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Analysing Gas Data using Deep Learning and 2D Gramian Angular Fields

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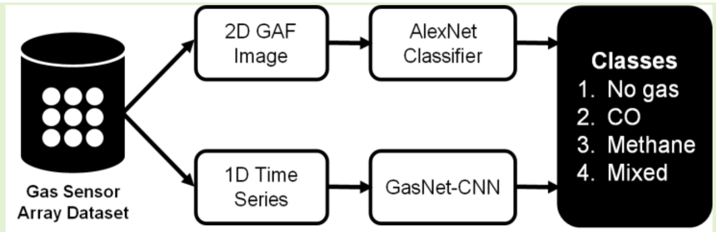
***Abstract*—The notion of employing a Deep Learning (DL) for gas classification has kindled revolution in the field that has both improved data collection measures and classification performance. Yet, the current literature, with its vast contributions, has potential in enhancing the current state-of-the-art by employing both DL and novel visualization methods to boost classification performance and speed. Therefore, this paper presents a dual classification system for high-performance gas classification: on 1D time series data and on 2D Gramian Angular Field (GAF) data. For the GAF case, 1D data is converted into 2D counterparts by means of normalization, segmentation, averaging, and color-coding. The Gas Sensor Array (GSA) dataset is used for evaluating the implemented AlexNet model for classifying 2D GAF data and an improved version of GasNet for 1D time-based data. Using a cloud-based architecture, the two models are evaluated and benchmarked with the state-of-the-art. Evaluation results of the modified GasNet model on time series data signifies state-of-the-art accuracy of 96.0%, while AlexNet achieved 81.3% test accuracy of GAF classification with near real-time performance on edge computing platforms.**



***Index Terms*—Artificial Intelligence, Gas Classification, Deep Learning, Gas Sensor Array, and Gramian Angular Field, Time Series.**

I. Introduction

The Electronic Nose (EN) is an advanced technology that detects gases based on the response pattern of a Gas Sensor Array (GSA) that has been configured into the device. An EN is primarily comprised of a GSA, signal conditioning, and pattern algorithms. Gas sensors may be divided into several types, including Metal Oxide (MOX) sensors, electrochemical sensors, conductive polymer sensors, among others. MOX gas sensors are extensively used in the industry as they offer the benefits of being small in volume, responding quickly, in addition to affordability and serviceability [1]. Thus, such sensors are frequently utilised in the identification of gases such as industry exhaust gases or combustible gases, as well as the analysis of odour in terms of strength or behavioural grade, among other applications [2,3,4]. GSAs can generate several response signals, which makes it a viable method for sensing and assessing a given gas mixture. To correctly establish the type different sensors used, and characteristics of the detected gas must be known [5].

Pattern recognition affects the accuracy for identification in various scenarios [16,29], and hence an enhanced identification technique can efficiently classify the components of a given gas mixture. Presently, models for identifying combined gases fall broadly into three categories: (1) detect any gas combination with great repeatability, both systematically and objectively, using the gas chromatography-mass spectrometry technique [6], however, this technology has limits owing to the costly and time intensive nature [6]; (2) using statistical analysis or Machine Learning (ML)/Computer Vision (CV) [7]; and (3) a sensor fusion, which can be used to improve performance accuracy by combining multiple statistical or ML approaches to identify gas mixtures [8].

Despite its popularity, it is worth noting that classifying gas data in their native format, i.e., as time series, has significant dimensionality and computational demands [9]. Yet, several new Time Series Classification (TSC) techniques have been suggested in recent literature. Such techniques were used to measure or estimate time series data [10-12], such as:

1. Bag of slow feature analysis symbols,
2. Collective of transformation ensembles,
3. Simple exponential smoothing,
4. Autoregressive Integrated Moving Average (AIMA)
5. Dynamic time warping.

There are also several ML approaches that have been used and utilised in conjunction with a variety of measuring techniques [13] to solve the TSC issues, which are known as Support Vector Machine (SVM), Decision Trees, and neural

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networks.

Elevating from a single dimension, Deep Learning (DL) has evolved not solve time series classification problem only, but also Two-Dimensional (2D) classification conundrums [14,15]. A popular DL model is the Convolutional Neural Network (CNN), which used to handle complex classification challenges across a wide range of fields. Because of the shared-weights design and translation invariance qualities, CNN models can efficiently be applied in audio video recognition, image processing, machine translation, and CV for the recognition of image and audio video [17,18], recommended systems [19], and natural language processing (NLP) [20].

The notion of employing a Deep Convolutional Neural Network (DCNN) for gas classification is initially described in reference [21], and a neural network named GasNet is created. Also, classifying gases can also be carried out using the LeNet-5 network [22], with features that can be automatically extracted from images using a One-Dimensional (1D) Deep Convolutional Neural Network (1D-DCNN) described in [23]. 1D-DCNN models require a small amount of input data, and it then can process two-dimensional time series data.

Also, in [24], CNN-based feature learning was used to categories time series data as inputs. Also, CNNs are used for time series analysis in [25], who also had encouraging results. Furthermore, a dilated CNN technique has proposed in [26] to classify images, the authors employed the same-size time series segments with sliding windows to resize images as needed.

In addition, Markov Transition Fields (MTF), Gramian Angular Fields (GAF), and chaos game representation techniques can be used along classification models (e.g., CNN) to classify gas mixtures in 2D form [25,29].

