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RESEARCH ARTICLE

# A Deep Neural Network to Identify Vacuum Degrees in Vacuum Interrupter Based on Partial Discharge Diagnosis

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**ABSTRACT** One of the most crucial parameters in operating a vacuum interrupter (VI) is internal pressure. The failure of switching or insulation occurs when the pressure rises above a specific level. Characteristics of partial discharge (PD) in VI can be used to measure the internal pressures of VI. This paper defines a classification problem for the degree of internal pressure in VI using PDs, which were measured using a capacitive PD coupler. Then, we propose a deep neural network to monitor the internal pressure of VI by analyzing PDs. Experimental results show that the proposed deep neural network monitors the internal pressure range, from $1.0 \times 10^{-2}$ torr to 10 torr in VI. The classification performance of the proposed method is significantly better than those of machine learning algorithms such as support vector machines and $k$-nearest neighbor algorithm and the proposed method achieves an 100% classification accuracy.

**INDEX TERMS** Vacuum interrupter, partial discharge, deep neural network.

## I. INTRODUCTION

Vacuum circuit breakers (VCBs) are most commonly used in medium voltage circuits. VCBs have been more used in switchgear during the last decade due to their better interruption ability and operating voltage. Because VCBs have great switching performance under a high degree of vacuum, the degree of vacuum in a vacuum interrupter (VI) is a critical parameter [1]. However, after a long period of service, the internal pressure of VI may gradually increase due to outgassing from materials inside VI and gas permeation through the metal flange or ceramic vessel [2].

Switching capability and insulation performance are the most critical characteristics of VCB, which are remarkably affected by the gas pressure of VI. Therefore, the gas pressure monitoring for VI has been one of the valuable fault diagnosis techniques in VCB operation [3]. The investigation of gas pressure, and practical application ability been carried out in VI [4], [5].

Test methods such as magnetron emission current, high-frequency current, interpole breakdown voltage, arc voltage type, and X-Rays have been utilized to detect the gas pressure of VI [6], [7]. These offline approaches require the interruption of service to measure the vacuum degree of VI. On-line monitoring technique has been studied using partial discharges (PDs) to monitor the vacuum degree of VI [8].

Nowadays, artificial intelligence and machine learning have been activated in various areas such as image processing, language processing, and many different purposes [9]. Deep Neural Networks (DNNs) can leverage large measures of data to be efficiently trained to perform challenging tasks such as translating languages and identifying objects in an

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**TABLE 1. List of acronyms and abbreviation phrases.**

| Acronyms | Description |
|---|---|
| VCB | Vacuum circuit breakers |
| VI | Vacuum interrupter |
| PD | Partial discharge |
| DNN | Deep Neural Network |
| SVM | Support vector machine |
| kNN | $k$-nearest neighbor |
| BPNN | Back Propagation Neural Network |
| PRPD | Phase-Resolved Partial Discharge |

image [10]- [11]. DNNs have been shown to achieve great accomplishment in complex tasks where traditional machine learning methods may fail [12]. A backpropagation neural network (BPNN) was proposed to estimate the gas pressure of VI. The BPNN method based on PD achieved a recognition rate of 93% to 98% [13].

Backpropagation neural network is the core of neural network training. The neural network weights are fine-tuned based on the error rate obtained in the previous epoch. Appropriate weighting allows to reduce the error rate and make the model better. In our method of using the DNN model, to achieve the optimized hyperparameters, we conducted extensive experiments with various parameters such as epochs, batch size, the number of layers, and the learning rate to adjust our model. Moreover, to show the effectiveness of the deep learning model compared to traditional machine learning methods, we perform experiments on popular classifier machine learning techniques such as SVM and KNN. In this paper, we define the classification problem for identifying the degree of vacuum in VI. Then, we propose a DNN-based classifier using PRPDs in VI. The patterns of PRPDs are analyzed in each pressure of VI, respectively. In the training process, we improve the performance by adjusting the number of hidden layers, the number of nodes in each hidden layer, and the type of activation to acquire the best performance of the network for classification. To investigate the performance of the proposed method, we use 80%, 10%, and 10% of the total data as training, validation, and test sets, respectively. Experimental results show that the proposed method outperforms traditional machine learning algorithms such as $k$-nearest neighbor (kNN) and support vector machine (SVM). Also, the proposed method achieves a 100% accuracy to recognize the gas pressure in a VI based on PRPDs.

