

APPLICATION OF AN INITIAL NEURAL NETWORK MODEL FOR VALIDATION OF PARTIAL DISCHARGE CLASSIFICATION ON STATOR COILS

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ABSTRACT

This paper presents the application of an initial neural network model for the validation of partial discharge classification in stator coils. The aim is to verify the model's ability to distinguish between different types of partial discharges in a stator coil based on signal processing and their representation using scalograms. The results highlight the potential of artificial neural networks in the classification of insulation systems of electrical machines, with the proposed model serving as a foundation for further development and optimization of more accurate classification methods.

Keywords: partial discharge, signal processing, scalogram, classification, machine learning, artificial neural network

1. INTRODUCTION

In the field of high-voltage engineering, diagnostic methods are focused on assessing the condition of insulation components in electrical equipment. Their purpose is to monitor and evaluate partial discharges, which over time may compromise the integrity of insulation and eventually lead to equipment failure [1]. Increasing attention is being given to the combination of signal processing techniques and machine learning (ML) methods, which enable faster and more accurate classification of discharge types and their origins. However, challenges remain in automated recognition, as the process is often affected by noise or variations in material properties and voltage levels [2].

For this reason, artificial intelligence algorithms and ML approaches have been increasingly applied in recent years, offering enhanced capabilities for detecting complex discharge phenomena and anomalies that are not directly observable [3][4]. This paper focuses on the application of transformation methods, specifically Wavelet Transform (WT), in combination with ML techniques to improve the classification of partial discharge signals.

The research addresses the problems of efficiently processing impulse signals measured directly on real samples and their subsequent transformation using WT into scalograms, which serve as input data for ML. The main objective is to design and implement suitable neural network architectures and to evaluate their ability to generalize to previously unseen inputs [2][4].

The application of ML in technical diagnostics provides new opportunities for assessing the condition of insulation systems [3]. The integration of signal processing methods with deep learning enables more detailed and reliable evaluation of discharge activity. Early and accurate identification of the type and origin of partial discharges contributes to fault prediction and thus helps prevent critical failures in electrical equipment [3][5]. The results of this work may be used as a foundation for the development of a convolutional neural network

(CNN), which, compared to the sequential model, represents a more complex and powerful architecture. may be applied in the modern intelligent diagnostic systems it can be created with potential use in maintenance, monitoring, and the assessment of insulation material lifetime [3][6].

2. MEASUREMENT AND PROCESSING OF PARTIAL DISCHARGE

The galvanic method is one of the most widely used approaches for partial discharge (PD) measurement. It is based on the direct observation of discharge current pulses in the circuit. The main evaluation parameter is the apparent charge q , which cannot be measured directly. Therefore, multiple measurements are carried out, and the responses of the apparent charge are compared. Before the actual measurement, the circuit must be calibrated. A known apparent charge is injected into the circuit by a calibration device, and the corresponding output signal is observed on the measuring instrument. Based on this known apparent charge, the value of the unknown apparent charge can be determined and recalculated [5][7]. The main advantage of the galvanic method is its high sensitivity in detecting partial discharges, while not endangering the insulation system during the measurement process. Its disadvantages include the need to add a measuring impedance and a coupling capacitor to the circuit, susceptibility to disturbances from various sources, and the requirement that the tested object must be taken out of service during measurement [7].

2.1. Wavelet transformation

The WT is a mathematical method used for analyzing signals in the time-frequency domain. It employs basis functions called wavelets, which are short, localized signals that allow the study of both temporal and spectral features of a signal. Unlike Fourier Transform (FT), which provides only global frequency information, WT is particularly suitable for analyzing non-stationary signals with time-varying frequency and amplitude [4]. At its core

is the called mother wavelet $\psi(t)$, which is scaled and shifted in time. The translation parameter τ determines the position of the wavelet on the time axis, while the scale parameter s controls its resolution [4]. In this work, the Morlet wavelet was selected as the mother wavelet, as its Gaussian-modulated complex exponential form provides a favorable trade-off between time and frequency localization, making it well suited for the impulsive, non-stationary character of partial discharge signals [3].

The Continuous Wavelet Transform (CWT) of a signal $x(t)$ is defined as [4]:

$$W_x(s, \tau) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{+\infty} x(t) \psi\left(\frac{t - \tau}{s}\right) dt \quad (1)$$

where s – scale, τ – translation, $\psi^*(t)$ – complex conjugate of the mother wavelet.

The result is a two-dimensional time-scale representation known as a scalogram, in which the color intensity at each point encodes the magnitude of the wavelet coefficient $W_x(s, \tau)$. Large scales correspond to low frequencies and capture global signal trends, while small scales resolve fine-grained, short duration features. This dual resolution makes the scalogram well suited for characterizing impulsive PD events, and the resulting images serve as input data for the ML model [4].