Moreover, the reviewed literature employs two core TSC approaches. The first approach depends on the time series itself, while the second method relies on DL algorithms with 2D data. Henceforth, image classification networks have made it easier for time series data to be encoded into images before they are classified. Accordingly, we set out to design improved feature extraction approaches using both approaches and benchmark their performance against the literature. Henceforth, we summarize the article contributions as follows:

1. Develop a novel 2D gas data visualisation technique is developed based on the GAF transformation that represents time series raw gas data as pictorial representations.
2. Implement a DL-based method for classification of the generated GAF representations with less computation time and promising performance.
3. Develop a DL-based incremental enhancement to benchmark against existing time series-based gas classification techniques that achieves higher classification accuracy.

The remainder of this article is structured with following manner. Section 2 described the related work, while section 3 explains the methods including data preparation, GAF processing, and classification. Further, the Section 4 summarises and discusses the findings of the study and then conclude the work in Section 5.

II. Related Work

When it comes to studying the classification of different gas mixtures, ML approaches are by far the most frequently employed research methodologies. In the study [30], Random Forest, SVM, and Shallow Multilayer Perceptron (MLP) techniques are used to distinguish the existence of less amounts of specific gases, and a suppressive SVM approach is devised to determine whether a particular gas is present in a gas mixture [31]. DL algorithms like CNN are increasingly being employed in the fields of classification and computer vision to identify important relevant features. It was developed by Hubel and

TABLE 1
ML TECHNIQUES USED FOR IMAGE-BASED GAS CLASSIFICATION

Ref.	Application	Array	Used Techniques	Methods	Accuracy
[7]	EN System	QCM Sensor Array	2 feed-forward multi-layer artificial neural networks (ANN)	Image Processing	93.87%
[8]	EN -Hybrid Gas Detection	MOX sensor array's	Kernel Principal Component Analysis – K-Nearest Neighbours	Classical ML	98.33%
[9]	EN -GIS	MOX sensor array's	CNN - Analogous-Image Matrix + Transfer Learning (ResNet34 and ResNet50)	Image Matrix	96.67%
[13]	UCR TSC 20 Datasets	N/A	Relative Position Matrix and Convolutional Neural Network	Image Processing	N/A
[14]	Polarimetric Synthetic Aperture Radar	N/A	11-Layer Deep Convolutional Neural Network	Image Segmentation	97.32%
[16]	Medical-Skin lesion	N/A	DL architecture	Pattern recognition	94%
[17]	YouTube Videos	N/A	Slow Fusion CNN	Image Processing	64%
[21]	EN System	MOX sensor array's	Deep Convolutional Neural Network (DCNN)	Image Matrix	95.2%
[22]	EN System	MOX sensor array's	CNN+LeNet-5	Image Processing	98.67%
[23]	EN System	MOX sensor array's	1D-DCNN	Image Matrix	96.30%
[30]	EN System	SnO2- MOX sensor array's	ANN	Image Matrix	>80%
[39]	EN System	MOX sensor array's	Genetic algorithm, C-means clustering + BPNN	Grey Image Processing	94.55 % - 100 %

Wiesel neurophysiologists, who were attracted first by the functional brain neural system of cats and monkeys. Deep CNN is first used to classify gases [21]. Also, ConvNet, a DL technique for CV, has become more popular in recent studies, with the first researchers to apply backpropagation in ConvNet were LeCun et al. [32]. Several notable architectures, including AlexNet [33], VggNet [34] and Residual Networks (ResNet) [35], Inception v3 [36], EmbraceNet [40] and GoogLeNet [37] have emerged since LeCun et al. [38], presented LeNet-5 in 1988. Table 1 displays the most used machine learning and deep learning algorithms for EN sensor data classification over the last several years.

ENs with LeNet-5 gas identification CNN are suggested in [38]. The identification and classification method of gases suggested in [21] using a deep CNN named "GasNet." The complete architecture of the GasNet consists of a global average pooling layer, the fully connected layer, and 38 network layers altogether. To obtain relevant representative features, each convolution block has a total of six layers, consisting of two convolutional layers, two bulk normalisation layers, and two Rectification Linear Units (ReLUs). The data is grouped using the SoftMax activation function and a multi-neuron layer with full connectivity. Further, due to the usage of an increasing number of different sensors, the regular gas data may have a complicated structure that is difficult to analyse. For unfolded data, and the parallel factor analysis with linear discriminant analysis, two types of techniques named: two-dimensional linear discriminant analysis and partial least squares discriminant analysis have been used in this study [41] to classify and identify the 8 Metal Oxide Semiconductor Sensors for EN.

Another Deep Convolutional Neural Network (DCNN) research is devised in [23] as a one-dimensional (1D) version. The expansion of such raw data into a 1D vector (16×100) resulted in a 1D-vector of size 1×1600. Additionally, a 1D filter has been used to extract the required information. The method, equipped with multi-labelling, where it is not only for to drastically reduces the label dimensionality but also often predicts the likelihood of each gas mixture component. The approach of transferring original data to analogous image matrix data and then manipulating the benefits of CNN based image processing for gas identification was suggested in [9]. Because the data dimensions are not being shrunk during the analogous-image matrix conversion, the raw time series data retains all its derived features, unless the model is quite complicated.