The contributions of our work are summarized as follows:

- To the best of our knowledge, a DNN is demonstrated for the first time to monitor the internal pressure of VI by analyzing PDs, which were measured using a capacitive PD coupler.
- The performance of our model achieved a classification performance of 100% and outperformed classification accuracy over traditional machine learning classification methods such as kNN and SVM algorithm.

The remainder of this paper is organized as follows. In Section II, the description of measurements for partial discharge in VI is represented. The proposed DNN-based classification method is presented in Section III. The experimental results are shown in Section IV. Finally, Section V gives conclusion remarks. In addition, Table 1 shows the acronyms used in this paper.

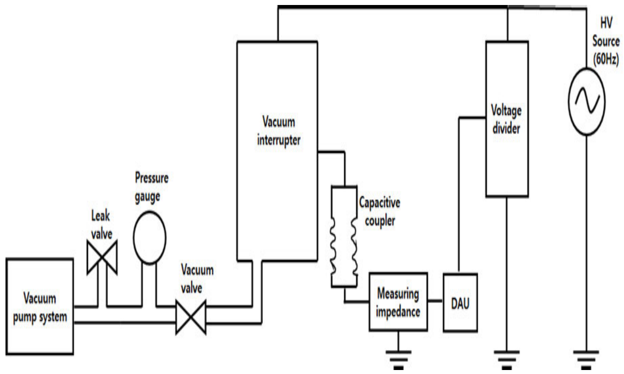



**FIGURE 1. A block diagram of PDs measurement system for controlling internal pressure of VI.**

## II. PRELIMINARIES

In this section, we present our experimental setup and experimental results for PRPDs in VI. We investigate the internal pressures of VI from $1.0 \times 10^{-2}$ torr to 10 torr.

Figure 1 shows a block diagram of the experimental system for PDs measurement inside the VI. The experimental system consists of a VI with close-state, a vacuum system, a high voltage (HV) source, a voltage divider, and a capacitive coupler with 160 pF [8], where the rated voltage of VI is 25.8 kV and the rated current of VI is 25 kA. AC transformer (60Hz) used as a high voltage source and voltage divider were connected in series with the VI to apply the voltage and extract the phase of applied voltage. A measuring impedance and a data acquisition unit (DAU) were connected with the VI to measure PRPDs. To control and maintain the internal pressure of the VI the rotary and turbo pump in the vacuum system and the valves were used. Specifically, we first adjusted the internal pressure of the VI less than $1.0 \times 10^{-6}$ torr using the pumps to confirm the outgassing influences. Second, we slowly opened the leak valve so that the vacuum degree is above 100 torr. After that the internal gas of VI was evacuated to the specific vacuum degree using the pumps and pressure gauge. Finally, the vacuum pump system and pressure gauge connected to the VI were disassembled and PD measurements were performed. The vacuum degree inside VI was maintained for about 30 minutes or more, and the PD measurement experiments were conducted within this period. We focus on the vacuum degrees from $1.0 \times 10^{-2}$ torr to 10 torr.

The measured PRPD is defined in matrix form as

$$\mathbf{X} = \begin{bmatrix} x(1,1) & x(1,2) & \dots & x(1,N) \\ x(2,1) & x(2,2) & \dots & x(2,N) \\ \vdots & \vdots & \ddots & \vdots \\ x(K,1) & x(K,2) & \dots & x(K,N) \end{bmatrix}, \qquad (1)$$