2.2. Transformation methods combined with machine learning

In the field of signal analysis, transformational methods play a crucial role in decomposing complex signals into their fundamental components. Transformations such as the Fourier and Wavelet transforms are widely applied in partial discharge analysis, vibration analysis, condition monitoring, and other areas where accurate examination of time-varying signals is required. A limitation of these methods, however, is that their application can be computationally demanding and time-consuming, especially when processing large datasets [3]. In recent years, artificial intelligence (AI) and ML have gained increasing importance in automating and accelerating such analyses. Artificial neural networks (ANN) have proven to be highly effective tools for pattern recognition and signal classification. Their functionality is based on learning from experience by training on historical data and examples, the network gradually learns to identify specific frequency and time-domain features associated with certain types of events [6]. In the case of partial discharges, neural networks (NN) can be trained to distinguish between different discharge types based on their frequency spectrum and temporal distribution [3][4]. Once trained, the network can analyze signals quickly and efficiently. When combined with transformational methods, ML enables faster and more accurate analysis, providing real-time decision making regarding the condition of analyzed systems [3]. NN can automatically detect anomalies in signals and classify them by type and severity, thereby reducing the time and resources required for manual analysis. The integration of transformational methods with artificial intelligence not only enhances the understanding of signal dynamics but also facilitates

the development of efficient systems for monitoring and predictive maintenance of technical equipment [2][3].

2.3. Supervised Learning

Supervised Learning is the most widely used approach in ML. It is based on training a model on labelled data, where each input is paired with the correct output or target value. During training, the model learns the relationships between inputs and outputs, allowing it to make accurate predictions for new, unseen data. Supervised learning is typically divided into two main categories [6]:

- Classification: the process of assigning input data to predefined categories or classes. For instance, in image recognition tasks, the model determines whether an image contains a cat, a dog, or another object [6].
- Regression: the prediction of continuous values based on input features. A common example is estimating the price of a house based on attributes such as location, size, or age [6].

In terms of NN design, one of the simplest approaches is sequential architecture. In this setup, layers are arranged linearly, with the output of one layer serving as the input to the next. The fundamental building block is the neuron, which computes a weighted sum of its inputs, adds a threshold term, and passes the result through an activation function. The network is trained by gradually adjusting the weights and thresholds using the backpropagation algorithm and optimization methods, which minimize the error between predictions and true outputs [3][6].

3. EXPERIMENTAL SETUP

At the Department of Electrical Power Engineering in Košice, measurements of partial discharges were carried out on two test samples using the galvanic method for the detection of partial discharge signals. The measured signals were recorded, stored, processed using the Wavelet transform, and evaluated for further use in the development of the initial neural network. The tested sample was a stator winding coil suspended on an insulating rope, with the coil ends connected by a homogenization sphere. Two different stator winding coils were used, which differed in material, type of epoxy layer, semiconductive coating, and size. For future purposes of processing data with the initial neural model, we will refer to them as Coil - Brown coating (Fig. 1) and Coil - White coating (Fig. 2).



Fig. 1 Stator coil with semiconductive coating (Brown)



Fig. 2 Stator coil without semiconductive coating (White)

3.1. Experimental workplace and used instruments

The laboratory measurement of partial discharges was carried out under controlled conditions at the Department of Electrical Power Engineering. The procedure followed recommended laboratory standards. The block diagram of the galvanic method for partial discharge measurement (Fig. 3)

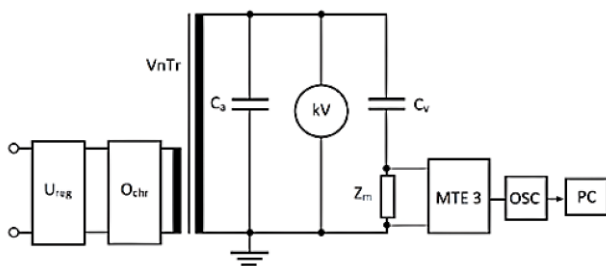


Fig. 3 Block diagram of the galvanic method

The block diagram consists of the following:

U_{reg} – Adjustable high-voltage source LSS020 220V/250V, $I_n = 20A$, $S_n = 5kVA$; O_{chr} – Protection; $VnTr$ – High-voltage transformer; C_a – Test object; kV – Kilovoltmeter; C_v – Coupling capacitor; Z_m – Measuring impedance; MTE 3 – Partial discharge detector; OSC – Digital storage oscilloscope Agilent Technologies DS07104B 1 GHz.