Moreover, Back Propagation Neural Network (BPNN) and C-means clustering are proposed to classify gas mixtures using grey processing to produce greyscale pictures used to identify the gases in [39].

The most appealing models within these methodologies are the Multiscale CNN (MCNN), Fully Convolutional Network (FCN), GAF-MTF, and Relative Position CNN (RPCNN) models [42–45]. Moreover, these techniques may be split into two groups based on the input dataset of CNN: MCNN and FCN employ 1D input with the preparation of original time series data, whereas GAF-MTF and RPCNN transform basic time series data to two dimensional images. A variety of operations on the original time series data are carried out using MCNN's multi scale and multi frequency branch.

Also, delving into DL methods, MLP [46], FCN, and ResNet [35], are implemented in TSC even without tailoring in feature extraction or data preparation, which implies that the 1D unprocessed time series data is correctly given to the classification algorithm. With a straightforward protocol and minimal complexities for model construction and deployment, FCN offers a solid foundation for future study. Furthermore, [44] explores the challenge of embedding time series data for images that empower computers to graphically distinguish, identify, and understand patterns and insights. The authors employ GAF to convert basic time series dataset into polar coordinates, whereas MTF is employed to calculate the transition probability beside the time axis using a first order Markov chain, which are handled as dynamic and static time series inputs. For the classification of time series, following GAF-MTF modelling with Tiled CNN [47] algorithm is used. It is possible that the lack of comprehensive dynamic information provided by MTF is to blame for the approach's low classification results when compared with other leading-edge approaches. Besides that, [45] suggests a modelling approach, which is focused upon RP [48], where raw time series data is converting to 2D images and using a CNN architecture for such TSC conversion. They consider time series to be many unique recurring tendencies, like variations and abnormal cyclicities, that are characteristic of complex systems, and the major goal of employing the RP approach is to determine the intervals at which itineraries revert to a previously determined state. The images created by RP are classified using a CNN model that includes a 2-convolution layer and two fully connected layers. The basic structure of the CNN model's leads to uneven results on common datasets, which is why their technique fails.

Continuing their research into image recognition using time series analysis, author in [49] provided a framework for prefixing 2-D images, where time series data converted into RGB inputs for the training of ConvNet, using time series analysis as inputs. 2D images just after dimensionality reduction are created using three feature encoding techniques, all of which adhere to the convention: Gramian Angular Summation Field (GASF), Gramian Angular Difference Field (GADF), and MTF. After that, these 2-D images were combined into another single large image split via RGB channels, where binary classification is performed after to fed into ConvNet.

To maintain the integrity of image recognition within a time series, a novel intrusion pattern recognition approach that relies on GAF and CNN is presented [50]. Using the GAF technique, 1-D time series incursion signals may be transformed into 2D images with higher detailed features while still preserving their time domain dependency. Therefore, when paired with the suitable CNN architecture, this GAF method can extract specific information about infiltration patterns and recognising them with accuracy. Relative Position Matrix (RPM) and Convolutional Neural Network (RPMCNN) is an advance DL technique in TSC challenges, that uses a RPM to convert original time series data into 2-D images. A TSC technique is also suggested in [27], where using 12 conventional datasets for separate GAF, MTF, and GAF-MTF images, which result from integrating MTF and GAF representation into a single image and a tiled convolutional neural network (Tiled CNNs) is then done to acquire high-level characteristics from the resulting images.

After examining the literature, a more cost-efficient GAF-based method is needed to advance the state-of-the-art defined TSC techniques simultaneously to improve the benchmark. According to the above literature review and after an extensive past study, we conclude our findings and contributions in following points:

1. 2D GAF-based image classification using AlexNet architecture.
2. An improved CNN based DL algorithms GasNet is applied for gas mixture classification and identification.
3. The suggested GasNet-CNN uses multi-labels as the desired outcome, which further drastically reduces the label dimensionality but also provides the likelihood of every gas element in a comprehensible manner.

III. EXPERIMENTAL SETUP

In this section, the data used in this work is described. As part of the BioCircuits Institute at the University of California San Diego, a gas distribution apparatus is used to collect a large-scale data set known as the GSA dataset [28]. A comprehensive setup for the entire experiment is depicted in Fig. 1. The GSA database stores time series records gathered from sixteen chemical sensors subjected to varying concentrations of ethylene in the air. Each sample is compiled by performing a nonstop collection of the data emanating from the 16-sensor array over the course of approximately 24 hours. The dataset used for this experiment is freely available in the University of California Irvine (UCI) ML Repository and contains 417,544 samples with 19 different properties. Analyses are conducted using model sensors, which represent how well sensors' conductivity changes when exposed to gaseous mixtures. In addition, the dataset was produced by employing combinations of binary gases with varying concentrations of each component. As a result, a variety of nonlinear changes in the sensors, each of which was produced by a distinct change in the intake, were incorporated into the dataset.

