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Stacking Deep Scalogram Features with the Enhanced GAN for Defect Recognition in Power Transformers with Highly Imbalanced Partial Discharge Signals

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***Abstract*— Measuring partial discharge (PD) in a power transformer (PT) is one of the most crucial metrics for determining how well an insulating system is performing. However, in onsite environments, single/multiple PD sources or imbalance conditions may limit the signal's acquisition ability. Numerous oversampling techniques are used on imbalanced datasets, but these techniques could be more extensive in displaying a non-deterministic correlation between the regional and global distributions. The proposed work uses stacking deep scalogram features with an enhanced generative adversarial network (SDSF-EGAN) for oversampling based on a minority sample global underlying structure. Three specific tactics are offered in our proposed work: The generator's input random vectors are sampled from a rough estimate of the minority sample distribution to create fake samples more accurately; a residual about minority samples is added to the discriminator to reinforce the loss function's constraint; and the generated samples are redistributed using a reshaper. At last, a fine-tuned VGG19 model and three different pre-trained DNN models, ResNet101, InceptionV2, and VGG16, are used for feature extraction to attain the varied SDSF map. The proposed results demonstrate that the system gets a realistic identification rate of 99.1% and is resistant to fluctuations in terms of occlusion and noise.**

***Index Terms*—defect diagnosis, generative adversarial network, partial discharge, scalogram pattern, stacking features.**

I. Introduction

Power transformers (PTs), a crucial portion of electrical equipment in the power system, are primarily responsible for either voltage decrease or increase [1]. Power equipment insulation is essential to maintaining the power system's safe and effective operation. However, the insulation of power equipment ages over time, and abnormal environmental activities like mechanical, electrical, and chemical stresses hasten this process [2]. PD, a local insulation breakdown, will result from high-voltage (HV) power equipment's continuing insulation deterioration [3].

Machine learning (ML) and deep learning (DL) are vital in many data analytics and recognition fields. However, to perform exceptionally well, these defect diagnostic techniques must collect enough samples and balance the quantity of various defect sample types [4].

Studies conducted for imbalanced datasets today can be broadly categorised into data-level and algorithmic levels. Data-level approaches directly rebalance imbalanced datasets to provide enough data information for prediction models. Positive samples are produced by oversampling techniques [5], and negative samples located in borderline or overlapping areas are sampled by under-sampling techniques [6]. According to [7], oversampling techniques are typically more successful than under-sampling.

Synthetic Minority Over-sampling Technique [8] and its variations [9] create samples that resemble raw positive samples. Despite this, these techniques can produce more samples in regions with a dense distribution of positive samples and fewer in areas with a sparse distribution of positive samples. Finding the actual global distribution of data, especially PD data, is challenging. Unbalanced datasets have recently been rebalanced using generative adversarial network (GAN) [10]. Using Conditional Wasserstein GAN [11], the datasets are rebalanced. Similarly, [12] creates samples by adding global information about the actual data distribution to the discriminator and generator.

For several decades, various representations of PD pulses have been used, including spectrograms [13], time-domain waves, frequency domain, phase-resolve partial discharge [14 & 15], and pulse sequence analysis. Furthermore, in the event of a multisource PD recognition, the pulse sequence analysis is ineffective in diagnosing the condition.

The measured PD signals are corrupted by external interferences [16]. Wavelet transform (WT) [17], radial basis function [18], and translation in-variant WT [19] are some of the current contemporary de-noising techniques. However, WT requires manual determination of mother wavelets and decomposition stages, which is not a self-adaptive and automatic decomposition technique

Developing new convolution neural network (CNN) architecture and its tuneable parameters fine-tuned by various

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approach can be enhanced by providing the relevant features extracted from the CNN. The RReliefF feature selection is applied to stacked features and finds the pertinent and non-redundant features from the dataset. The first two approaches select the top 43 features using merit scores and remove the remaining dataset. The confusion matrix of the proposed algorithm is shown in Fig. 10.

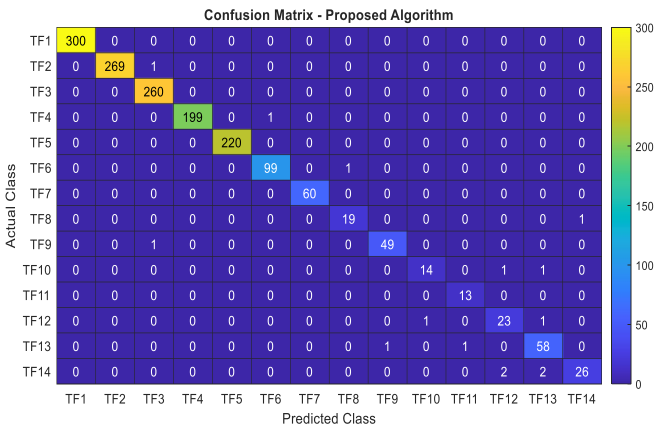

Fig. 10. Confusion Matrix for the proposed algorithm

In continuation, the second approach chooses the top 35 features fed to RFE to find the optimal subset of features. The final selected list of features from the filter approach is then formed by combining the features chosen by RReliefF and Mutual information. RFE is then used to adjust these particular properties. The ideal subset of features is determined by choosing 15 features.

D. Case 3: Practicality verification of proposed model

The proposed baseline model is selected based on the above cases, and the model has been tested for practicality verification for the new field dataset from PT in substation.

TABLE VI
CROSS-VALIDATION ACCURACY OF CLASSIFIERS FOR PRACTICALITY DATASET

Feature Extraction	**Practicality Dataset**			
	MLP	**KNN**	**SVM**	**LDA**
VGG 19	95.0	90.0	89.7	88.7
IncpetionV2	91.0	91.2	88.8	85.4
ResNet 101	85.0	87.2	87.2	86.1
VGG 16	88.0	80.1	82.1	87.2
Stacked Features	96.7	93.7	89.1	86.7

The accuracy rate for various feature extraction pre-trained CNN models, along with the ML approach, is shown in Table VI. The MLP classifiers with stacked features (256*4) produce a better recognition rate of 96.7%, which is superior to other methods. The claim of the SDSF-EGAN model to PD data expansion is motionless in its beginning, and there are numerous problems well-intentioned of examination. Thus, to solve the issue mentioned above in recognizing the type of fault that occurs in the PT, an SDSF-EGAN model is proposed. The proposed work can tackle the dataset imbalance issue, generating a high-quality dataset and solving training instability. The proposed work performs better than the other baseline DNN models, with an accuracy rate of 96.7%.

VI. CONCLUSION

To improve GAN performance in producing unbalanced PD datasets, this proposed work uses SDSF-EGAN, an oversampling technique that takes advantage of the distribution properties of positive datasets. SDSF-EGAN presents three innovative techniques that provide thorough and trustworthy insights into the density distribution of positive samples, which are advantageous for the discriminator, generator, and shaping of generated samples, respectively. Results from practicality verification show that SDSF-EGAN significantly outperforms existing GAN-based techniques. The proposed work exhibits a better recognition rate even under highly imbalanced data proportions.

Using matrices and statistical expertise, SDSF-EGAN explicitly improves the generated samples, opening up a wide range of intriguing related research avenues. The few drawbacks of the proposed algorithm are: (1) transforming the PD signal into scalogram patterns may increase the computation time and memory allocation during hardware implementation, but the recognition rate depends on the intensity of pixels of the scalogram pattern. (2) In a natural network setting, when training a learning model requires just an incremental fraction of the training dataset, the established approach might not function. Viewing the development of incremental/online learning as future work is possible.

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