3.2. The details of the experiment

The circuit connected according to the block diagram was carefully inspected before the measurement to avoid any connection errors. Each measurement was carried out inside a metallic enclosure to prevent external interference. At the beginning of the measurement, the oscilloscope connected to the partial discharge detector MTE3 recorded interference effects, which were caused by the detector itself. This interference was eliminated by applying additional shielding and a filter between the measuring equipment and the MTE3 detector. Subsequently, the voltage gradually increased using an autotransformer, with the voltage magnitude indicated

and monitored on a physical kilovoltmeter. The first identified partial discharges on the stator coils, displayed on the oscilloscope, were recorded and stored in CSV format on a USB drive. The results from the oscilloscope were then processed and evaluated in the Scilab software, where they were used for graphical representation by means of the Wavelet transform.

It was chosen as the transformation method primarily because of its ability to analyze nonlinear and non-stationary signals. It provides information on both the frequency content and the temporal localization of impulsive phenomena. This makes it possible to capture short-term and dynamic variations in the signal that would remain hidden when using other transformation methods.

3.3. Processing of measured data

All measured partial discharge signals were processed into a suitable format for ML purposes using a custom script written in the Scilab environment. The CWT was computed using the built-in `cwt()` function with the Morlet mother wavelet and a scale range of $s = 1$ to 50. The signals were acquired at a sampling frequency of $f_h = 2$ MHz, and the selected scale range was chosen to cover the frequency components most characteristic of partial discharge activity in stator coil insulation. Each computed scalogram was exported directly as a PNG image at a native resolution of 1033×878 pixels without additional amplitude normalization, preserving the relative energy distribution encoded in the wavelet coefficient magnitudes. Prior to input into the neural network, all scalogram images were resampled to 517×439 pixels. This factor of two reduction was adopted to decrease the computational cost of training while retaining the dominant time–frequency features relevant for classification. Intensity normalization was not applied at the image level. It is handled implicitly by the BatchNormalization layer at the input stage of the neural network, as described in Section 3.6. In total, 436 partial discharge scalograms were prepared in this way (Fig. 4). From the perspective of neural networks, this represents a relatively small dataset, as typical training sets usually contain thousands of images.

The main goal of combining the WT with deep learning is to achieve the ability for automatic categorization of previously unseen partial discharge samples. In this approach, the neural network is not only used for the classification of known samples but also for clustering data to discover new patterns. Processing partial discharge signals using WT followed by ML analysis provides more accurate recognition and categorization of these phenomena.

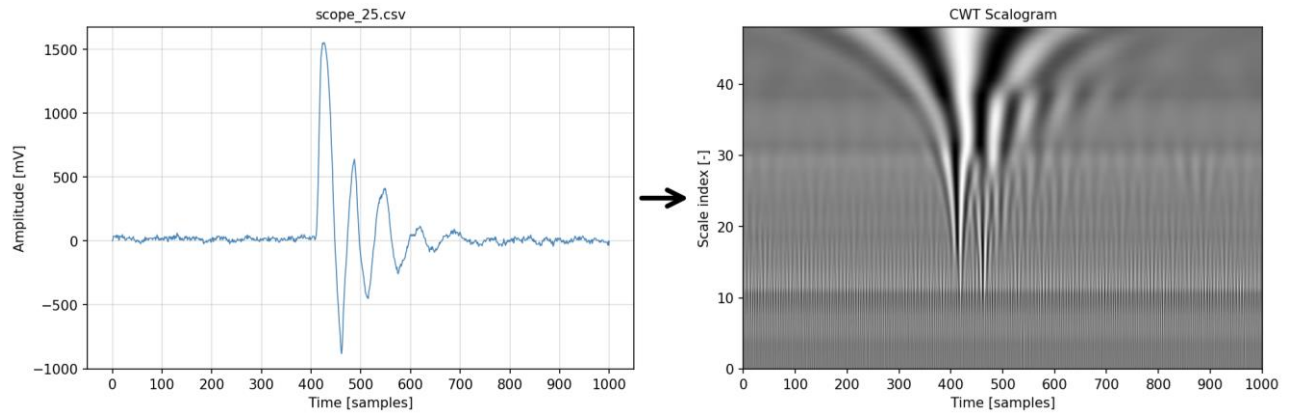


Fig. 4 Partial discharge signal processing by WT

3.4. Defining samples class for dataset

From the measured and processed data, it was necessary to classify the individual scalograms into the corresponding dataset classes for their further use in ML. These classes serve as the input categories for the proposed initial neural network. The specific classifications are illustrated in (Fig. 5), where the visual differences between the two stator coils, as well as the variations in voltage levels at which the partial discharges were measured, can be observed.

