2-D CNN needs input in the form of a 2-D/3-D matrix (grayscale/color image). A feature vector of the smallest sensor array of length 2 units is incompatible for converting into a 2-D matrix. Therefore, the sample obtained from this sensor array cannot be feed as input into the 1-D CNN or the 2-D CNN and the subsequent higher dimensional version 3-D CNN.

Consequently, a sample obtained from the least feasible gas sensor array or the gas sensor array with two sensor elements is insufficient to deal with the 1-D CNN and the 2-D CNN. Moreover, these samples will also be insufficient to the subsequent higher dimensional version of CNN that is 3-D CNN. Hence a technique called mirror mosaicking has been proposed so that each sample obtained from any sensor array can be analyzed using 2-D CNN. The popularity of 2-D CNN has been proved worldwide by computer vision and image classification applications.

2.2 Implementation of Mirror Mosaicking

The proposed mirror mosaicking is the approach in which each sample vector obtained from any gas sensor array can be converted into a 2-D matrix of significant size so that a 2-D CNN can be applied at the sample level (Chaudhri et al., 2020). First of all, the original sample feature vector is converted into the square 2-D matrix using zero-padding if required. Subsequently, the mirror mosaicking technique is applied to this square 2-D matrix to obtain the desired mosaicked sample compatible with the 2-D CNN.

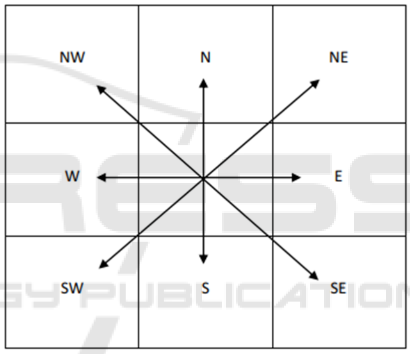

Figure 1: Directions of Mirrors.

Let's assumed that eight mirrors are placed around the square 2-D matrix obtained from the original sample feature vector using zero-padding if required. The corresponding directions of the mirrors are shown in Figure 1. The obtained corresponding mirror images of the square 2-D matrix at the center are mosaicked with it at their respective locations to obtain the desired mosaicked sample. Thus, the obtained mosaicked sample of the corresponding original sample now compatible as input to the 2-D CNN. Further, the depth of the used 2-D CNN is the thing to note down. There is no restriction for the depth of the network based on the fully connected layers provided the increasing number of layers makes the model complex. But concerning the convolutional and the pooling layers, the network depth depends on the size of the input. Considering the case of the smallest feasible gas sensor array a shallow convolutional neural network (SCNN) has been designed that can be extended according to the size of the input by adding more convolutional or pooling layers. The word shallow indicates that few convolutional layers in the designed 2-D CNN are two according to the size of the input.

3 SHALLOW CONVOLUTIONAL NEURAL NETWORK (SCNN)

As quoted in Section 2, the designed shallow convolutional neural network (SCNN) has two convolutional layers. Depending on the size of the available input sample, convolutional and pooling layers can be increased in the designed model. Mainly pooling layers are used in those deep networks which are specifically designed to deal with image-related tasks because images are made of large 2-D matrices. In our work, SCNN is designed to classify the gases using gas sensor array responses which have a limited sample size. But the SCNN can be extended to classify the responses obtained from the gas sensor array having any number of sensor elements. The used SCNN has the following layers:

- Convolutional Layers (Input Layer)
- Flatten Layer
- Dense or Fully Connected Layers
- Dropout Layers
- Softmax Layer (Output Layer)

The SCNN with the mentioned layers has been designed considering the smallest gas sensor array. A brief theoretical introduction for the basic layers is given below (Bhandare et al., 2016):

Convolutional Layers.
The model attains the leading significance of automatic feature extraction by this layer. In this layer, the number of kernels is initialized, which are used to produce the same number of feature maps. The feature maps are obtained from the convolution of the input and the kernel. All the stacked feature maps are forwarded to the next layer in the form of input.

Pooling Layers.
It is used for down-sampling. There are three basic types of pooling namely max pooling, min pooling, and average pooling. Out of the three types, max pooling is used widely.

Flatten and Fully Connected Layers.
The flatten layer is used after all the used convolutional and pooling layers to convert the output feature map into the vector format. Subsequently, the dense layers or the fully connected layers are used. A fully connected layer is that in which each neuron is connected to each neuron of the previous and next layer.

Softmax Layer.
The softmax layer is the output layer in which the number of neurons must equal to the number of targets. In this layer, for each input, the membership fraction corresponding to each target is obtained.

Dropout and Normalization Layers.
The dropout and the normalization, both layers are used to get rid of overfitting. In the dropout layer, a dropout amount is initialized to discard the neurons containing the value less than or equal to the dropout amount. The value of the dropout amount always lies between 0 and 1. While, the normalization is required for improving the speed, performance, and stability of the network, in the complex network models.

After the brief introduction of the layers, the architecture of the designed SCNN can be explained easily. This model contains two convolutional layers, the flatten layer, a fully connected layer, and the softmax layer. The model termed as shallow network instead of a deep network, due to the use of only two convolutional layers. A schematic diagram of the proposed network is shown in Figure 2. Since the input size is limited, so there is no need for down-sampling. Accordingly, the pooling layer has not been used in the proposed network. If the CNNs are used to deal with image data (large matrices), then pooling layers are essentially used in the designed network.

