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# Detection and Classification of Defects in XLPE Power Cable Insulation via Machine Learning Algorithms

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***Abstract*—Due to high electric stresses in power equipment, insulation degradation has been prevalent as a result of increased PD exposure. In this paper, we study different machine learning (ML) methods for the detection and classification of partial discharges (PDs) for assessing the reliability of insulation systems. We introduce and examine a set of features using selected machine learning-based algorithms. The aim is to detect and classify PDs transpiring within insulation systems. Therefore, this paper presents tools to detect defects using suitable PD sensors and Machine Learning algorithms to facilitate diagnostics and enhance isolation system design. Experiments are being conducted on several voids in the insulator with varying shapes and sizes. A PD sensor is used for detecting the PDs taking place. Due to the presence of noise and other external interferences, appropriate filters and denoising methods are implemented. After that, the relevant PD features, such as the PD magnitude, PD repetition rate, statistical features, wavelet features, etc., are extracted. This study attempts to emphasize the importance of classifying the type of defect, as this will allow engineers to determine the severity of the fault taking place, and take the proper countermeasures.**

***Index Terms*—Ensemble methods, electromagnetic emissions, feature engineering, Machine Learning, Partial Discharge, Support Vector Machine, Wavelet Decomposition**

## I. Introduction

Due to the increasing use of cross-linked polyethylene (XLPE) cables for power transmission systems in the medium voltage (MV) and high voltage (HV) range, faults occurring in the insulating medium are critical to system performance. These faults are due to defects found in the XLPE insulation [1]. The main defects are voids, which can initiate electrical trees that propagate through the insulation until a connection is established with the outer semi-conductive screen. To determine the characteristics of any defect, partial discharge (PD) measurements are normally carried out [2]. Many PD testing methods are being applied for HV cables under AC voltages for condition monitoring purposes [3]. Therefore, it is vital to model and study the characteristics of PD to find countermeasures against their effects.

Due to high electric stresses in power equipment, insulation degradation has been prevalent as a result of increased PD exposure. Ionization can occur in insulation systems, leading to bond breaking of the insulation or charge recombination. Bond breaking creates a void at the electrode, leading to the inception of the electrical tree. If the tree keeps growing until the counter electrode, then the runaway stage begins, and a breakdown of the insulating medium takes place.

The PD signal is usually subject to noise originating from the environment in the vicinity of the PD source. The detection of PD in insulation materials in general, and in cables specifically, encounters some challenges up to this day for reasons such as:

1) The signal produced from the PD is normally attenuated as it propagates through the conductors in the power cables. Therefore, choosing an optimized position of the PD detection device is vital and influences the sensitivity of the detection.
2) Attenuation is also a consequence of the shielding effect of uniformly distributed current pulses in the vicinity of the cable sheath, making it difficult for the inductive coupling devices to identify the PDs initiated.
3) The PD signal is usually superimposed with noise originating in the vicinity of the PD source. The cable termination to overhead lines are also the underlying reason for the presence of noise in power cables. This is because these lines emulate the behavior of antennas, instigating noise.
4) Calibrating the signal to determine the size and type of defect is also difficult [4–6].

The main contribution in this paper is testing several XLPE samples with different void types to obtain the PD signals using a PD sensor, and to correlate each signal to its associated defect using a variety of ML algorithms. Knowing the type of defect is essential to determining the appropriate mitigation techniques, to avoid any detrimental effects to the insulation and the surrounding devices and systems. Wavelet Decomposition is used to remove unwanted noise that might have occurred during the test. The flowchart of this process is shown in Figure 1. We study various learning algorithms such as Decision Tree (DT) and Support Vector Machine (SVM). DT is a supervised learning algorithm utilized in