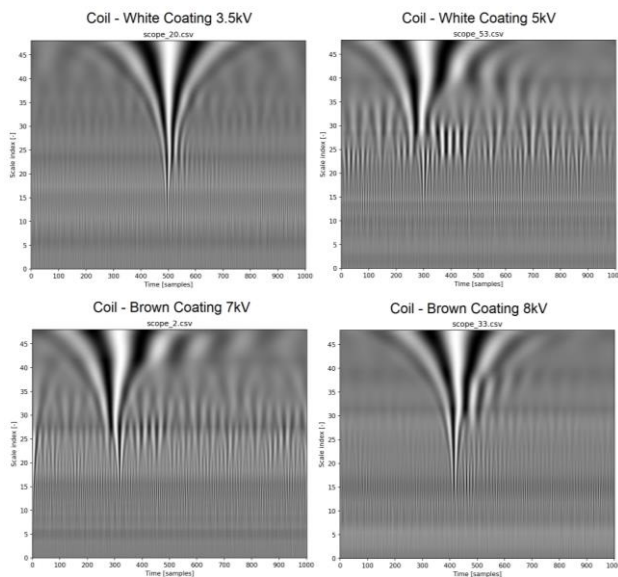


Fig. 5 Classification assignment of classes to datasets

3.5. Splitting datasets for training and validation

The next step in the development of the initial neural network model was to divide the created datasets into a training set, which provides the model with the opportunity to learn pattern recognition, and a validation set, which serves as an independent verification of its predictions. It was necessary to determine a suitable ratio between the training and validation sets, as an incorrect split could lead to biased model evaluation. For this reason, a consistent ratio of 80% for training and 20% for validation was chosen. This ensured enough samples for effective training while keeping the validation set large

enough for objective assessment. An equally important aspect was to ensure that the training and validation sets did not contain the same processed scalograms. If identical data were present in both sets, the results could become inaccurate, and the model might learn to recognize duplicates rather than genuine patterns.

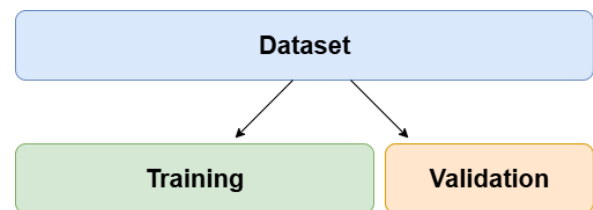


Fig. 6 Splitting dataset

To ensure that the trained model was able to make accurate predictions on the validation data, we applied data augmentation techniques such as random contrast adjustment, brightness variation, and noise addition to the training dataset. This approach was intended to prevent the model from overfitting to specific patterns within the training set, which could otherwise result in overtraining during the learning process. The application of data augmentation can be observed in the results section on (Fig. 9).

3.6. Initial design of the sequential model

In the design of the initial model for partial discharge classification on stator coils using a neural network, sequential architecture was chosen at first, as it allows for simple and transparent layer stacking in a linear order, making it a fundamental model in the field of ML. The Sequential API in Keras was used to define the basic layers, activation functions, and pooling operations. The goal was to create a model capable of effectively extracting features from scalograms and subsequently classifying them into the corresponding classes within the dataset. The design of the sequential model consisted of followings parts. The input layer, which specifies the dimensions and format of the input data, a BatchNormalization layer, which stabilizes learning by normalizing the input data at the beginning of processing. Then, a GlobalAveragePooling2D layer, which reduces the spatial dimensions of the extracted

features by averaging, and classification dense layers, which are fully connected layers that map the extracted features onto the output classes.

The main classification part of the initial model consists of seven Dense layers, which gradually reduce the number of neurons from larger to smaller values, specifically 256, 128, 64, 32, and 16. This approach is applied to allow the model to first learn more complex and general patterns with a larger number of neurons and then progressively compress the information into smaller, more specialized representations focused on recognizing finer details. Each of these layers is activated by the ReLU function, except for the final Dense layer, which uses Softmax activation. It serves as the model's final decision-making function, providing a probabilistic distribution over the predicted classes. Each Dense layer is complemented by LayerNormalization, which stabilizes learning by normalizing activation values across neurons within the layer. This prevents extreme fluctuations in activations and enables faster and more reliable convergence of the model. To mitigate overfitting, a Dropout layer was also implemented with a progressively decreasing dropout rate (0.6, 0.5, 0.4, 0.3, 0.2). Dropout works by randomly disabling a portion of neurons during training, preventing the model from over-adapting to specific patterns in the training data. This layer forces the model to learn more robust features and improves its ability to generalize to unseen data.

The model was compiled using the Adam optimizer, which was selected for its adaptive learning rate properties and robust convergence behavior on small datasets. To further stabilize training, a CosineDecay learning rate schedule was applied with an initial value of 3×10^{-4} and a decay step count of 5000. Under this schedule, the learning rate decreases smoothly following a cosine curve from its initial value towards zero, which reduces the risk of overshooting the loss minimum in later training epochs. A batch size of 16 was chosen to reflect the limited size of the dataset.