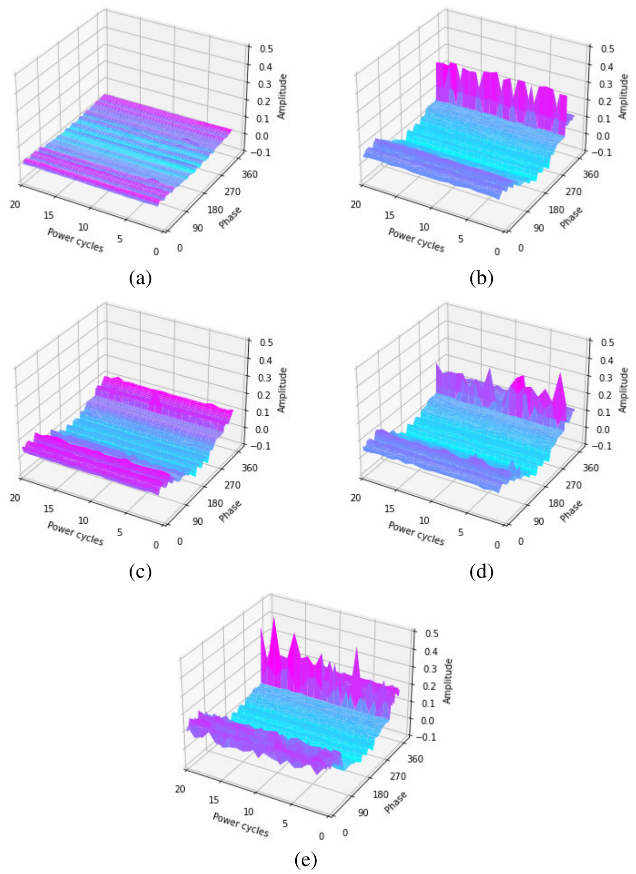



FIGURE 2. Examples of on-site vacuum interrupter for a) $1.0 \times 10^{-2}$ torr, b) $1.0 \times 10^{-1}$ torr, c) $5.0 \times 10^{-1}$ torr, d) 1.0 torr, e) 10 torr.

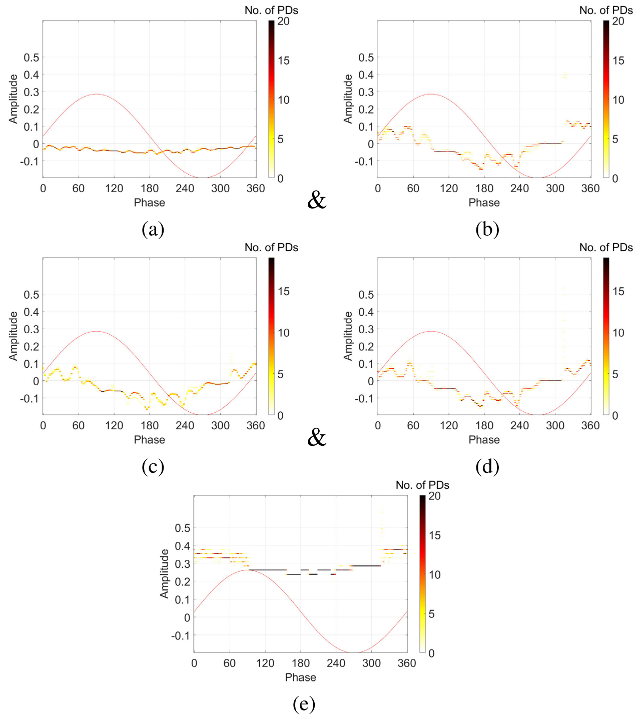



FIGURE 3. Examples of 2D representation of on-site vacuum interrupter for a) $1.0 \times 10^{-2}$ torr, b) $1.0 \times 10^{-1}$ torr, c) $5.0 \times 10^{-1}$ torr, d) 1.0 torr, e) 10 torr.

where $K$ is the number of phase angles (or samples in each power cycle), $N$ represents the number of power cycles, and $x(k, n)$ is the maximum value of PD pulses at the $k$-th data point for the $n$-th power cycle.

Figures 2 and 3 show five types of PRPD signals of on-site vacuum interrupters under different vacuum degrees. Figure 2 presents sequential data with $K=128$ and $N=20$ power cycles and Figure 3 shows the corresponding 2D representations. From Figures 2(a) and 3(a), it can be seen that with small amplitudes, the pulses of signals are sparse and scattered without regularity in all ranges of phase and power cycles. As can be seen from Figures 2(b)-2(e) and 3(b)-3(e), the discharge pulses are observed separately at both a positive and negative half cycle near 90° and 360°. Comparing Figures 3(a) and 3(e), it can be seen that the amplitude of the PRPD signals increases as the vacuum degrees increase.