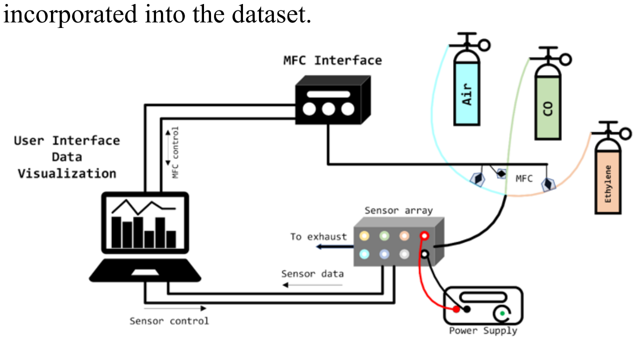

Fig. 1. GSA Data Collection Setup (adapted from [23])

Owing to its popularity, extensive testing with the dataset [21] has been carried out for the categorization of mixed gases. This data collection includes two binary mixtures of gases: ethylene-methane and ethylene-carbon monoxide in the air. The raw data at the input was collected using sixteen MOX. These sensors are subjected to a wide range of gas conditions and comprise four distinct classes (TGS-2600, TGS-2602, TGS-2610, and TGS-2620). The sensors' response signals were recorded with a 100Hz sampling frequency when a 5V operational voltage was selected. This process was repeated continuously for a period of 24 h. The raw dataset has 417,8504 + 420,8261 = 838,6765 occurrences between Ethylene-Methane and Ethylene -CO.

IV. METHODS

A. One-Dimensional Data (1D) Processing and Classification Method

1) 1D Data Post Processing

In this article, a labelled version of the GAS dataset is depicted in . A value of "1" indicates that the associated gas exists, whereas a value of "0, 0" indicates that there is neither the target gas nor the standard gas (i.e., air) present. In this work, divide the classification problem into two binary classification challenges, each with its own single label: 'Ethylene,' 'Ethylene' and 'CO,' CO'.

TABLE 2
MULTI-LABEL GAS SENSOR DATASET

Class	CO (ppm)	Ethylene (ppm)	Class Code
No gas	0	0	0
CO	0	1	1
Ethylene	1	0	2
Ethylene/CO	1	1	3

2) 1D Data Classification Using GasNet Architecture

This section describes the model used in time series gas mixture classification and identification on the GSA dataset. The GasNet [21] architecture is made up of convolutions, batch normalizations, and pooling operations in general. The word "convolution block" was chosen by the authors to describe a blend of convolution layers, activation layers, and batch normalization layers. The VGG-Net [34] was utilised as a model for the GasNet design. The design of the GasNet classification algorithm is depicted in . There are a total of 36 layers. Pooling layers divide convolution blocks, and the final convolution block is followed by a global average pooling layer. The fully connected layer is used at the end, which computes class scores and makes predictions. GasNet's input tensor shape is $m \times n \times 1$, where m represents used sensors quantity and dimensionality for each sensor as n, and the tensor output shape is $m/4 \times n/4 \times 128$ after final convolution block for the activations of each feature map a global average pooling layer averages is used and produces a shape of tensor with the $1 \times 1 \times 128$. Also, the network returns class values for each input vector, which represents four different types of gas concentrations.

In this work, the GSA dataset is split into two subsets: training data (70%) and test data (30%). Hyper parameters were set as follows: number of epochs, 20 and batch size, 32. To regularize the model a 0.5 dropout layer is placed between fully connected layer and global average pooling layer with a learning rate of 0.0001 is used. An early stopping optimization technique is used to avoid overfitting.

B. Two-Dimensional (2D) processing and Classification Method

1) 2D Data Post Processing

As described earlier, transforming 1D data into its 2D counterpart can produce higher quality classification results using less computational resources. Also, 2D images can reveal characteristics and patterns rarely present in the time series data. In this work, the GAF transformation is employed, after reviewing its benefits in the literature. Using a polar coordinates-based matrix, GAF can retain an actual temporal relationship in the time series images [44]. This equation (1) shows how to change the original time series (x) so that it falls between 0 and 1.

$$\bar{x}_0^t = \frac{\mathrm{x(t)} - \min(x)}{\max(x) - \min(x)} \tag{1}$$

The rescaled data is then encoded into polar coordinates using angular cosine and the time stamp. A symmetrical image layout is achieved by aligning it with the raw time series spanning top-left to bottom-right and by using a single major diagonal. By virtue of this property, the polar coordinates may be transformed back to the original time series. GAF can generate two pictures using a distinct equation. Mathematically, the GASF is specified in Equations 2 and 3:

$$GASF = \begin{bmatrix} \cos(\emptyset_1 + \emptyset_1) & \cdots & \cos(\emptyset_1 + \emptyset_n) \\ \cos(\emptyset_2 + \emptyset_1) & \cdots & \cos(\emptyset_2 + \emptyset_n) \\ \vdots & \ddots & \vdots \\ \cos(\emptyset_n + \emptyset_1) & \cdots & \cos(\emptyset_n + \emptyset_n) \end{bmatrix} \tag{2}$$

Whereas

$$\{\emptyset_i = arcos(x_i), -1 \leq x_i \leq 1, x_i \in \tilde{X} \tag{3}$$

In this implementation, the GASF is adapted to encode GAS dataset into a series of 2D images to take advantage of visually interpreting Gas Sensor data, in which 1D time series signals are represented in the form of 2D images. As described earlier, the GSA dataset is comprised of two gases mixtures: CO and Ethylene.

In terms of the GAS image dataset, a 16 GAF image is created in every 100 s throughout the dataset from each sensor raw reading. In total 1,664 GAF images were created from 16 gas sensor data. Fig. 4 shows a sample GAF for a 16-sensor array.