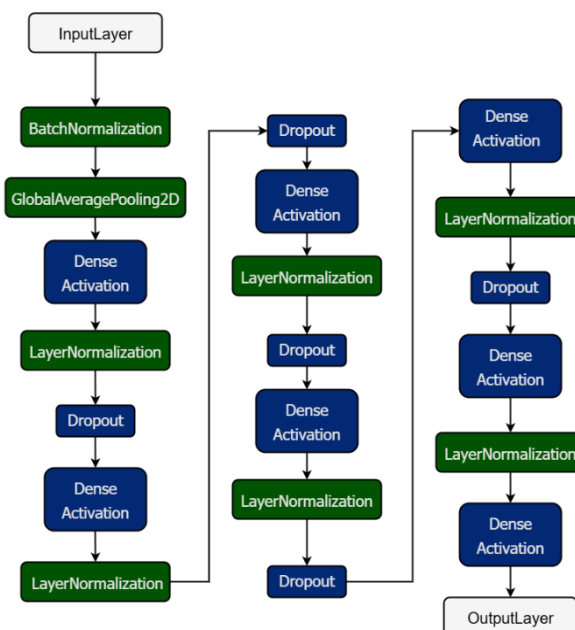


Fig. 7 Structure of initial model

3.7. Output of precision and loss of sequential model

The model was trained for a total of 100 epochs, a value determined empirically as the point beyond which the validation loss ceased to improve and overfitting became evident. The training progress of the initial sequential model for classifying partial discharge scalograms on stator windings is illustrated in (Fig. 8). The left graph shows accuracy, representing the proportion of correctly classified samples relative to the total number of samples. The graph on the right shows the loss value, which indicates the difference between the model predicted outputs and the actual classes, the lower the loss, the better the model adjusts its weights. The x-axis represents the epoch, meaning one complete pass of the model through the entire training dataset.

On the right-hand side of the graph in (Fig. 8), we can observe an increase in training accuracy (blue curve), which gradually rises with the growing number of epochs, reaching approximately 86%. The validation accuracy (orange curve) follows a similar trend until around the 40th epoch, after which it starts to fluctuate significantly and shows a slight decrease at around 70%. In the second graph, the training loss (blue curve) decreases steadily, indicating that the model is successfully learning to distinguish between the predicted and actual classes in the training data. The validation loss (orange curve) follows a similar downward trend until approximately the 60th epoch, where it begins to fluctuate abruptly and its value increases. This behavior indicates the onset of overfitting, with a higher number of epochs, the model starts memorizing specific patterns from the training dataset instead of generalizing them. As a result, it becomes less capable of correctly applying the learned features when predicting on the validation dataset.

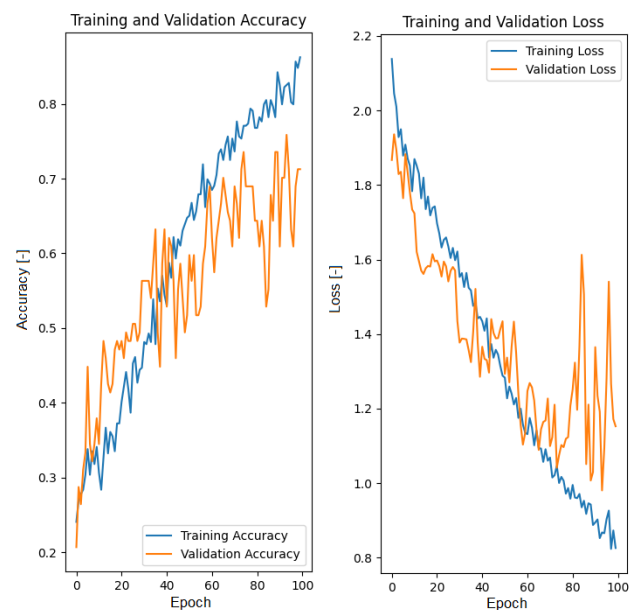


Fig. 8 Learning progress of the initial sequential model

From the observed training process in (Fig. 8), it is evident that prolonged training may lead to overfitting. Possible ways to mitigate this issue include some regulatory algorithms such as, early stopping, regularization, bigger dataset augmentation, increasing

the dropout rate or larger dataset samples. Another approach would be to employ CNN, which represents a more complex model capable of extracting more detailed features from scalograms. In the next section, however, the focus will be placed on a detailed evaluation of individual validation samples, to verify what extent our initial sequential model is capable of correctly distinguishing new input data.

4. RESULTS

We focus on the classification of scalograms of partial discharges in stator winding coils using the validation dataset. The model assigns individual samples to the most appropriate class based on the knowledge acquired from the training dataset. In addition, the model's ability

to generalize to unseen data, which were not part of either the training or validation sets, is also evaluated. These unseen data form the so-called verification set, which is used to assess the overall robustness and capability of the model to correctly classify new inputs.

