 doi:10.20944/preprints202306.0942.v1

Article

Detection and Classification of Partial Discharge by Hybrid Neural Network Algorithms in Air-Insulated MV Switchgear

Paweł Kluge *, Andrzej Łasica and Jacek Starzyński

Institute of Theory of Electrical Engineering, Measurement and Information Systems; Faculty of Electrical Engineering; Warsaw University of Technology, Warsaw, Poland

* Correspondence: pawel.kluge@pw.edu.pl

Abstract: The correct classification of defects originating from partial discharges (PD) in medium-voltage (MV) switchgears with air insulation (AIS) remains a challenging research topic for scientists worldwide. In this article, the authors simulated four possible defects occurring in the power industry, including one that is a simultaneous combination of two commonly ones. In addition, the correctness of the algorithm was checked by adding a classification class without any fault. The measurement signals were recorded with TEV sensors. The effectiveness of various hybrid-connected neural networks was tested and discussed: GoogleNet and SqueezeNet based on spectrograms, SAE with FNN, 2D-CNN with LSTM, and hybrid AE combined with CNN and LSTM. The highest effectiveness – approximately 97% – was demonstrated by the GoogleNet and SqueezeNet networks. The research results are expected to form the basis for the development of a universal and wireless capacitive sensor for monitoring the level of PD in switchgears.

Keywords: deep learning; partial discharge; convolutional neural network; medium voltage switchgear; air-insulated switchgear; autoencoder; long short-term memory

1. Introduction

Correct detection of partial discharge problems in MV switchgear is the foundation of its safe usage. Early recognition of the type of fault inside the switchgear can significantly reduce financial losses and, at an early stage of operation, save lives. Incorrect exploitation, environmental conditions (temperature, humidity, etc.), natural ageing of the insulation, as well as human mistake, have a huge impact on the possibility of unwanted PD occurring.[1,2].

The dynamic development of Artificial Intelligence (AI) has significantly improved the effectiveness of the safe operation of electrical power equipment. The use of convolutional and deep neural networks, together with additional development of the architecture (the addition of different modules, depending on the type of measurement data), gives a satisfactory level of effectiveness in classifying faults caused by PD [3]. The continuous technological progress allows for the use of increasingly practical and cheaper methods of detecting disturbances from the point of view of switchgear manufacturers. In the industry, the classical electrical method using capacitive TEV sensors, High-Frequency Current Transformers (HFCT) or Ultra-High-Frequency (UHF) sensors still finds wide application. After a thorough review of the literature, a Transient Earth Voltage (TEV) sensor was used for signal measurement due to its reliability, simplicity of construction, ease of installation, and low cost [4–7]. These sensors are mounted on the outer surface of the metal housing of the switchgear. When PD occurs, the electromagnetic waves propagate away from the discharge point as a transient voltage. The transient voltage inside the metal shell cannot be detected directly from the external surface by the skin effect, However, the EM wave can propagate to any space where there is an electrical discontinuity in the metal shell, which can generate a series of transient voltage peaks at

 doi:10.20944/preprints202306.0942.v1

the surface. These peaks are called TEVs and were first proposed by Dr John Reeves in 1974 [8–10].

In the process of the research, the last fault, which is a series of many different signals superimposed on each other simultaneously - mainly signals from the partial discharges of faults one and two - was simulated artificially. Detection of single PDs from multi-source is still a challenge for individual differentiation and effective evaluation by different types of classifiers [11–13].

During the research process, it was decided to investigate the effectiveness of GoogleNet and SqueezeNet in classification based on the researchers' publications [14–16]. GoogleNet was checked, for example, during the recording of images of the corona around power transmission lines [17]. The authors decided to check the effectiveness of the aforementioned networks by creating spectrograms before the learning process [18–20]. The article continues with a study of the use of a hybrid combination of networks Stacked Autoencoder (SAE) with Feedforward Neural Network (FNN) [21–24], Convolutional Neural Network (CNN) combined with Autoencoder (AE) and Long Short-Term Memory network [25–31].

The first section of the article describes how the previous measurement and classification processes were carried out, presents how the MV switchgear defects were simulated, and then describes the test methods used during the research.

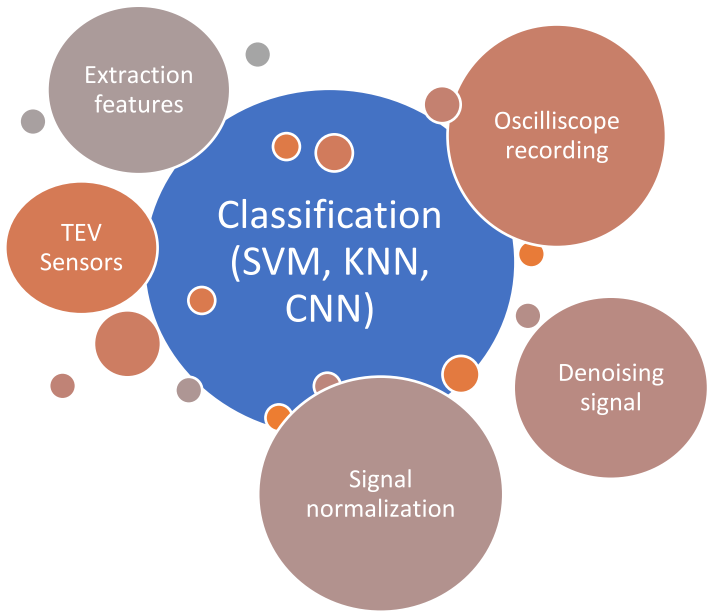
The next section briefly characterises the deep neural networks used for classification. The hybrid combinations of CNN, LSTM, SAE and GoogleNet and SqueezeNet used are described, and the classification results are then presented.