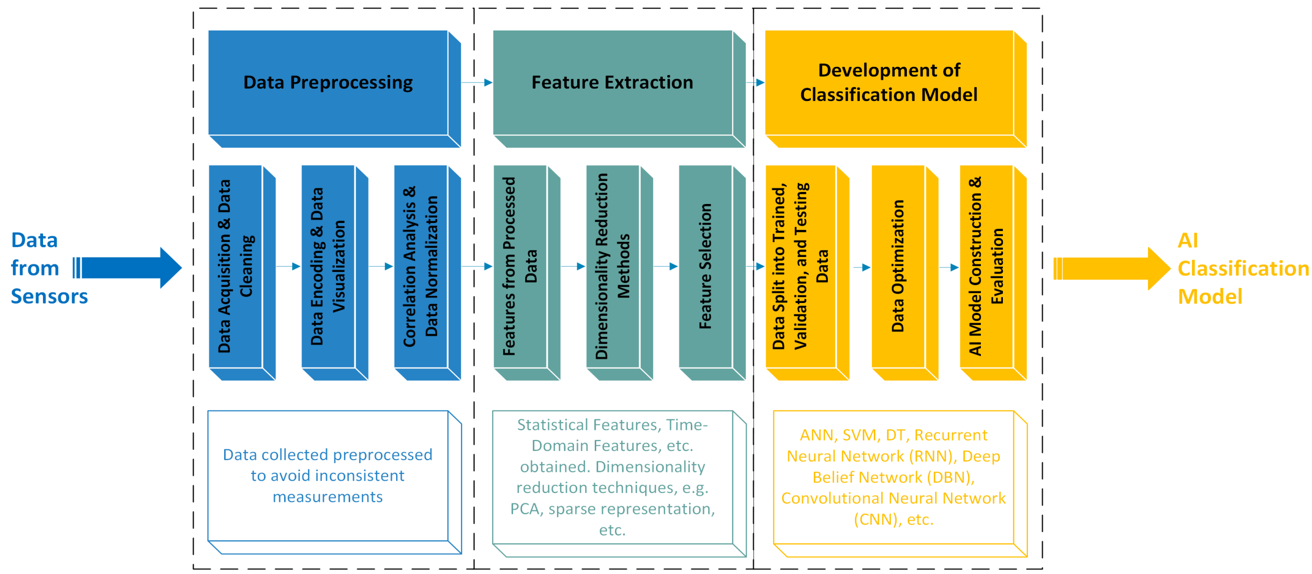


Fig. 1. Block Diagram of component monitoring system.

classification problems, which seperates the input space into a certain number of branches or regions with certain parameters. DT is a decision-making algorithm that gives the connection between the attributes and the class with a flowchart-like structure [7]. Therefore, it is useful for PD classification as it shows superior performance compared to other algorithms. The reason for this is because PDs are usually unstable, and a minute variation in the data can lead to a large variation in the behavior of the DT algorithm.

Support vector machine (SVM) is a supervised learning algorithm [8]. It is a description of data points in space parted by a gap that is optimally wide. A boundary that characterizes a certain class is defined as a hyperplane, and the values nearest to the hyperplane are defined as support vectors. SVM works efficiently if one has a small amount of training data, nonlinear, and high dimensionality pattern recognition applications. As a result of the size and high dimensionality of the training data available, SVM is known to be suitable for this problem. Previous applications have shown that SVMs are more superior than neural networks in certain disciplines such as engineering, information retrieval, and bioinformatics [9].

In order solve nonlinearly separable data in SVM a kernel function is applied as it maps the data acquired to higher dimensionality feature space. This method improve the complexity of the computations being made and hence, one does not have to calculate the inner product space in the feature space [5]. Yet, the computations require a sufficiently high number of training patterns so a large training set is favourable for optimized results. The equation for the computations made are shown in Equation (1) and Equation (2) [5]:

$$K(x, x') = < x, x' >^{d} \tag{1}$$

$$K(x, x') = (< x, x' > +1)^{d} \tag{2}$$

where K(x, x') is the kernel function responsible for the non-linear mapping into the high dimensional feature space, and d is the distance of the vector to the hyperplane represented by Equation (3):

$$d(w, b; x) = \left(\frac{| < w, x^{i} > +b|}{||w||}\right) \tag{3}$$

where w is the weight vector in the seperating plane The rest of the paper is organized as follows. Section II describes the condition monitoring applications of Machine Learning in Smart Grids (SG). Section III discusses the experimental setup. Section IV analyzes the results acquired. Section V concludes the paper.