2) *AlexNet Image Classification Algorithm*

AlexNet architecture is used for the classification as the image classifier, to identify gas types from generated GAF representations. The AlexNet model [33] is a widely used image classification research. It is well-known owing to high computational efficiency compared to related models. depicts the AlexNet architecture for GAF image classification. AlexNet's architecture is made up of five convolutional layers and three fully connected layers.

In this implementation, the model is trained using the GAF GSA dataset and classified into four classes (). The GAF image dataset split into two subsets: training dataset (80%) and validation dataset (20%). The pre-processing was used to resize the image for the model's input size of 227 × 227 × 3. The test accuracy is obtained using test data on the model for prediction. A learning rate of 0.0001 is employed for model tuning to reduce overfitting and increase classification accuracy. In addition, early stopping is used as a means of preventing overfitting. We empirically tested the different numbers of epochs to determine the optimum number. As shown in Fig. 5, seven epochs provide better accuracy than other epochs. Therefore, we have tuned the hyper parameters as follows: number of epochs, 7 and batch size, 32.

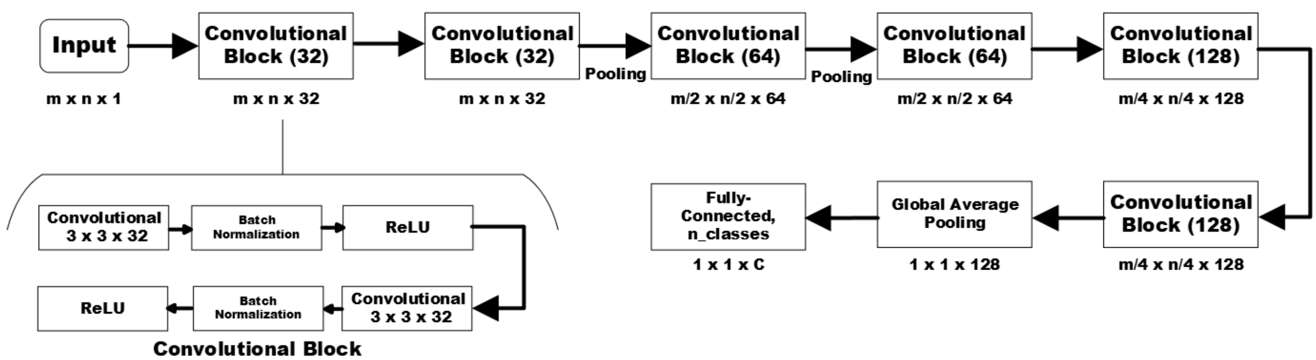

Fig. 2. The 1D Classification GasNet Model Architecture

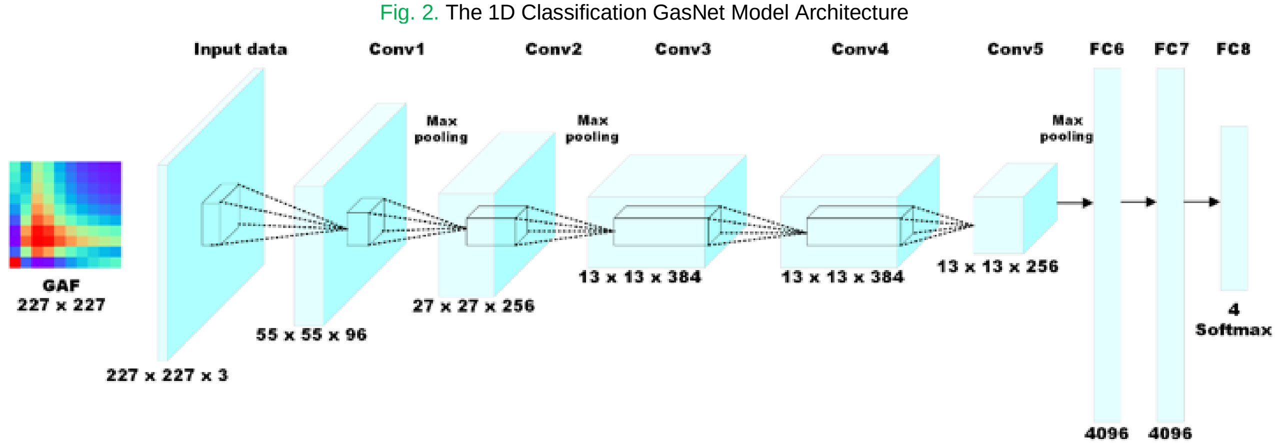

Fig. 3. The 2D GAF AlexNet Model Architecture

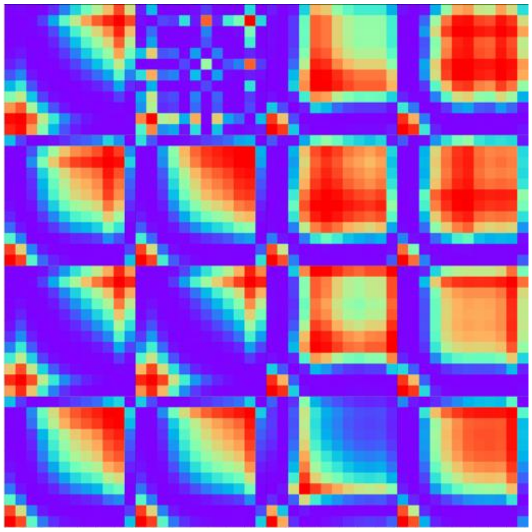

Fig. 4. Sample Gas GAF Grid Representing 16 raw Sensors' Data

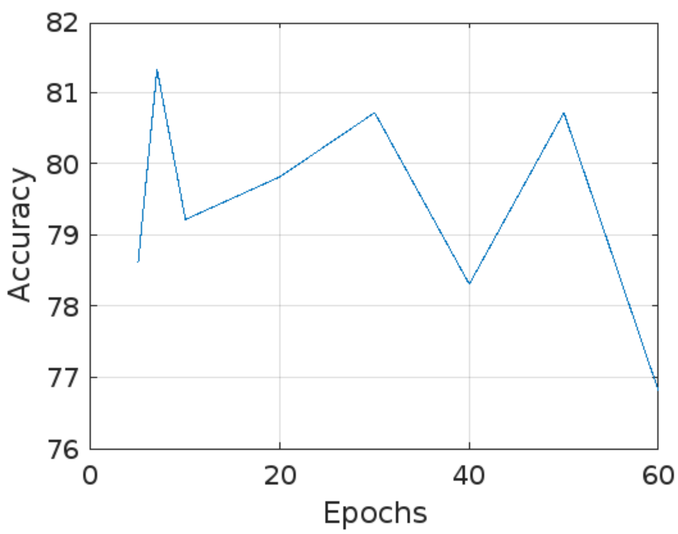

Fig. 5. Accuracy vs Number of Epochs for the AlexNet Model

V. Results and Discussion

Outcomes after the employment of (a) GasNet for time series classification; and (b) AlexNet GAF data classification on the GSA dataset are compared and discussed in this section.

The GSA dataset has been analysed using two separate architectures. A total of 1,664 GAF images have been produced from GSA dataset. The AlexNet architecture has been used to train 1332 GAF images. The training performance has been evaluated using validation data consisting of 332 GAF images. On the other hand, a time series data classification is made using GasNet architecture. Because of the kernel size selection and use of the convolutional block, the GasNet model learns features more effectively [21].