At the end, the last part of the article summarises the results of the research and indicates the next possible research steps.

2. Measurements and Methods

2.1. Previous research

During previous research [32], the authors carried out experiments to simulate, "artificially", the various possible faults in MV switchgear. TEV sensors were placed on a metal plate. The measured insulation defects originated from electrodes placed behind the metal housing. First, a de-noising process was carried out, then normalisation and finally extraction of the relevant signal features. The complexity of the method is shown in Figure 1.



Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 June 2023 doi:10.20944/preprints202306.0942.v1

Figure 1. Block diagram of signal measurement and processing during previous research, where SVM – Support Vector Machine; KNN – K-Nearest Neighbors; CNN – Convolutional Neural Network.

2.2. Current research and measuring system with TEV sensors

The authors carried out the research at the High Voltage Hall at the Faculty of Electrical Engineering, Warsaw University of Technology. The following measurement equipment was used to carry out the research: a 220/100,000V, 10 kVA test transformer, a NorthStar VD-100 voltage divider and a brushless voltage regulator. The electrical schematic of the measurement system is shown in Figure 2.

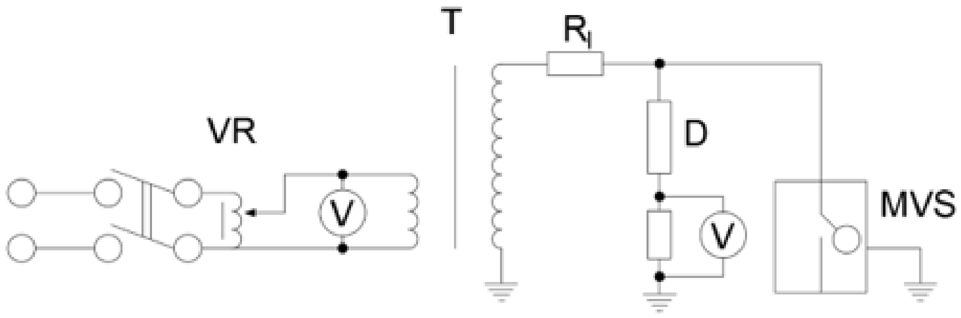


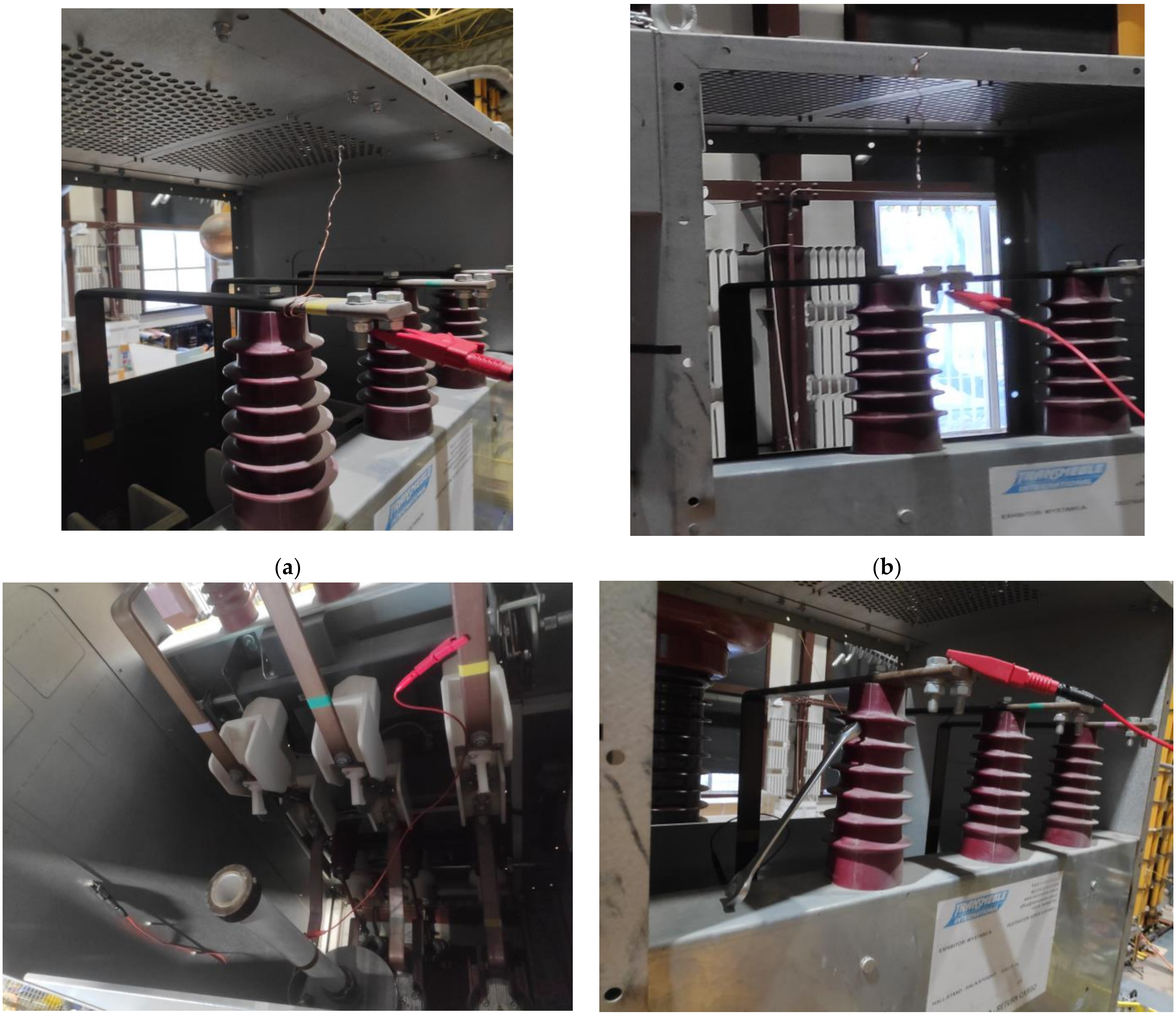
Figure 2. The measuring system used during the research, where: VR - voltage regulator, T - transformer, Rl - limiting resistor, D - voltage divider, MVS – MV Switchgear