From the validation dataset, an individual scalogram of a partial discharge was selected, and the trained model assigned the samples to the most corresponding class based on the knowledge acquired from the training dataset in (Fig. 9). A scalogram from the validation dataset can never be 100% identical to a scalogram from the training dataset, as these datasets do not contain identical patterns. The correctness of the model's prediction was confirmed on the validation dataset, with samples being successfully assigned to the most appropriate class.

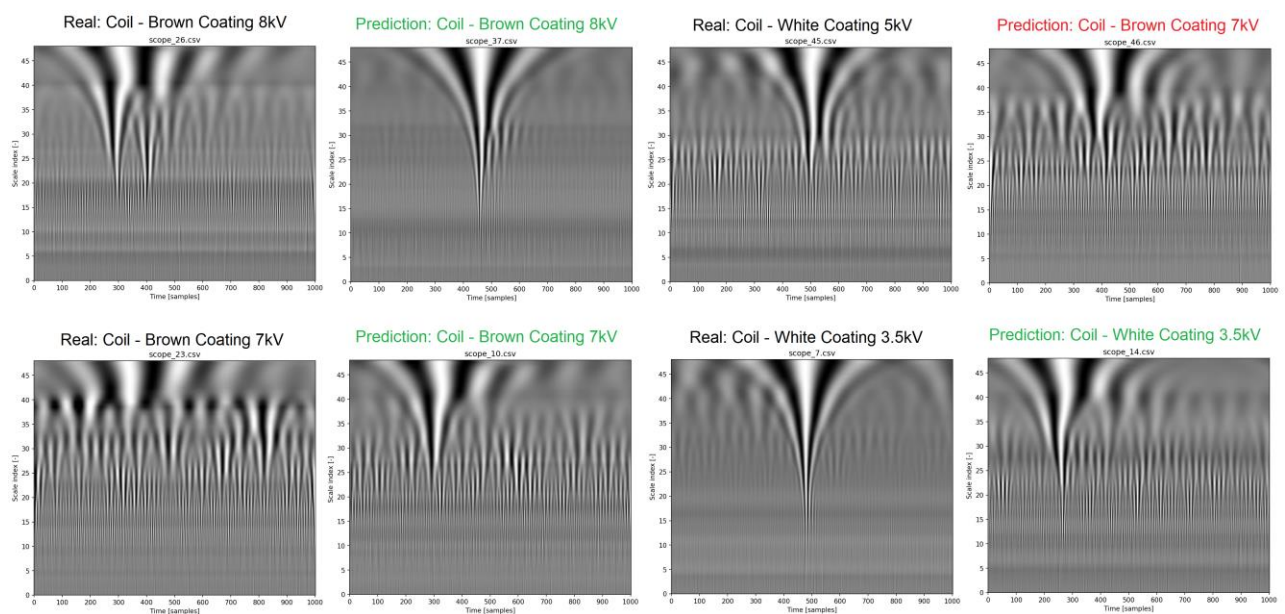


Fig. 9 Verifying the validation classification of the trained model

On the predicted scalograms, the effects of augmentation can be observed, such as adjustments in contrast, brightness, or the addition of noise. The classification was successfully verified across all variations of stator winding coil groupings. For the illustration of validation classification shown in (Fig. 9), one sample was selected from each class, with a single scalogram chosen to represent each class. The validation samples were then matched with the most similar scalogram from the training set, i.e., the one from which the model identified the most indicative features characteristic of the predicted class of the validation sample. When visually comparing these scalograms by eye, it is difficult to determine whether they belong to the same class, unlike in traditional image datasets (such as shapes or objects), which are much easier to distinguish. It can also be observed that the assigned training scalograms differ visually from the actual validation samples, which is a result of the data augmentation applied to the training set during model development. In total, all scalograms in the validation sets were evaluated, with the ongoing results presented in (Table 1).

Tab 1 Validation classification of samples

Number of samples	Real Class Coil	Predicted Class Coil	Correct Prediction
0	White - 3.5kV	White - 3.5kV	TRUE
1	White - 5kV	White - 3.5kV	FALSE
2	White - 3.5kV	White 3.5kV	TRUE
3	White -3.5kV	White - 3.5kV	TRUE
...	...	...	...
82	Brown - 7kV	White - 3.5kV	FALSE
83	Brown - 8kV	Brown - 8kV	TRUE
84	White - 3.5kV	White - 3.5kV	TRUE
85	Brown - 8kV	Brown - 8kV	TRUE

Each validation sample from the respective classes was verified, allowing the model to demonstrate its ability

to recognize characteristic features between the scalograms of partial discharges in stator coils. The individual validation classification accuracy achieved is approximately consistent with the model's training output (Fig. 8), at around 70.11%.