The outcomes are shown in TABLE 3. Detecting different gas concentrations is achieved successfully using two different architectures, as seen in the table. AlexNet's training accuracy is 93.5%. To assess the model's efficiency, test accuracy is used. The model's test accuracy is 81.3%. When compared to AlexNet, GasNet, another method based on time series data computing, outperforms it in terms of accuracy. For the GasNet architecture, the training accuracy is 96.8% and the test accuracy is nearly identical at 96%.

It is worthy to mention that the results are obtained through a Python Jupyter notebook running on Google Collab (Intel(R) Xeon(R) CPU @ 2.20GHz, 13 GB RAM, Nvidia Tesla T4 GPU). The training time of the 2D GAF AlexNet implementation is averaged at 7 sec while the 1D Time Series GasNet classifier has averaged at 222 sec. On the other hand, when testing the 2D and 1D classifiers, an average test computation time of 1 sec and 35 sec is achieved, respectively.

TABLE 3
CLASSIFICATION RESULTS FOR 1D AND 2D DATA

Approach	Training Accuracy (%)	Training Time (s)	Test Accuracy (%)	Test Time (s)
2D GAF: AlexNet	93.47	7	81.3	1.00
1D Time Series: GasNet	96.8	222	96.0	35.0

TABLE 4
1D TIME SERIES CLASSIFICATION RESULTS COMPARISON

Metric	This Work	[7]	[9]	[21]	[23]
Test Accuracy (%)	96.8	93.0	96.0	95.0	96.0

As shown in table 4, compared with the reviewed literature, the test accuracy using the improved GasNet achieved was on par or even higher than the methods reviewed, particularly [7] (93.0%), [9] (96.0%), [21] (95.0%), and [23] (96.0%).

In contrast, despite relatively lower test accuracy, GAF classification using AlexNet was carried out in about 1 sec, which is quite promising in terms of computational efficiency and in real-time gas classification applications.

Overall, the presented results show that deep learning, hand in hand with creative data visualisation, can result in higher classification performance and can open doors to efficient, real-time gas classification.

However, the current implementation can be improved in the following directions:

1. Increase GAF classification accuracy by (a) optimizing AlexNet for GAFs and (b) modify the GAF creation process to include more distinct difference between each instance.
2. The GasNet-CNN architecture in this study is suitable for EN devices, making it suitable for the gas identification and classification according to the requirement. The employed GasNet-CNN might be used to increase performance by using augmentation approaches.
3. Test the implemented models on other publicly available datasets for wider performance benchmarking.

It is of our future work to address the limitations above and evaluate the presented models on high performance edge computing platforms such as the ODROID-XU4 and the Jetson Nano. That evaluation will help understand the viability of using the presented models for real-time gas classifications.