2.2.1. Simulation of possible switchgear failures

The authors decided to use a three-phase, single-pole air-insulated MV switchgear as the research object. The measurements were recorded by a Tektronix MSO56B oscilloscope. An internal 100 Hz high-pass filter was used for more precise recording.

It was determined to simulate four types of faults and one additional algorithm validation (five class):

- The first one (Class 1) - a copper wire was attached to one phase of the switchgear, which was at high potential;
- The second (Class 2) - a copper wire was attached to a grounded metal switchgear enclosure;
- Third (Class 3) - surface partial discharges were artificially induced inside the switchgear;
- The fourth (Class 4) - contained a confusion of multiple defects, including: leaving a wrench in the switchgear along with fault one, surface discharge with fault from high potential and surface discharge with fault from low potential;
- The last one (Class 5) - an additional class to validate the algorithm, which was actually the measured noise level.



(a) (b) (c) (d)

Figure 3. Simulated faults from partial discharges: (**a**) Partial discharge from high potential; (**b**) Partial discharge from low potential; (**c**) Surface partial discharge; (**d**) Mounting error - spanner left in switchgear.

2.2.2. Placement of TEV sensors

Firstly, the effect of the placement of the HVPD TEV sensors (15 – 70 MHz frequency response) on the quality of the measured signal was checked during the research. Three TEV sensors were placed at three different locations on the switchgear:

- Close to the power supply;
- On the front door of the switchgear;
- At the point furthest from the PD source.

No differences were observed during the signal measurement. Placing the sensors at different distances from the discharge source did not affect the quality of the measured signal.

This time it was decided to use the raw signal waveform for the classification process, without manual feature extraction and de-noising process. The number of signals was 2000: 360 for fault 1, 480 for Class 2, 420 for fault 3, 600 for fault 4 and 140 for last Class 5. The length of each signal was 62494. Three examples (for Class 1, 2 and 3) of signals used during the conducted research are shown in Figure 4. In the given waveforms it can be observed a high background level and the individual pins come from the PD.

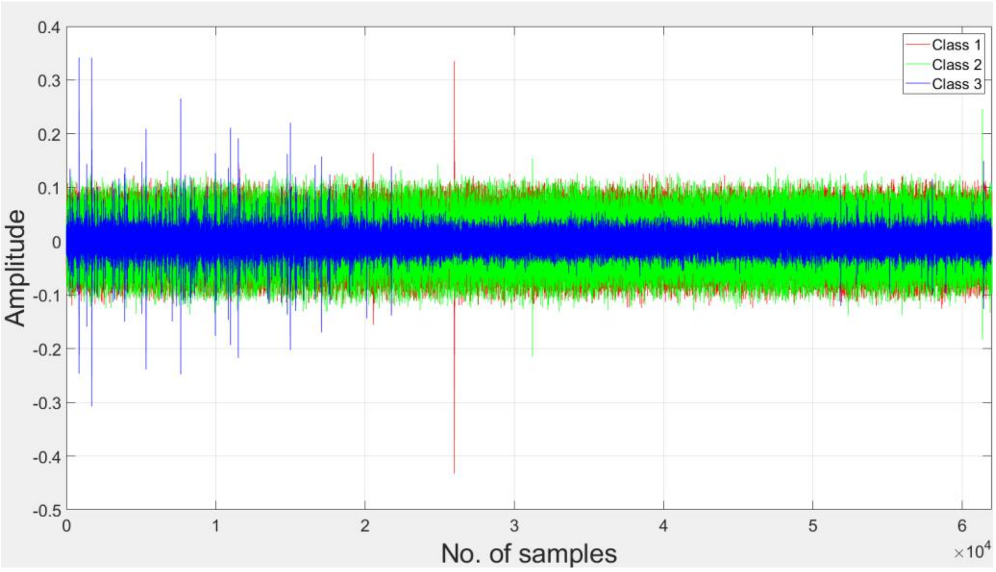


Figure 4. Partial discharge on raw signal waveforms for Class 1, 2 and 3.

2.3. GoogleNet and SqueezeNet + Spectrograms

GoogleNet is a convolutional neural network (CNN) model developed in 2014. It consists of 22 neural network layers, including convolutional layers, dimension reduction layers, batch normalisation layers, ReLU activation layers and softmax output layers. A distinguishing feature of the GoogleNet architecture is the use of a so-called 'Inception module', which allows objects of different sizes and orientations to be detected in a single network laye [33].