4 USED MATERIAL

In this work, the material used to verify the proposed methodology has been taken from a thick film gas sensor array. This gas sensor array consists of the following four sensors:

- Cadmium sulfide (CdS)
- Molybdenum Oxide (MoO)
- Tin Oxide (SnO_2)
- Zinc Oxide (ZnO)

Four gases had been exposed to this array in the ambiance of Nitrogen (N2). These gases are mentioned below:

- Acetone (CH_3COCH_3)/ACE
- Carbon Tetrachloride (CCl_4)/CAR
- Ethyl Methyl Ketone ($C_2H_5COCH_3$)/EMK
- Xylene ($CH_3C_6H_4CH_3$)/XYL

The steady-state response of the mentioned gas sensor array has been taken to verify the results. The SCNN has been trained with exclusive samples from the test samples. Later on, the classification performance is obtained using test samples. The performance of the classifier model on a smaller dataset signifies the applicability of the proposed methodology using the mirror mosaicking technique. Moreover, our methodology is not limited to the number of samples or number of the sensor elements in the gas sensor array. It can be used for any gas sensor array. The explained details about the gas sensor array and its response are given in (Nayak et al., 1994; Rajput et al., 2010).

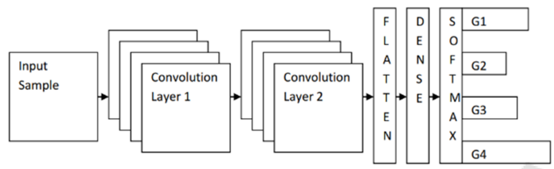

Figure 2: Schematic block diagram of SCNN.

5 RESULTS AND DISCUSSION

The results obtained from the classifying network SCNN after applying on the steady-state response dataset has been discussed in this section. The parameters that are used to tune the classifying network have been listed in Table 1. The classification of all the instances proves the applicability and efficiency of our proposed technique. The classification report is shown in Table 2. Precision, Recall, and F1-score metrics are shown in the report. The expressions for all the metrics have been given in equation (1), (2), and (3) respectively. All the aforesaid metrics have been calculated based on the confusion matrix. A confusion matrix is a square matrix of size equal to the targets. The elements of this matrix show the description of the reference points and the corresponding predicted outputs.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

$$\text{F1 Score} = \frac{2 * (\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{3}$$

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{TN}) + (\text{FP} + \text{FN})} \tag{4}$$

The overall accuracy has been given by equation (4). The term TP, TN, FP, FN in equation (1), (2), (3), and (4) represent the correctly predicted positive values, correctly predicted negative values, actual negative predicted positive, and actual positive predicted negative values respectively. Using equation (4) the overall accuracy has been obtained equal to 1.00. In terms of the percentage, it is obtained as 100%, as shown in Table 2. Moreover, the overall classification accuracies for the used dataset have been given in Table 3 using various classifying techniques.

The proposed technique is a comprehensive approach that can also be used to classify the dataset obtained from the transient response of a gas sensor array. There are two ways to deal with the transient response. Firstly, the last observation of transient response can be considered as a steady-state response. Secondly, the averaged transient response can be considered as a steady-state response. In this way, the huge computational cost can be reduced up to a very low cost. Moreover, the pre-processing and classification procedure will remain the same.

Table 1: Model Parameters.

Size of input samples	6×6
Convolutional layer 1 Number of kernels Size of kernels Activation	64 3×3 tanh
Convolutional layer 2 Number of kernels Size of kernels Activation	64 3×3 tanh
Flatten layer	( )
Fully connected layer 1 Number of neurons Activation	64 tanh
Dropout layer 1	0.25
Softmax layer Number of targets Activation	4 softmax
Optimizer Learning rate	Adam 0.001

6 CONCLUSIONS

The proposed technique provides all the samples well-classified that proves the significance of the mirror mosaicking technique. The proposed technique can be used to classify any gas sensor array response using well-known CNN-based pattern recognition techniques. In a nutshell, the points of significance of this paper can be stated as follows:

- A new technique "Mirror Mosaicking" of data pre-processing has been proposed.
- The dataset obtained from the response of the least feasible size gas sensor array can be classified using a convolutional neural network using mirror mosaicking.

Table 2: Classification Accuracies for Classical Machine Learning Datasets using Convolutional Neural Network based on Mirror Mosaicking Approach.

Datasets	Train/Test Samples	Overall Test Accuracy (%)
IRIS Dataset	120/30	100
Wine Dataset	112/66	98.48
Parkinson's Dataset	136/59	100

Table 3: Classification Report.

	Precision	Recall	F1 Score	Support
ACE	1.00	1.00	1.00	2
CAR	1.00	1.00	1.00	3
EMK	1.00	1.00	1.00	6
XYL	1.00	1.00	1.00	5
Avg./ Total	1.00	1.00	1.00	16
Test Accuracy	100%			

The proposed technique is a generic approach that can be used to classify any other non-imaging datasets, obtained from any other sensor arrays in various fields. For example, various classical machine learning datasets viz., iris data, wine data, Parkinson's disease data (Dua et al., 2019; Little et al., 2007), etc. can be classified accurately by using the proposed technique. The classification accuracies for these datasets have been given in Table 4 which have been obtained using convolutional neural networks based on the mirror mosaicking approach.

Table 4: Classification Accuracies using Various Classifiers.

Classifier	Overall Accuracy (%)
KNN	87.50
Linear SVM	81.25
RBF SVM	87.50
Random Forest	93.75
Naïve Bayes	87.50

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