VI. Conclusions

This paper presents a dual classification system for high-performance gas classification: on 1D time series data and on 2D

GAF data. For the GAF case, 1D data is converted into 2D counterparts by means of normalization, segmentation, averaging, and color-coding. The GSA dataset is used for evaluating for the implemented AlexNet model for classifying 2D GAF data and an improved version of GasNet for 1D time-based data. Using a cloud-based architecture, the two models are evaluated and benchmarked with the reviewed literature. Current results signify higher accuracy using GasNet (~96%), a steady improvement upon the literature, while AlexNet achieved 81.3% test accuracy with outstanding computational time of two seconds. Future work includes further model optimizations, improving the GAF creation process, and testing the models on various datasets on high-performance edge computing platforms, enabling real-time gas classification applications for research and development as well as industrial facilities.

REFERENCES

[1] Yan, L., Liu, J., Jiang, S., Wu, C., & Gao, K. (2017). The regular interaction pattern among odorants of the same type and its application in odour intensity assessment. *Sensors*, *17*(7), 1624. [110]

[2] Rutolo, M. F., Iliescu, D., Clarkson, J. P., & Covington, J. A. (2016). Early identification of potato storage disease using an array of metal-oxide based gas sensors. Postharvest Biology and Technology, 116, 50-58. [111]

[3] Giungato, P., Di Gilio, A., Palmisani, J., Marzocca, A., Mazzone, A., Brattoli, M., ... & De Gennaro, G. (2018). Synergistic approaches for odor active compounds monitoring and identification: State of the art, integration, limits, and potentialities of analytical and sensorial techniques. TrAC Trends in Analytical Chemistry, 107, 116-129.[112]

[4] Mumyakmaz, B., Özmen, A., Ebeoğlu, M. A., & Taşaltın, C. (2008). Predicting gas concentrations of ternary gas mixtures for a predefined 3D sample space. *Sensors and Actuators B: Chemical*, *128*(2), 594-602.[113]

[5] Xu, Y., Zhao, X., Chen, Y., & Zhao, W. (2018). Research on a mixed gas recognition and concentration detection algorithm based on a metal oxide semiconductor olfactory system sensor array. Sensors, 18(10), 3264.[100]

[6] Han, L., Yu, C., Xiao, K., & Zhao, X. (2019). A new method of mixed gas identification based on a convolutional neural network for time series classification. *Sensors*, *19*(9), 1960. [114]

[7] Bagnall, A., Lines, J., Bostrom, A., Large, J., & Keogh, E. (2017). The great time series classification bake off: a review and experimental evaluation of recent algorithmic advances. *Data mining and knowledge discovery*, *31*(3), 606-660. [115]

[8] Schäfer, P. (2015). The BOSS is concerned with time series classification in the presence of noise. Data Mining and Knowledge Discovery, 29(6), 1505-1530. [116]

[9] Bagnall, A., Lines, J., Hills, J., & Bostrom, A. (2015). Time-series classification with COTE: the collective of transformation-based ensembles. *IEEE Transactions on Knowledge and Data Engineering*, *27*(9), 2522-2535. [117]

[10] Chen, W., & Shi, K. (2019). A deep learning framework for time series classification using Relative Position Matrix and Convolutional Neural Network. *Neurocomputing*, *359*, 384-394. [118]

[11] Wang, S. H., Sun, J., Phillips, P., Zhao, G., & Zhang, Y. D. (2018). Polarimetric synthetic aperture radar image segmentation by convolutional neural network using graphical processing units. Journal of Real-Time Image Processing, 15(3), 631-642. [119]

[12] Zhang, X. M., Grolinger, K., Capretz, M. A., & Seewald, L. (2018, December). Forecasting residential energy consumption: Single household perspective. In 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA) (pp. 110-117). IEEE. [120]

[13] Jaworek-Korjakowska, J. (2019, March). Acral melanocytic lesion segmentation with a convolution neural network (U-Net). In Medical Imaging 2019: Computer-Aided Diagnosis (Vol. 10950, pp. 1083-1089). SPIE. [121]

[14] Karpathy, A., Toderici, G., Shetty, S., Leung, T., Sukthankar, R., & Fei-Fei, L. (2014). Large-scale video classification with convolutional neural networks. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition (pp. 1725-1732). [122]

[15] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. nature, 521 (7553), 436-444. [123]

[16] Gong, Y., & Zhang, Q. (2016, July). Hashtag recommendation using attention-based convolutional neural network. In IJCAI (pp. 2782-2788). [124]

[17] Severyn, A., & Moschitti, A. (2015, August). Learning to rank short text pairs with convolutional deep neural networks. In Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval (pp. 373-382). [125]

[18] Zheng, Y., Liu, Q., Chen, E., Ge, Y., & Zhao, J. L. (2014, June). Time series classification using multi-channels deep convolutional neural networks. In International conference on web-age information management (pp. 298-310). Springer, Cham. [126]

[19] Wei, G., Li, G., Zhao, J., & He, A. (2019). Development of a LeNet-5 gas identification CNN structure for electronic noses. *Sensors*, *19*(1), 217. [78]

[20] Zhao, X., Wen, Z., Pan, X., Ye, W., & Bermak, A. (2019). Mixture gases classification based on multi-label one-dimensional deep convolutional neural network. *IEEE access*, *7*, 12630-12637. [104]

[21] Peng, P., Zhao, X., Pan, X., & Ye, W. (2018). Gas classification using deep convolutional neural networks. *Sensors*, *18*(1), 157. [77]

[22] Gamboa, J. C. B. (2020). Deep learning for time-series analysis. arXiv 2017. arXiv preprint arXiv:1701.01887. [127]