SqueezeNet is a deep neural network model characterised by a smaller size than traditional models. This allows it to be used on devices with limited computing power, such as mobile devices or embedded systems. The main feature of SqueezeNet is the use of 1x1 convolutional layers instead of the traditional 3x3 or 5x5. These layers use fewer parameters, leading to a smaller model size, while still providing similar classification performance. Squee-zeNet also includes so-called 'fire modules', which are blocks that combine 1x1 convolution layers and 3x3 or 5x5 [34].

First, a spectrogram was created for each signal. These were then passed through the two networks mentioned above - GoogleNet and SqueezeNet - the process is shown in Figure 5.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 June 2023 doi:10.20944/preprints202306.0942.v1

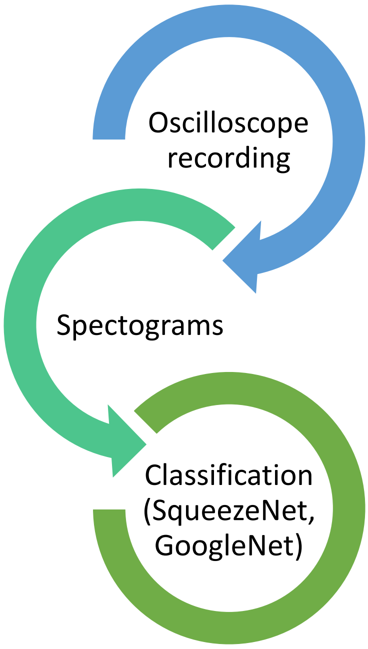


Figure 5. Block diagram of signal measurement and processing during current research.

2.4. Hybrid Neural Network

2.4.1. SAE+FNN

A hybrid model was used to train the neural networks: Stacked Autoencoder consisting of two hidden layers of 100 and 50 neurons each. The layers were trained in an unsupervised manner to extract features from the training data. Testing was carried out in MatLab - in the Deep Learning Toolbox environment. Network parameters: Epochs: 100; L2WeightRegularisation: 0.001; SparsityRegularisation: 4; Sparsity-Proportion: 0.1. The FNN was trained using the Adam optimisation algorithm with the following parameters: Learning Rate: 0.001; Epochs: 100 Batch size: 32.

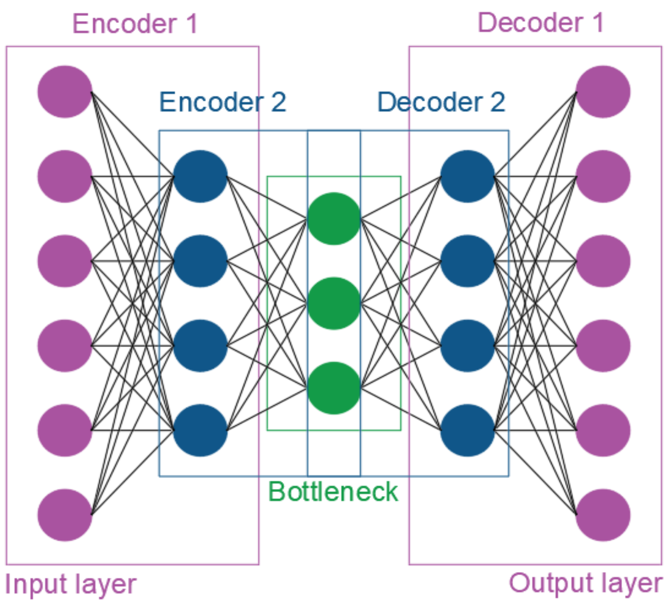


Figure 6. Stacked autoencoder structure.

2.4.2. 2D-CNN+LSTM

For the hybrid combination of CNN and LSTM, the Keras [35] and Tensorflow [36] libraries were used. Network learning was carried out on an RTX 3070 graphics card, using mainly Conv2D layers with 64 filters, BatchNormalisation, Re-Lu activation, drop-out, as well as an LSTM recursion layer with 200 units and a sequence return option. The network model was compiled with the Adam optimiser taking on the following parameters: Learning Rate: 0.001; Epochs: 50 Batch size: 32.

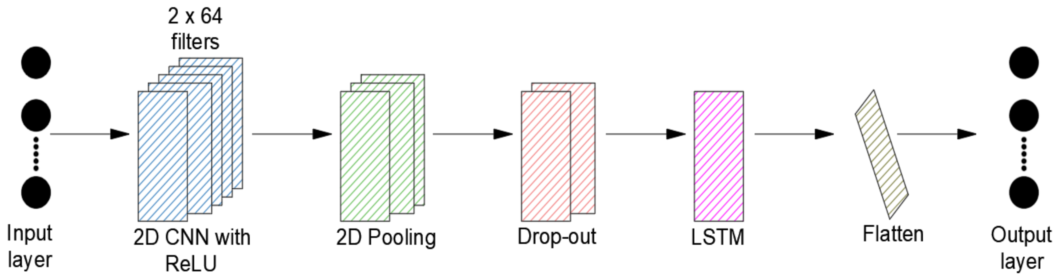


Figure 7. 2D CNN + LSTM architecture.