It is known that the internal pressure of VI should be maintained below 0.5 pa( $\approx 3.75 \times 10^{-3}$ torr) [14]. When the VI has the sufficient vacuum degree, discharges are not detected by the detecting resistor sensor [3]. If PD occurs in the VI, it can be considered as a bad condition. In this paper, we focus on how to find and classify the degree of bad conditions of VI using PD measurements.

## III. PROPOSED SCHEME

In this section, we define the classification problem to monitor vacuum degree. The proposed model employs a DNN using capacitive PD coupler and classifies $M = 5$ classes to estimate the internal pressures in VI, where the internal pressure range is from $1.0 \times 10^{-2}$ torr to 10 torr in VI. A DNN is a collection of neurons combined into multiple layers, where neurons receive the neuron activations from the previous layer and implement a computation [15].

Figure 4 represents the structure of the proposed DNN network. The structure of DNN contains an input layer, hidden layers, and an output layer. We used PRPDs for classifying the internal pressures of VI including five types i.e., $1.0 \times 10^{-2}$ torr, $1.0 \times 10^{-1}$ torr, $5.0 \times 10^{-1}$ torr, 1.0 torr, 10 torr. The proposed model will be able to classify which class the input data belongs to, which means that the output of the model is five classes to be measured.

The network is trained by a reconstructed process of forwarding propagation and backward propagation [16]. The nodes of an input layer represent input variables, and the output nodes of an output layer define output variables. The hidden layers perform mapping functions between input variables and output variables. The number of nodes in the output layer was set as $M = 5$ to match 5 different classes. The critical parameters that manage the performance of the network are the number of hidden layers, the number of nodes in each hidden layer, and the type of activation function. In the proposed model, the ReLU (rectified linear units) is used as the activation function in the hidden layer [17] since this makes learning much faster than other activation and it is shown as $f(z) = \max\{0, z\}$.

For classification tasks, the output denotes class probabilities. At the output layer, a softmax activation function is used as

$$\mathbf{f} = [f_1, \cdots, f_M] = \sigma(\mathbf{h}). \tag{2}$$

where $h = [h_1, \ldots\ldots, h_M]$. The softmax function is defined as

$$f_m = \sigma(\mathbf{h})_m = \frac{e^{h_m}}{\sum_{j=1}^{M} e^{h_j}}, \tag{3}$$

where $m = 1, \ldots .M$.

The mini-batch gradient descent approach was used to adjust model parameters throughout the training process in order to reduce the following total loss:

$$J(\Theta) = \frac{1}{|\mathcal{B}|} \sum_{v \in \mathcal{B}} Loss(v), \tag{4}$$

where $\mathcal{B}$ is minibatch sampled from the dataset with size $|\mathcal{B}|$ and $Loss(v)$ is the loss computed from samples $v \in \mathcal{B}$ and $\Theta$ is a vector that contains every parameter in the model that needs to be determined. Here, we employed the categorical cross-entropy as the loss function in this paper, which is a regularly used loss function in multiple classification problems.

$$Loss(v) = -\sum_{i=1}^{M} y_i \cdot \log\,(f_i^{v}). \tag{5}$$

where the superscript $(v)$ is the index for the $v$-th training sample in the minibatch $\mathcal{B}$, when the index $i$ is the index for the ground truth, $y_i = 1$, and $y_i = 0$ otherwise.

The weights were updated based on the gradient information of loss function. Stochastic gradient descent optimization algorithms like AdaGrad, AdaDelta, and Adam are utilized to minimize the loss function [18]- [19]. In our experiments, the Adam optimizer is used to update the learnable network parameters.