The evaluated predictions for the validation datasets achieved approximately 70% accuracy, with exactly 25 misclassified scalograms of partial discharges in stator coils. A closer examination of the individual classes revealed where the model faced the greatest difficulties in distinguishing between classes and making accurate predictions. For this reason, (Fig. 10) presents the comparison between the number of actual validation samples and the number of predicted classes according to the initial model.

The results show that the trained initial model was unable to reliably recognize and predict the class Coil - White Coating 5 kV, where the number of correctly predicted samples was significantly lower compared to the actual number of samples in that class. On the other hand, most of the misclassified predictions were assigned to the class Coil - White Coating 3.5 kV, indicating that the model was at least capable of identifying the correct coil, while the misclassification stemmed primarily from differences in the voltage at which the partial discharges were measured. Regarding the classes Coil - Brown Coating 7 kV and 8 kV, the discrepancies between predicted and actual samples were less pronounced. Despite the smaller voltage difference in this case compared to the white coil, the model was able to distinguish between these classes more effectively and predict them with higher accuracy.

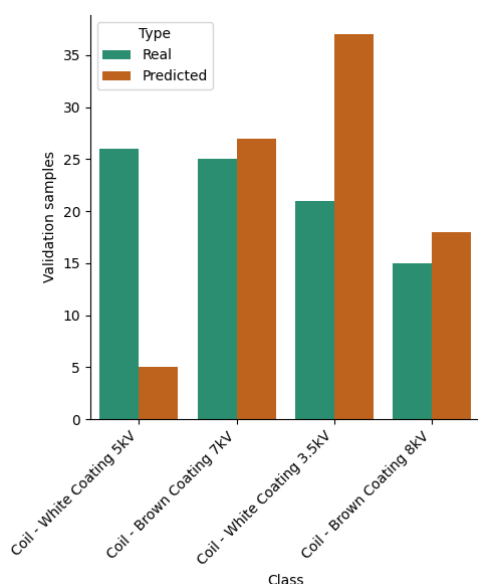


Fig. 10 Number of real and predicted samples

A more detailed view of the classification behavior is provided by the confusion matrix in (Fig. 11), which shows the number of samples assigned to each predicted class against the true class for the entire validation dataset.

The diagonal entries represent correctly classified samples, while off-diagonal entries indicate misclassifications. The Coil - Brown Coating 8 kV, achieved perfect classification with all 15 samples correctly predicted and no misclassifications. The class Coil - White Coating 3.5 kV also performed well, with 20 out of 21 samples correctly classified and only 1 sample misassigned to Coil - Brown Coating 8 kV. For Coil - Brown Coating 7 kV, 21 out of 25 samples were correctly predicted, with the remaining 4 samples split between Coil - Brown Coating 8 kV and Coil - White Coating 3.5 kV, suggesting some overlap in the time-frequency features between these two voltage levels on the brown coil. The most problematic class was Coil - White Coating 5 kV, where only 5 out of 26 samples were correctly classified. The remaining 21 samples were predominantly misassigned to Coil - White Coating 3.5 kV and Coil - Brown Coating 7 kV.

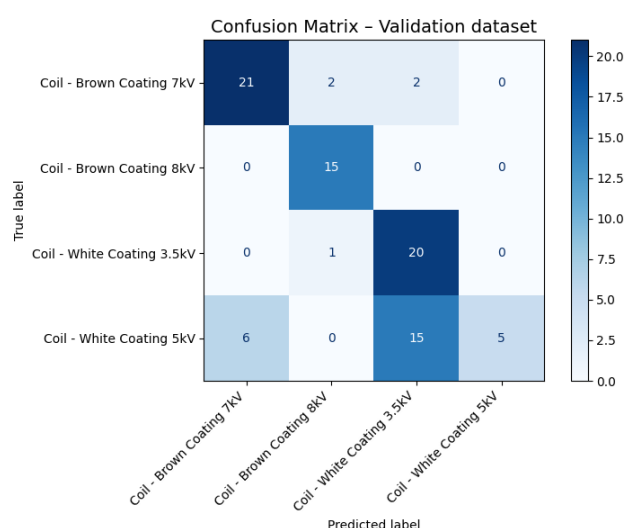


Fig. 11 Confusion Matrix – Validation dataset

4.1. Testing unknown scalogram samples for model

The trained initial model was tested on unknown scalogram patterns that were not part of the dataset used for training. Each insert scalogram represented classes on which the model had originally been trained. The aim was to verify the model's ability to correctly classify and predict the category of an unseen sample (Fig. 12). To some extent, the classification was successful, as the model correctly assigned unknown scalograms to the categories Coil - Brown Coating 8kV and Coil - White Coating 3.5kV, achieving an accuracy of approximately 44%. However, for the categories Coil - Brown Coating 7kV and Coil - White Coating 5kV, the model failed to classify correctly, with the resulting accuracy being around 35%. Overall, each stator coil category of the unknown samples was tested, with an average accuracy of about 40%, indicating that the model is not yet capable of reliably generalizing to unseen data.