2.4.3. AE+1D-CNN+LSTM

The last hybrid combination investigated,

also using the Keras and Tensorflow library, was a combination of SA, CNN and LSTM networks. This time an autoencoder with a hidden layer of size 1984 was used. Learning parameters: Epochs: 150; Batch size: 32; Validation split: 0.2. The created CNN and LSTM network model consisted of Conv1D layers with 64 filters, batch normalisation, MaxPooling, as well as LSTM(256 and 128 respectively) and Drop-out. The optima-lizer Adam was used, with paramters: Learning Rate: 0.0005; Epochs: 1200 Batch size: 32. The full architecture of the layers of the networks mentioned above is shown in Table 1.

Table 1. Architecture of used neural networks

SAE+FNN	2D-CNN + LSTM	AE + 1D-CNN + LSTM
Encoder(100)	2DConv(64)	Encoder(1984)
Decoder	BatchNormalization	Dense(RELU)
Encoder(50)	Activation(RELU)	Dense(Sigmoid)
Decoder	2DConv(64)	Decoder
fullyConnectedLayer(256)	BatchNormalization	1DConv(128-RELU)
RELULayer	Activation(RELU)	BatchNormalization
fullyConnectedLayer(128)	GlobalAveragePooling2D	MaxPooling
RELULayer	Drop-out	1DConv(64-RELU)
fullyConnectedLayer(64)	LSTM(200)	BatchNormalization
RELULayer	Flatten	MaxPooling
fullyConnectedLayer(4)	Dense(4)(SoftMax)	Drop-out
SoftMaxLayer		LSTM(256)
ClassificationLayer		Drop-out
		LSTM(128)
		Drop-out
		Dense(4)(SoftMax)

3. Results and Discussion

Based on the collected measurement data during operation of the MV switchgear, a number of experiments were carried out to illustrate the effectiveness of the developed and used algorithms in PD detection and classification in the switchgear. The highest accuracy was obtained for the SqueezeNet and GoogleNet convolutional networks. MatLab's Deep Learning Toolbox environment allowed easy access to both networks. The

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 June 2023 doi:10.20944/preprints202306.0942.v1

modelled algorithm first created a spectrogram for each signal to be analysed, then the completed images were subjected to learning. Unfortunately, the time to create the spectrograms was quite long. The results for both cases are shown in Figure 8 and Figure 9.

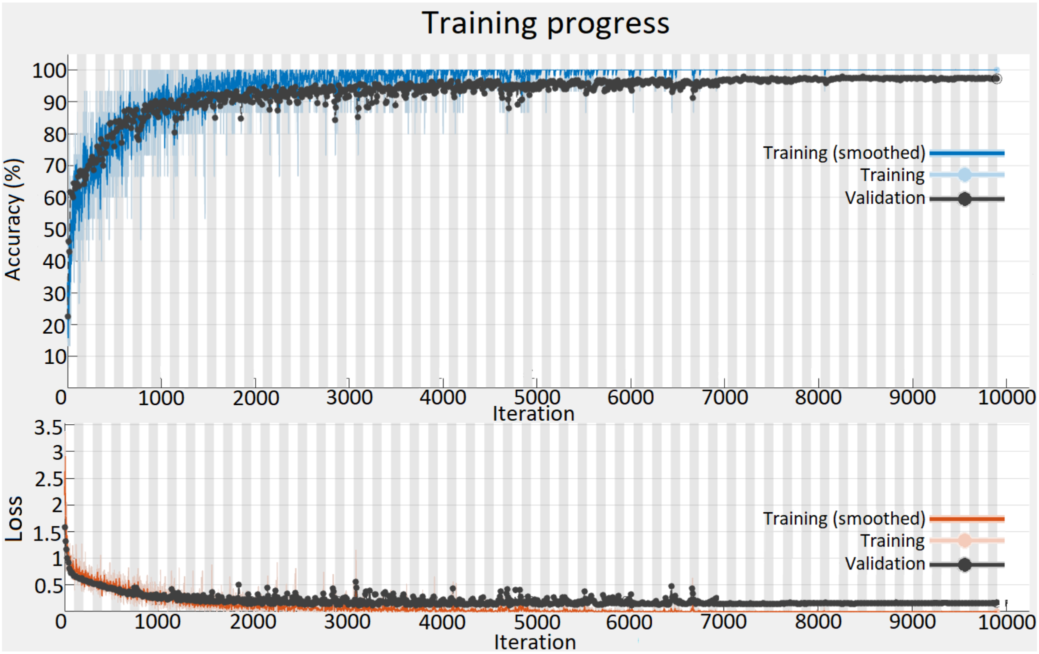


Figure 8. Training progress by GoogleNet.