## IV. EXPERIMENTAL RESULTS

In this section, we present the performance evaluation of the proposed DNN-based classifier to monitor vacuum degrees. We have performed PRPD experiments according to 5 vacuum degrees for a total of 3,490 power cycles. To increase the number of training samples and overcome the issue of overfitting, we employ data augmentation [20]. Figure 5 presents the data augmentation and the experimental data was sliced with overlap to increase training samples. Here, PRPD experiments with 780 power cycles can provide 761 training samples for 1.0 torr, each with a length of $N = 20$ when the number of overlap is 19 and the shift size is 1. After data augmentation, the total number of experimental samples in our dataset is $3,395$ in Table 2. The number of samples for five classes, namely, $1.0 \times 10^{-2}$ torr, $1.0 \times 10^{-1}$ torr, $5.0 \times 10^{-1}$ torr, 1.0 torr, and 10 torr are numbered as 0, 1, 2, 3, and 4, respectively. Therefore, for our model, the input is X in (1) and the outputs are 5 classes for vacuum degrees, where $K$=128 and $N$=20.

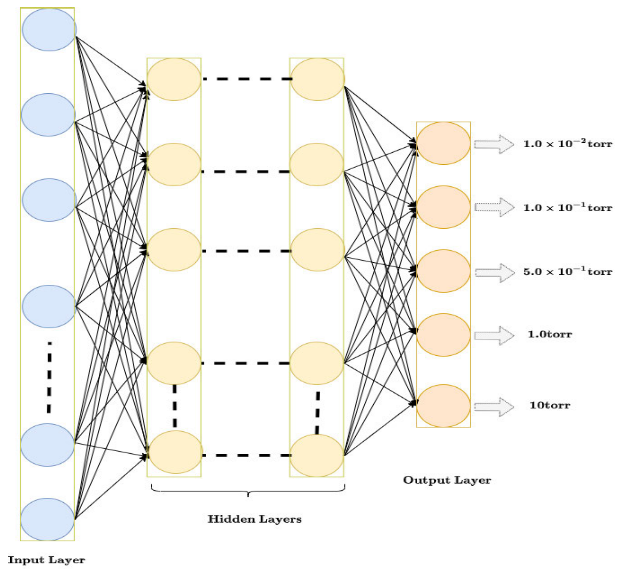



**FIGURE 4. Proposed Deep neural network.**

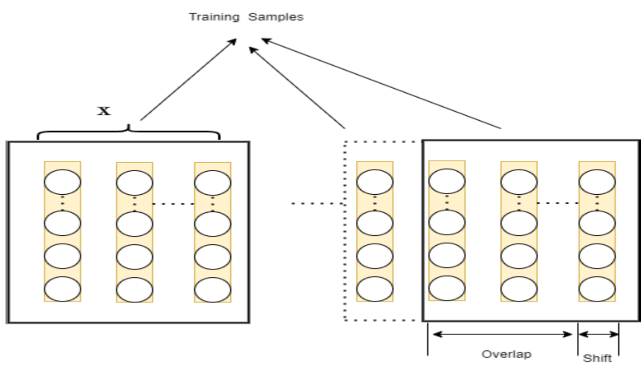


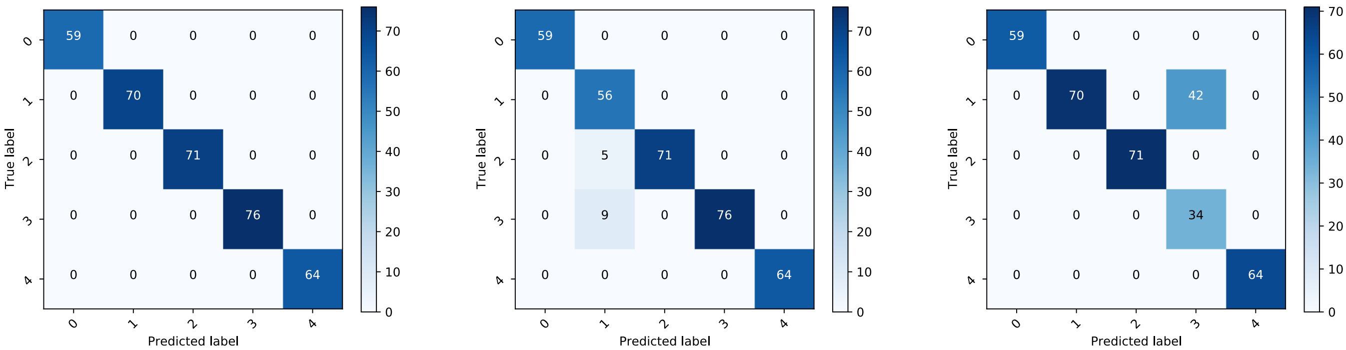

**FIGURE 5. Data augmentation for training dataset.**

In our experiments, we separated the data into training, validation, and test datasets at the following ratio: 80% for training and 10% for validation, and 10% for testing. Then, the training, validation, and test samples are 2,716, 339, and 340, respectively. We randomly select training and test data multiple times, and we average the test performance based on the test dataset. We used TensorFlow to develop and perform the proposed DNN model and scikit-learn library for SVM and kNN algorithms [21], where TensorFlow is a Google-developed open-source software library for numerical calculation utilizing data flow graphs frameworks [22]. A NVIDIA Titan X GPU with 3584 cores running at 1.2 GHz was used to train and test the models.

