

Intelligent partial discharge evaluation with Machine Learning Methods

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Motivation

As a result of the privatization of the energy market and the associated increase in price pressure, the need for service life extensions and load optimization of components from the energy supply system has risen sharply in recent years. For this reason, the assessment of component conditions, especially the diagnosis of insulation systems, is becoming increasingly important.

Data preprocessing

- Phase Resolved Partial Discharge (PRPD) images were used as input for the classifier (Figure 1)
- The color scaling in the images may vary
 - Transformation into a uniform format is necessary (Figure 2)

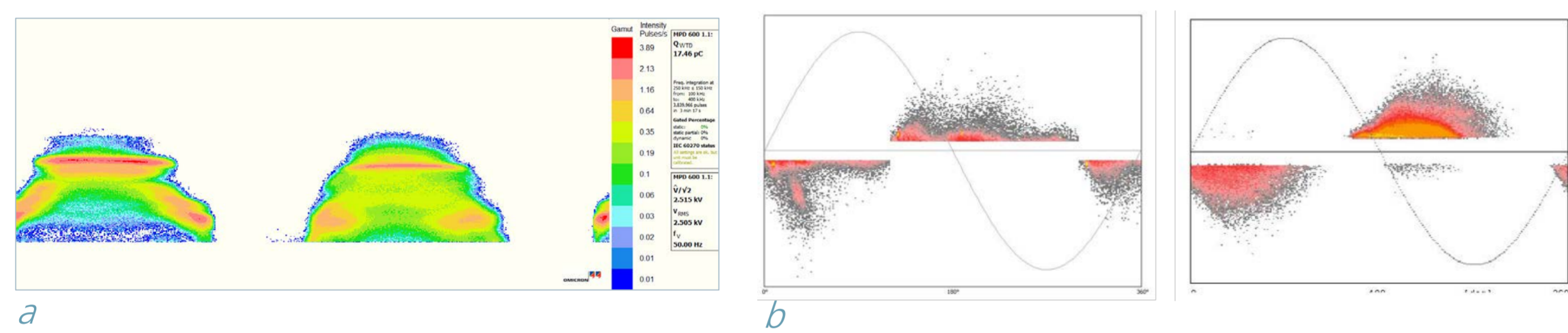


Figure 1: Example images of PRPD diagrams ; (a) own measurement (b) IEC TS 60034-27-2:2012

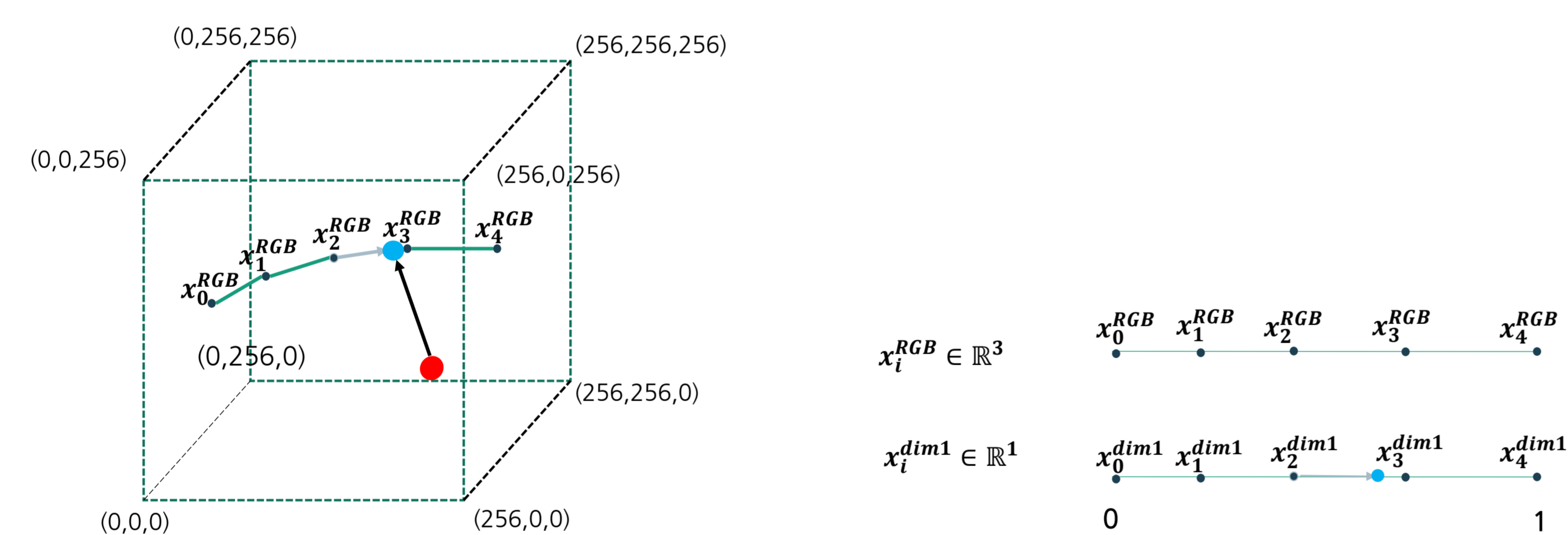


Figure 2: Dimensional reduction from RGB space to one-dimensional space

Data augmentation

- Based on the seven types of partial discharge patterns for each pattern, 400 images were generated to train and test the classifier
- Both online and offline measurements were used for each type