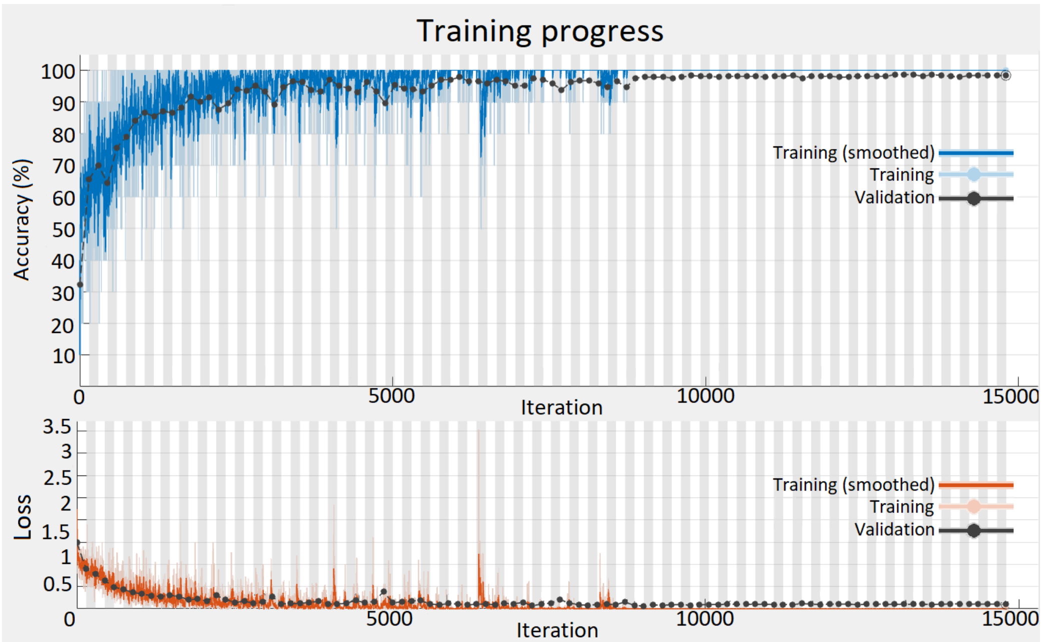


Figure 9. Training progress by SqueezeNet.

The classification results for each classification method are summarised in Table 2 and Table 3. Based on Table 2, it can be determined that the classification of fault 1 - PD from high potential - caused the most problems. This may be due to the least amount of measurement data for this class. It is noteworthy that the classification of Class four was successful, despite the combination of signals resulting from multiple disturbances occurring simultaneously in the switchgear or human errors of the assemblers. The results of the last Class confirm that the algorithm performs well with basic PD detection.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 13 June 2023 doi:10.20944/preprints202306.0942.v1

Table 2. Classification result for each class.

Neural Network	Class	Recall	Precision	F1-Score
GoogleNet	1	90.42%	93.91%	92.09%
	2	97.15%	96.42%	98.97%
	3	97.18%	98.88%	97.92%
	4	93.57%	94.47%	95.34%
	5	100%	100%	100%
SqueezeNet	1	94.64%	97.65%	96.15%
	2	99.78%	98.43%	99.53%
	3	98.48%	99.91%	99.04%
	4	99.98%	99.49%	98.19%
	5	100%	100%	100%
SAE + FNN	1	54.72%	48.12%	56.16%
	2	51.98%	49.78%	55.65%
	3	83.84%	83.65%	84.11%
	4	79.12%	83.21%	85.24%
	5	100%	100%	100%
CNN + LSTM	1	68.12%	73.44%	70.68%
	2	83.33%	79.44%	81.35%
	3	55.17%	94.12%	69.57%
	4	97.39%	74.12%	84.21%
	5	100%	100%	100%
AE+CNN+LSTM	1	52.72%	56.72%	54.29%
	2	67.37%	65.31%	66.32%
	3	81.25%	90.28%	85.53%
	4	89.52%	89.52%	85.71%
	5	100%	100%	100%

The combination of SAE+FNN, CNN+LSTM and AE+CNN+LSTM networks achieved an accuracy of approximately 82%. The best result was achieved by the networks SqueezeNet and GoogleNet – 98.39% and 97.31%.

Table 3. The result of the classification of the neural networks used

Neural Network	Accuracy
GoogleNet	97.31%.
SqueezeNet	98.39%
SAE+FNN	80.98%
CNN+LSTM	83.91%.
AE+CNN+LSTM	81.21%.

4. Conclusions

In the presented article, different methods were used to classify partial discharges occurring in MV switchgear in air insulation. The results obtained show that it was possible to significantly speed up the processing of the signal measured by the TEV sensors by using hybrid classification algorithms. Both GoogleNet and SqueezeNet achieved satisfactory classification results – 98% - on the basis of the created spectrograms, despite the addition of an ambiguous fourth fault. The other results obtained show the effectiveness of the adopted classification methods to be around 82%.

The result of the research prompts the creation of a universal capacitive sensor that continuously measures the possibility of partial discharge in MV switchgear. For this purpose, the authors will consider how to accelerate the creation of the spectrogram, as well as how to create an even more universal hybrid neural network.

In addition, the authors plan to investigate the effects of EMC disturbances, such as Burst - which simulates sparking at the contacts of electrical apparatuses in MV switchgear - and Surge, on the correct operation of a universal sensor placed on the external enclosure of an MV switchgear.