In order to achieve the optimized hyperparameters, such as epochs, batch size, and learning rate, we conducted extensive experiments with different parameters to adjust our model. In addition, we investigated the network performance by changing both the number of layers and the number of

**TABLE 2.** Experimental dataset.

| Name of class | $1.0 \times 10^{-2}$ torr (0) | $1.0 \times 10^{-1}$ torr (1) | $5.0 \times 10^{-1}$ torr (2) | 1.0 torr (3) | 10 torr (4) |
|---|---|---|---|---|---|
| Number of samples | 585 | 701 | 707 | 761 | 641 |




(a) proposed DNN (b) SVM (c) KNN model

**FIGURE 6.** Confusion matrix of (a) proposed DNN, (b) SVM model, and (c) KNN model.

**TABLE 3.** Hyperparameter optimization.

| Hyperparameter | Value |
|---|---|
| Number of hidden layers | 5 |
| Batch size | 64 |
| The number of epochs | 300 |
| Learning rate | 0.001 |
| Optimizer | Adam |

**TABLE 4.** Comparison of classification accuracy.

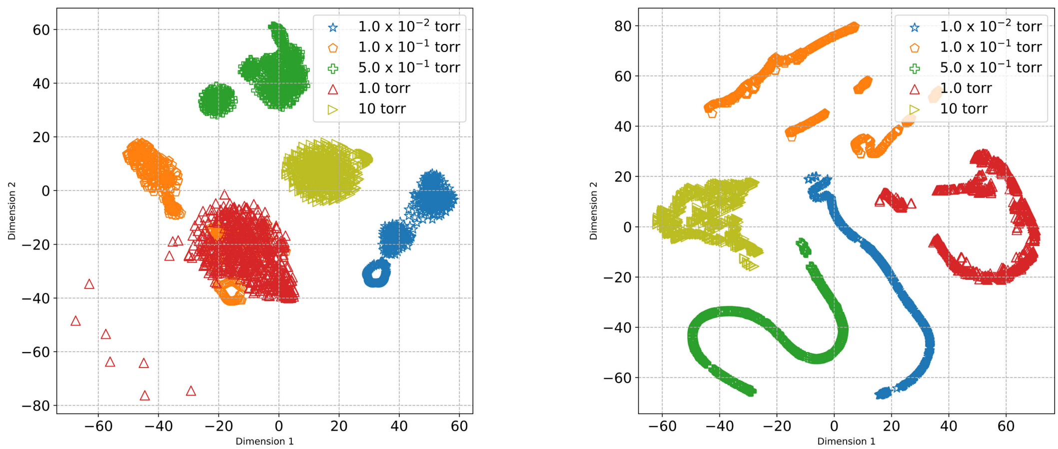
| Methods | Classification accuracy |
|---|---|
| KNN model [23] | 87.6% |
| SVM [24] | 95.8% |
| BPNN [13] | 97.9% |
| Proposed DNN | 100% |

the node. The number of hidden layers changed from 1 to 8, and the number of nodes in each hidden layer was changed from 2 to 128. The best combination will be selected to get the highest result at the end of the tuning process. The parameters of the model was established as shown in Table 3. Furthermore, the performance of DNN was evaluated utilizing several activations in hidden layers, such as ReLU, Sigmoid, Tanh, LeakyRelu, and Swish, ELU, Maxout all with the same optimized hyperparameter. The outcomes reveal that the ReLU function outperforms other activation functions in terms of classification accuracy.