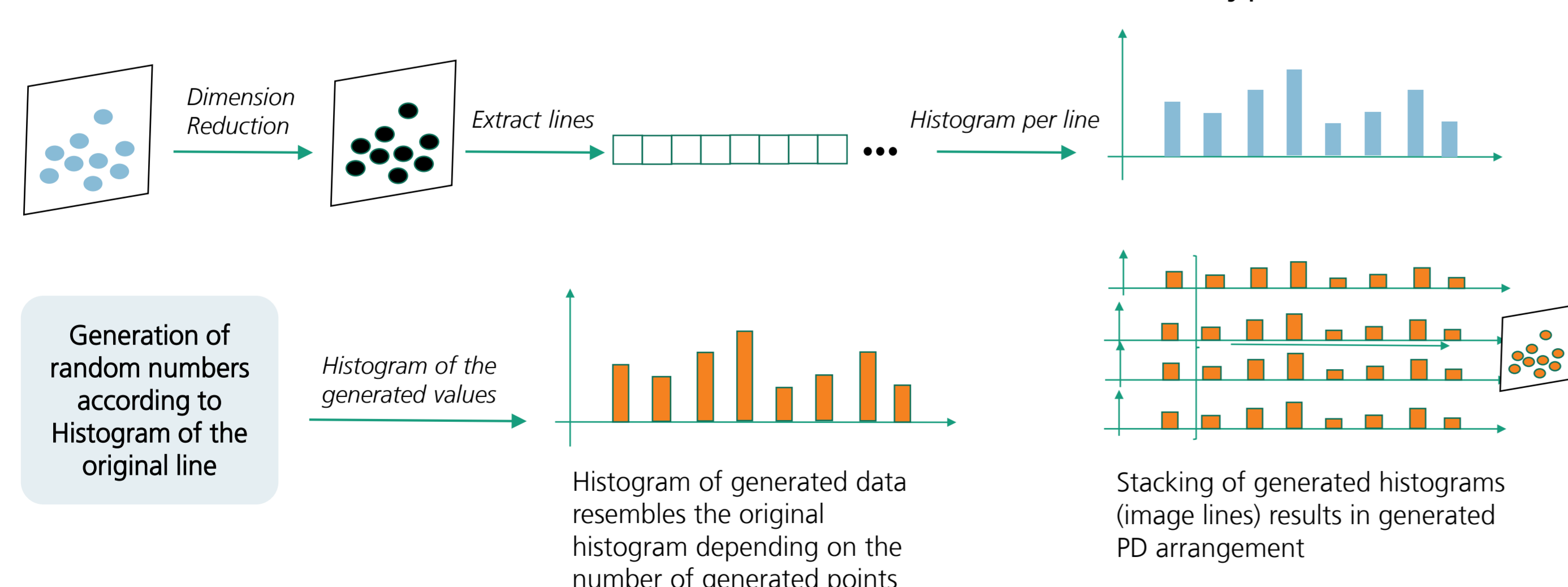


Figure 3: Resampling process for data augmentation

Partial Discharge Types

- 7 classes of Partial Discharge Patterns were defined in accordance with IEC TS 60034-27-2:2012 and IEC TS 60034-27-1:2017 (Figure 4).

Cat 1	Partial Discharge at Winding Ends		Internal Partial Discharge			Slot Discharge	
Cat 2	Online						
	Offline						
Cat 3	Phase to Phase	Surfaces Discharges	Gap Type Discharges	Delamination between conductors / insulation	Internal Delamination	Inner hollow space discharges	Slot Discharge
Cat 4	- online	- online	- online	- online	- online	- online	- online
	- offline	- offline	- offline	- offline	- offline	- offline	- offline

Figure 4: Categories for classification used in the CNN based on different partial discharge phenomena and measurement techniques in rotating electrical machines

CNN-Classifer

A classic CNN setup was followed along the lines of M. Florkowski (2020) tracked

- Conv2D-layer: kernel = 5x5, stride=(1,1)
- Max-pooling-layer: kernel = 2x2, stride = kernel size (2,2)
- Activation function: ReLu (Conv2D-layer and fully-connected-layer)

Results & Conclusion

- The classifier was reliably able to distinguish the 3 main classes. For more than that the accuracy was still 84.5 %, but nevertheless reliable. (Tbl. 2)
- One challenge is the lack of measurement data, so the quality of the algorithm depends on data augmentation.
- The model could only conditionally distinguish between classes zero, three and five, which can be attributed to the similarity of the PD patterns. (Figure 5, Tbl. 1)