Author Contributions: Conceptualization, P.K. and J.S.; methodology, P.K. and A.Ł.; software, P.K.; validation, P.K., A.Ł. and J.S.; formal analysis, P.K and J.S.; investigation, P.K. and A.Ł.; resources, P.K.; data curation, P.K.; writing—original draft preparation, P.K.; writing—review and editing, P.K, A.Ł. and J.S.; visualization, P.K.; supervision, P.K. and J.S.; project administration, J.S.; funding acquisition, J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Subramaniam, A.; Sahoo, A.; Manohar, S.S.; Raman, S.J.; Panda, S.K. Switchgear Condition Assessment and Lifecycle Management: Standards, Failure Statistics, Condition Assessment, Partial Discharge Analysis, Maintenance Approaches, and Future Trends. *IEEE Electrical Insulation Magazine* **2021**, *37*, 27–41, doi:10.1109/MEI.2021.9399911.
2. Hussain, G.A.; Zaher, A.A.; Hummes, D.; Safdar, M.; Lehtonen, M. Hybrid Sensing of Internal and Surface Partial Discharges in Air-Insulated Medium Voltage Switchgear. *Energies (Basel)* **2020**, *13*, doi:10.3390/en13071738.
3. Zhou, X.; Wu, X.; Ding, P.; Li, X.; He, N.; Zhang, G.; Zhang, X. Research on Transformer Partial Discharge Uhf Pattern Recognition Based on Cnn-Lstm. *Energies (Basel)* **2019**, *13*, doi:10.3390/en13010061.
4. Subramaniam, A.; Janaki Raman, S.; Kumar Panda, S. Comparison of Partial Discharge Signal in a Three Phase Transformer by UHF, TEV and HFCT Sensors; Comparison of Partial Discharge Signal in a Three Phase Transformer by UHF, TEV and HFCT Sensors. **2021**, doi:10.1109/ICPEE50452.2021.9358502.
5. Zhang, C.; Dong, M.; Ren, M.; Huang, W.; Zhou, J.; Gao, X.; Albarracín, R. Partial Discharge Monitoring on Metal-Enclosed Switchgear with Distributed Non-Contact Sensors. *Sensors (Switzerland)* **2018**, *18*, doi:10.3390/s18020551.
6. Ji, K.H.; Xiao, J.X.; Li, W. Bin; Wang, X.F.; Song, P.; Si, W.R. Review of Partial Discharge Detection Technology for Transient Earth Voltage of HV Switchgear Cabinet. In Proceedings of the Proceedings - 2020 13th International Conference on Intelligent Computation Technology and Automation, ICICTA 2020; Institute of Electrical and Electronics Engineers Inc., October 1 2020; pp. 735–739.
7. Montanari, G.C.; Ghosh, R.; Cirioni, L.; Galvagno, G.; Mastroeni, S. Partial Discharge Monitoring of Medium Voltage Switchgears: Self-Condition Assessment Using an Embedded Bushing Sensor. *IEEE Transactions on Power Delivery* **2022**, *37*, 85–92, doi:10.1109/TPWRD.2021.3053658.
8. Ewaida, R.F.; Wani, N.R.; Khan, Y.; Al-Arainy, A.A. Defect Localization inside Simulated Mv Switchgear Based on Cumulative Energy Curve Using Transient Earth Voltage Sensors. *Energies (Basel)* **2021**, *14*, doi:10.3390/en14020320.
9. Ren, M.; Dong, M.; Ren, Z.; Peng, H.D.; Qiu, A.C. Transient Earth Voltage Measurement in PD Detection of Artificial Defect Models in SF 6. *IEEE Transactions on Plasma Science* **2012**, *40*, 2002–2008, doi:10.1109/TPS.2012.2199135.
10. Zhao, M.; Cao, X.; Zhou, K.; Fu, Y.; Li, X.; Wan, L. Flexible Sensor Array Based on Transient Earth Voltage for Online Partial Discharge Monitoring of Cable Termination. *Sensors (Switzerland)* **2020**, *20*, 1–15, doi:10.3390/s20226646.
11. Florkowski, M. Classification of Partial Discharge Images Using Deep Convolutional Neural Networks. *Energies (Basel)* **2020**, *13*, doi:10.3390/en13205496.
12. Mantach, S.; Ashraf, A.; Janani, H.; Kordi, B. A Convolutional Neural Network-Based Model for Multi-Source and Single-Source Partial Discharge Pattern Classification Using Only Single-Source Training Set. *Energies (Basel)* **2021**, *14*, doi:10.3390/en14051355.
13. Wang, Y.B.; Chang, D.G.; Qin, S.R.; Fan, Y.H.; Mu, H.B.; Zhang, G.J. Separating Multi-Source Partial Discharge Signals Using Linear Prediction Analysis and Isolation Forest Algorithm. *IEEE Trans Instrum Meas* **2020**, *69*, 2734–2742, doi:10.1109/TIM.2019.2926688.
14. Raymond, W.J.K.; Xin, C.W.; Kin, L.W.; Illias, H.A. Noise Invariant Partial Discharge Classification Based on Convolutional Neural Network. *Measurement (Lond)* **2021**, *177*, doi:10.1016/j.measurement.2021.109220.