Table 4 shows the comparison of classification accuracy between a KNN [23], an SVM [24], and a BPNN [13]. The proposed DNN can reach an overall of 100% in the classification problem. Here, we randomly select training and test data multiple times, and we average the test performance based on the test dataset. Due to its simplistic structure, a KNN model was ineffective in classifying the data with a performance of 87.6%. The proposed DNN has 12.4% and 4.2%, and 2% performance improvements compared to KNN, SVM, and BPNN models, respectively. Compared to the BPNN, the proposed DNN has conducted extensive experiments for hyperparameter optimization.

The Figure 6 illustrates confusion matrix results from the test set by the proposed DNN model, SVM, and KNN model. Figure 6(a) shows that all of the test samples were correctly predicted by using the proposed DNN model. In contrast, some miss prediction test samples are shown in Figures 6(b) and 6(c). From Figure 6(b), we can see that the SVM model incorrectly predicted some samples of class 3, and it can be seen from Figure 6(c) the KNN model incorrectly predicted some instances of class 2 and 3. Meanwhile, the proposed model correctly predicts 100% of the samples in the test set. These results confirm that the proposed model perfectly classifies vacuum degrees in VI based on PRPDs.

In order to evaluate and better understand the effect of the proposed model in classifying the vacuum degrees, we used the t-distributed StochasticNeighbor Embedding (t-SNE) method which is a tool for visualizing high-dimensional data [25]. In principle, the t-SNE embeds high-dimensional vectors to 2D spaces while retaining the pairwise similarity [25]. The t-SNE algorithm is only interested in the distance between the points; the algorithm locates the points on a plane. This paper uses the t-SNE method to visualize the data before and after training by the deep neural network method. Here, t-SNE has helped reduce the data dimension from multi-dimensional to only 2-dimensional space with change and visualize similar samples transformed into neighboring points. Using the t-SNE algorithm, input data will be transformed into new expressions in the form of points and illustrated in Figure 7(a). As shown in Figure 7(a), it is noticed that the input data for the 5 classes overlap and are remarkably




(a) (b)

**FIGURE 7.** Visualize data using t-distributed stochastic neighbor embedding (t-SNE) algorithm (a) with the feature vector of layer input (b) last hidden layer in DNN model.

close to each other. Therefore, it is so difficult to classify all cases based on the data input. In contrast, as shown in Figure 7(b), the vector feature of the layer output, five classes are separate. It shows that the classification improvement has been significantly improved in the last layer of the model, leading to accurate classification results of the proposed DNN model.

## V. CONCLUSION

The internal pressures are critical parameters in operating a VI. In this paper, we proposed a DNN-based classifier for vacuum degrees in VI. We used PRPDs for classifying the internal pressures of VI included five types i.e. $1.0 \times 10^{-2}$ torr, $1.0 \times 10^{-1}$ torr, $5.0 \times 10^{-1}$ torr, 1.0 torr, 10 torr. To adjust parameters in the proposed model, we conducted extensive using capacitive PD coupler. The experimental results showed that the proposed DNN conducted a classification of 100% and had 4.2% and 12.4% higher classification performance than machine learning algorithms such as SVM, and KNN model. Therefore, the proposed DNN model could be an effective diagnostic technique in vacuum degrees of VI based on PRPDs. In future studies, we intend to obtain more measurements to verify the proposed method and conduct further analysis of the effect of external noise on PRPD measurements for VI.

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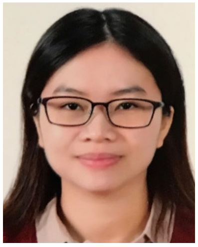

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