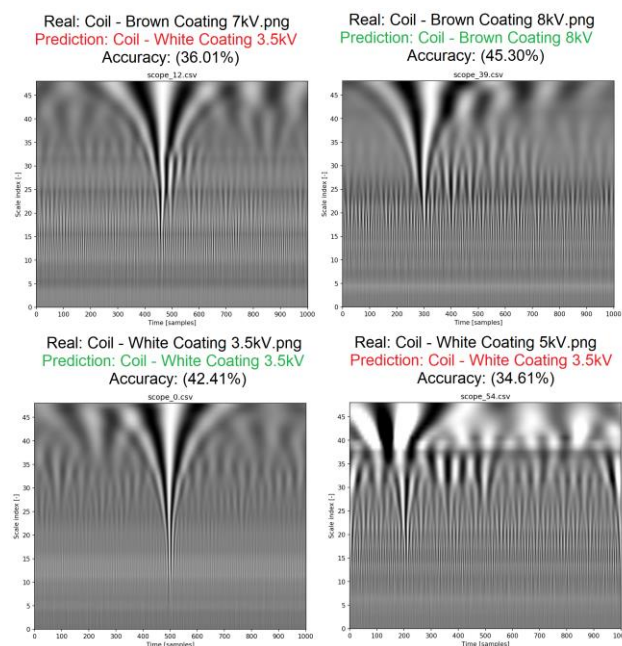


Fig. 12 Verifying initial model accuracy

5. CONCLUSIONS

This article presented the development and evaluation of an initial sequential neural network model for the classification of partial discharge signals in stator coils, represented as scalograms generated by the CWT with a Morlet mother wavelet. Four classes were defined, corresponding to two physically distinct stator coils measured at different voltage levels. The validation accuracy of approximately 70% was achieved on a dataset of 436 scalograms. Given the limited size of this dataset, which is considerably smaller than the thousands of samples typically required for reliable neural network training, this result is consistent with the expected performance of an initial model under constrained data conditions. However, 70% accuracy is insufficient for practical diagnostic deployment, where misclassification of a partial discharge type could lead to incorrect assessment of insulation condition. The result should therefore be interpreted as a baseline that establishes the feasibility of the scalogram-based classification approach, rather than a production-ready solution.

Analysis of the validation results revealed that classification performance was not uniform across classes. The confusion matrix (Fig. 11) confirmed that the model achieved reliable predictions for the Coil - Brown Coating classes 7 kV and 8 kV, where the presence of a semiconductive layer produces more distinct time-frequency patterns in the scalograms. In contrast, the model struggled to separate Coil - White Coating 3.5 kV and 5 kV classes, with the majority of misclassifications occurring between these two categories. This behavior is attributed to the absence of a semiconductive coating on the white coil, which reduces the visible contrast between scalogram patterns at the two voltage levels.

In the external evaluation on previously unseen scalograms not included in either the training or validation

datasets, the model achieved an average accuracy of approximately 40%, with correct classifications reaching up to 44% for the brown coating classes and dropping to around 35% for the white coating classes. This significant decrease relative to validation accuracy indicates that the initial sequential model does not generalize sufficiently to new, unseen inputs and confirms the need for architectural and methodological improvements.

The primary limitation of the current model is the sequential dense architecture, which lacks the spatial feature extraction capabilities required for reliable scalogram classification. The most important next step is the transition to a CNN, which processes input images hierarchically, extracts local time-frequency features through learned filter banks, and identifies spatially localized patterns characteristic of each discharge class. In addition, expanding the dataset through further measurements would directly address the data scarcity that constrained the present model. Despite its limitations, the initial model provides a functional baseline and confirms that the CWT scalogram representation carries sufficient discriminative information to support automated partial discharge classification, a foundation on which more advanced architectures can be built.

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Received October 1, 2025, accepted April 22, 2026

BIOGRAPHIES

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using acoustic methods intelligent electrical installations, and surge protection systems. He is involved in the development and application of advanced measurement techniques and diagnostics in the field of electrical power engineering.

Ardian Hyseni is a PhD student at the Department of Electrical Power Engineering, Technical University of Košice. He received his bachelor's degree in 2020 with a thesis focused on the *Design of a Teaching Aid for Power Engineering*, and his master's degree (Ing.) in 2023 with a thesis titled *Benford's Law and Its Application in Power Engineering*. His current research focuses on the analysis of big data in electrical distribution networks, aimed at increasing the reliability and efficiency of power distribution