15. Uckol, H.I.; Ilhan, S.; Ozdemir, A. Workmanship Defect Classification in Medium Voltage Cable Terminations with Convolutional Neural Network. *Electric Power Systems Research* **2021**, *194*, doi:10.1016/j.epsr.2021.107105.
16. Raymond, W.J.K.; Azil Illias, H.; Mokhlis, H. Novel Data Augmentation for Improved Insulation Fault Diagnosis under Nonideal Condition. *Expert Syst Appl* **2022**, *209*, doi:10.1016/j.eswa.2022.118390.
17. Davari, N.; Akbarizadeh, G.; Mashhour, E. Corona Detection and Power Equipment Classification Based on GoogleNet-AlexNet: An Accurate and Intelligent Defect Detection Model Based on Deep Learning for Power Distribution Lines. *IEEE Transactions on Power Delivery* **2022**, *37*, 2766–2774, doi:10.1109/TPWRD.2021.3116489.
18. Barrios, S.; Buldain, D.; Comech, M.P.; Gilbert, I.; Orue, I. Partial Discharge Classification Using Deep Learning Methods - Survey of Recent Progress. *Energies (Basel)* 2019, *12*.
19. Barrios, S.; Buldain, D.; Comech, M.P.; Gilbert, I. Partial Discharge Identification in MV Switchgear Using Scalogram Representations and Convolutional AutoEncoder. *IEEE Transactions on Power Delivery* **2021**, *36*, 3448–3455, doi:10.1109/TPWRD.2020.3042934.
20. Classify Time Series Using Wavelet Analysis and Deep Learning - MATLAB & Simulink Example Available online: https://www.mathworks.com/help/deeplearning/ug/classify-time-series-using-wavelet-analysis-and-deep-learning.html (accessed on 10 April 2023).
21. Alsumaidaee, Y.A.M.; Yaw, C.T.; Koh, S.P.; Tiong, S.K.; Chen, C.P.; Ali, K. Review of Medium-Voltage Switchgear Fault Detection in a Condition-Based Monitoring System by Using Deep Learning. *Energies (Basel)* 2022, *15*.
22. Zemouri, R.; Levesque, M.; Amyot, N.; Hudon, C.; Kokoko, O.; Tahan, S.A. Deep Convolutional Variational Autoencoder as a 2D-Visualization Tool for Partial Discharge Source Classification in Hydrogenerators. *IEEE Access* **2020**, *8*, 5438–5454, doi:10.1109/ACCESS.2019.2962775.
23. Thi, N.D.T.; Do, T.D.; Jung, J.R.; Jo, H.; Kim, Y.H. Anomaly Detection for Partial Discharge in Gas-Insulated Switchgears Using Autoencoder. *IEEE Access* **2020**, *8*, 152248–152257, doi:10.1109/ACCESS.2020.3017226.
24. Lu, S.; Chai, H.; Sahoo, A.; Phung, B.T. Condition Monitoring Based on Partial Discharge Diagnostics Using Machine Learning Methods: A Comprehensive State-of-the-Art Review. *IEEE Transactions on Dielectrics and Electrical Insulation* **2020**, *27*, 1861–1888, doi:10.1109/TDEI.2020.009070.
25. Zhou, X.; Wu, X.; Ding, P.; Li, X.; He, N.; Zhang, G.; Zhang, X. Research on Transformer Partial Discharge Uhf Pattern Recognition Based on Cnn-Lstm. *Energies (Basel)* **2019**, *13*, doi:10.3390/en13010061.
26. Liu, T.; Yan, J.; Wang, Y.; Xu, Y.; Zhao, Y. Gis Partial Discharge Pattern Recognition Based on a Novel Convolutional Neural Networks and Long Short-term Memory. *Entropy* **2021**, *23*, doi:10.3390/e23060774.
27. Li, Z.; Qu, N.; Li, X.; Zuo, J.; Yin, Y. Partial Discharge Detection of Insulated Conductors Based on CNN-LSTM of Attention Mechanisms. *Journal of Power Electronics* **2021**, *21*, 1030–1040, doi:10.1007/s43236-021-00239-3.
28. Li, G.; Wang, X.; Li, X.; Yang, A.; Rong, M. Partial Discharge Recognition with a Multi-Resolution Convolutional Neural Network. *Sensors (Switzerland)* **2018**, *18*, doi:10.3390/s18103512.
29. Mohammed Alsumaidaee, Y.A.; Yaw, C.T.; Koh, S.P.; Tiong, S.K.; Chen, C.P.; Yusaf, T.; Abdalla, A.N.; Ali, K.; Raj, A.A. Detection of Corona Faults in Switchgear by Using 1D-CNN, LSTM, and 1D-CNN-LSTM Methods. *Sensors* **2023**, *23*, 3108, doi:10.3390/s23063108.
30. Nguyen, M.T.; Nguyen, V.H.; Yun, S.J.; Kim, Y.H. Recurrent Neural Network for Partial Discharge Diagnosis in Gas-Insulated Switchgear. *Energies (Basel)* **2018**, *11*, doi:10.3390/en11051202.
31. Duan, L.; Hu, J.; Zhao, G.; Chen, K.; He, J.; Wang, S.X. Identification of Partial Discharge Defects Based on Deep Learning Method. *IEEE Transactions on Power Delivery* **2019**, *34*, 1557–1568, doi:10.1109/TPWRD.2019.2910583.
32. Kluge, P.; Lasica, A. Non-Invasive PD Measurement Method in Air-Insulated Switchgear - Signal Processing. In Proceedings of the 2022 23rd International Conference on Computational Problems of Electrical Engineering, CPEE 2022; Institute of Electrical and Electronics Engineers Inc., 2022.
33. Szegedy, C.; Liu, W.; Jia, Y.; Sermanet, P.; Reed, S.; Anguelov, D.; Erhan, D.; Vanhoucke, V.; Rabinovich, A. Going Deeper with Convolutions. In Proceedings of the Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition; IEEE Computer Society, October 14 2015; Vol. 07-12-June-2015, pp. 1–9.
34. Iandola, F.N.; Han, S.; Moskewicz, M.W.; Ashraf, K.; Dally, W.J.; Keutzer, K. SqueezeNet: AlexNet-Level Accuracy with 50x Fewer Parameters and <0.5MB Model Size. **2016**.
35. Keras: Deep Learning for Humans Available online: https://keras.io/ (accessed on 17 April 2023).

 doi:10.20944/preprints202306.0942.v1

36. TensorFlow Available online: https://www.tensorflow.org/ (accessed on 17 April 2023).