[23] Fonollosa, J., Sheik, S., Huerta, R., & Marco, S. (2015). Reservoir computing compensates slow response of chemosensor arrays exposed to fast varying gas concentrations in continuous monitoring. Sensors and Actuators B: Chemical, 215, 618-629 [49]

[24] Wang, Z., & Oates, T. (2015, April). Encoding time series as images for visual inspection and classification using tiled convolutional neural networks. In Workshops at the twenty-ninth AAAI conference on artificial intelligence. [128]

[25] Kumar, N., Lolla, V. N., Keogh, E., Lonardi, S., Ratanamahatana, C. A., & Wei, L. (2005, April). Time-series bitmaps: a practical visualization tool for working with large time series databases. In Proceedings of the 2005 SIAM international conference on data mining (pp. 531-535). Society for Industrial and Applied Mathematics. [129]

[26] Craciunescu, T., Murari, A., & Gelfusa, M. (2018). Improving entropy estimates of complex network topology for the characterization of coupling in dynamical systems. Entropy, 20(11), 891. [130]

[27] Krivetskiy, V., Efitorov, A., Arkhipenko, A., Vladimirova, S., Rumyantseva, M., Dolenko, S., & Gaskov, A. (2018). Selective detection of individual gases and CO/H2 mixture at low concentrations in air by single semiconductor metal oxide sensors working in dynamic temperature mode. Sensors and Actuators B: Chemical, 254, 502-513. [131]

[28] Fonollosa, J., Rodríguez-Luján, I., Trincavelli, M., Vergara, A., & Huerta, R. (2014). Chemical discrimination in turbulent gas mixtures with mox sensors validated by gas chromatography-mass spectrometry. Sensors, 14(10), 19336-19353. [132]

[29] Kim, Y. J., & Hong, J. S. (2015). Urban traffic flow prediction system using a multifactor pattern recognition model. IEEE Transactions on Intelligent Transportation Systems, 16(5), 2744-2755. [133]

[30] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. Advances in neural information processing systems, 25. [82]

[31] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556. [134]

[32] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778). [84]

[33] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2818-2826). [83]

[34] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., ... & Rabinovich, A. (2015). Going deeper with convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1-9). [136]

[35] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324. [137]

[36] Chu, J., Li, W., Yang, X., Wu, Y., Wang, D., Yang, A., ... & Rong, M. (2021). Identification of gas mixtures via sensor array combining with neural networks. *Sensors and Actuators B: Chemical*, *329*, 129090. [137]

[37] Leonardi, S. G. (2017). Two-dimensional zinc oxide nanostructures for gas sensor applications. Chemosensors, 5(2), 17. [138]

[38] Wei, G., Li, G., Zhao, J., & He, A. (2019). Development of a LeNet-5 gas identification CNN structure for electronic noses. Sensors, 19(1), 217. [78]

[39] Cui, Z., Chen, W., & Chen, Y. (2016). Multi-scale convolutional neural networks for time series classification. arXiv preprint arXiv:1603.06995. [139]

[40] Choi, J. H., & Lee, J. S. (2019). EmbraceNet: A robust deep learning architecture for multimodal classification. Information Fusion, 51, 259-270. [81]

[41] Wang, Z., & Oates, T. (2015, June). Imaging time-series to improve classification and imputation. In *Twenty-Fourth International Joint Conference on Artificial Intelligence*. [140]

[42] Hatami, N., Gavet, Y., & Debayle, J. (2018, April). Classification of time-series images using deep convolutional neural networks. In Tenth international conference on machine vision (ICMV 2017) (Vol. 10696, p. 106960Y). International Society for Optics and Photonics. [141]

[43] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1985). Learning internal representations by error propagation. California Univ San Diego La Jolla Inst for Cognitive Science. [142]

[44] Quoc, L., Ngiam, J., Chen, Z., Chia, D., Koh, P. W., & Ng, A. (2010). Tiled convolutional neural networks. Advances in Neural Information Processing System. [143]

[45] Jp, E. (1987). Recurrence plots of dynamical systems. Europhysics Ltters, 5, 973-977. [144]

[46] Yang, C. L., Chen, Z. X., & Yang, C. Y. (2019). Sensor classification using convolutional neural network by encoding multivariate time series as two-dimensional colored images. Sensors, 20(1), 168. [145]

[47] Lyu, C., Huo, Z., Cheng, X., Jiang, J., Alimasi, A., & Liu, H. (2020). Distributed optical fiber sensing intrusion pattern recognition based on GAF and CNN. Journal of Lightwave Technology, 38(15), 4174-4182. [146]

[48] Mouhcine, E., Mansouri, K., & Mohamed, Y. (2018). Solving traffic routing system using VANet strategy combined with a distributed swarm intelligence optimization. J. Comput. Sci, 14, 1499-1511. [147]

[49] Wan, J., Liu, J., Shao, Z., Vasilakos, A. V., Imran, M., & Zhou, K. (2016). Mobile crowd sensing for traffic prediction in internet of vehicles. Sensors, 16(1), 88. [148]

[50] Nagem, T. A. H., Qahwaji, R., & Ipson, S. (2017, July). Deep learning technology for the prediction of solar flares from GOES data. In 2017 Computing Conference (pp. 697-700). IEEE. [149]