Predicted Class	Target Class						
	1	2	3	4	5	6	7
1	4	0	1	8	0	9	0
2	0	34	0	0	0	0	0
3	0	0	31	0	0	0	0
4	0	0	0	31	0	0	0
5	0	0	0	0	29	0	0
6	0	1	0	1	1	7	0
7	0	0	0	0	0	0	33

Table 1: Confusion matrix of model 4 showing the target class compared to the predicted class

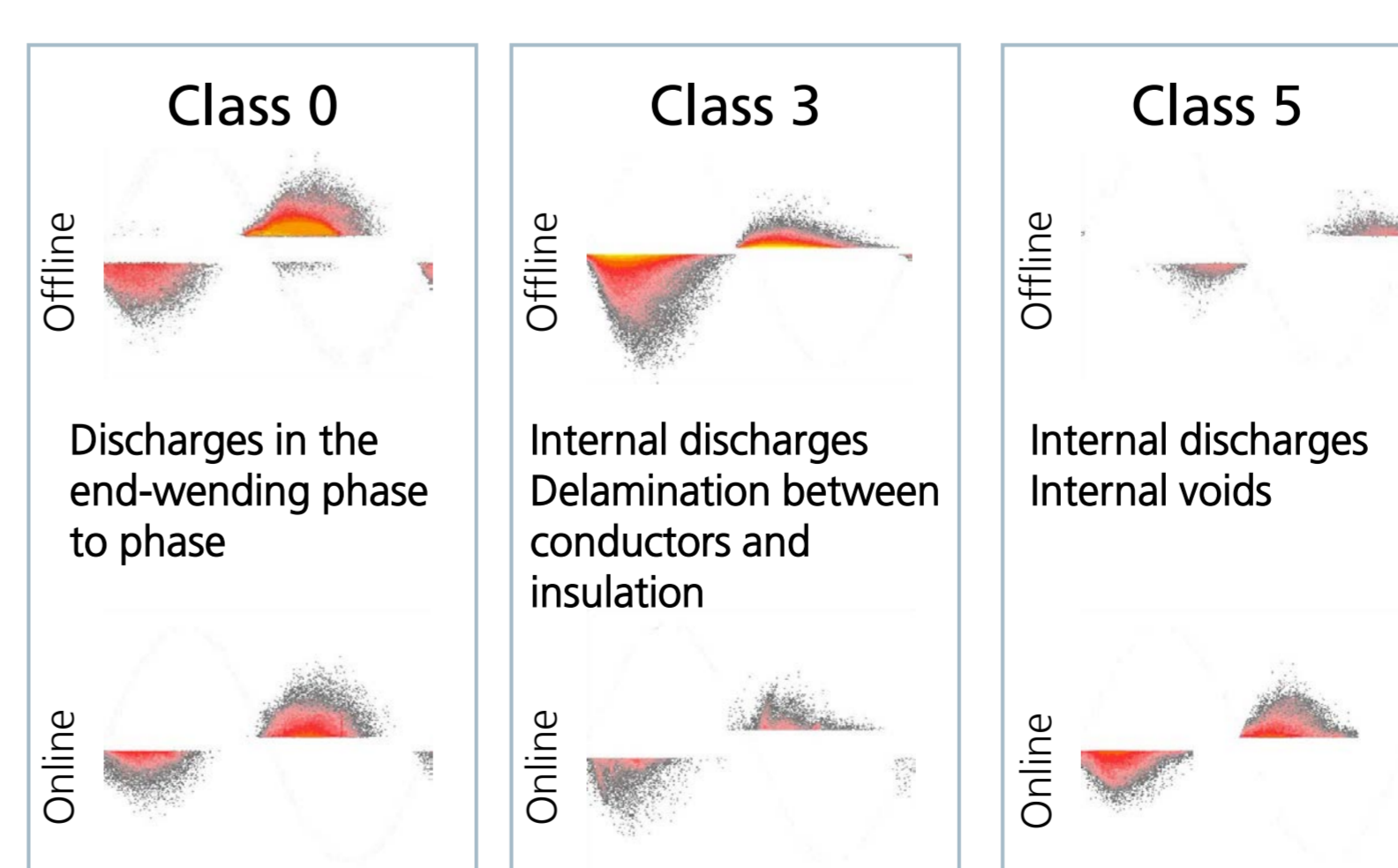


Figure 5: Plots of the patterns of class 0, 3 and their difference in offline/online measurement.

Model	Classes	Test Accuracy in %
Model 1	3	100
Model 2	3	83.5
Model 3	3	83.5
Model 4	7	84.5
Model 5	7	64
Model 6	7	70

Table 2: Training behavior and performance of the studied architectures