## II. APPLICATIONS OF MACHINE LEARNING IN PD ANALYSIS

The advent of machine learning, integrated with efficient big data management and analytics platforms may help in transforming the industry assets condition monitoring market. A research framework that monitors the health of the equipment, models their degradation level, and computes the remaining useful life using historical and online available data would be a breakthrough. The framework can be tested on various case studies in smart grids (SG) and communication infrastructures while using ML and Deep Learning (DL) techniques. Information from industrial fields, weather information, and diagnostics data can be utilized for data-driven models toward a powerful preventive maintenance strategy in SG. The ML and DL techniques that can be implemented are supervised, unsupervised, and semi-supervised learning algorithms. Examples of the algorithms that can be implemented are Support Vector Machine (SVM), K- Nearest Neighbor (KNN), Random Forest (RF), Long-Short Term Memory (LSTM), Decision Trees (DT), Recurrent Neural Networks (RNN), Convolutional

Neural Networks (CNN), Generative Adversarial Networks (GAN), Deep Reinforcement Learning, etc. The algorithms can be used and compared to build such data-driven models. The correlation between the faults in the past and the features extracted from the data should be studied. These models must converge fast enough to predict the faults in timely manner and with high accuracy.

Data analytics and management are the perfect recipes for maximizing the value of condition monitoring in SG. This approach can allow managing vast amounts of data by using appropriate processing algorithms combined with machine learning techniques. The unsupervised machine learning algorithms analyze and reveal the hidden dataset correlations and detect abnormal data patterns. They predict future failures, which ultimately save operation cost, in addition to personnel time and their safely. Such schemes automatically adjust their internal parameters based on the newly received data, while detecting and alerting operators on any severe issues in real time. The proposed solution could be the initial step that helps decrease the downtime of electric assets, allowing utilities and electric industries to improve the overall infrastructure reliability and the lifetime of their assets, in addition to the reduction of their fixed and variable costs related to the future maintenance requirements.

The significance of XLPE as insulation of power cables encourages researchers to explore numerous different experimental approaches to determine an accurate behavior regarding the state of the insulation as it ages. The knowledge emanating from this investigation enables engineers and researchers to comprehend the dielectric materials degradation mechanisms under operating conditions. Moreover, the current research is concentrated on the XLPE insulation morphological structure to learn if this dielectric medium can be reused [9]. Recently, multiple studies have endeavored to diagnose the electrical treeing mechanism in XLPE cables [10–13]. The impact of PDs on the insulation properties of the cable has been covered by many publications [14,15]. Extensive work was conducted regarding the chemical changes induced through aging and its repercussions on the cables properties [16–20]. Nevertheless, these studies are cost-effective and highly time-consuming. It occasionally requires a number of years to acquire an adequate database to find solutions for the economical difficulties of energy and employ maintenance procedures in the easiest way possible. Therefore, work has been directed to the field of modeling. The most recent strategies are predicated on the usage of Artificial Intelligence (AI) techniques, more specifically, Feature Engineering (FE), ML, and DL. These new approaches enable scientists, researchers, and engineers to utilize the data/features available efficiently and ultimately determine the future condition of the insulation system subjected to aging accurately in a shorter time. Hence, this paper aims to classify the PD signals as a way of determining the type and severity of the defect in order to get an insight on the danger inflicted on the cable.

Nowadays, various modeling and projection techniques based on artificial neural networks (ANNs), fuzzy logic (FL), decision trees (DT), etc. models have become prevalent and implemented by researchers for numerous engineering applications [21–24]. In High Voltage (HV) Engineering, many practical uses of ANN were demonstrated [2528]. For instance, Chen et al. [27] developed a novel ANN model in PD pattern classification in HV equipment. Forecasting the value of the breakdown voltage during the occurrence of PD for various dielectric materials by multilayer feed-forward network and radial basis function network has been studied in [28]. In [29] and [30], two NN models were examined, RBFG and MLP to predict the flashover of contaminated HV outdoor insulators. In [31], the RBFG neural network trained was implemented with a two-algorithm (BP and ROM) method (a type of ML stacking) to forecast the leakage current during aging of non-ceramic insulators. In [18], the fuzzy logic (FL) ML model was investigated to determine, during thermal aging, the mechanical properties of XLPE cables. The results obtained from this model were compared with NN models (RBFG trained with the random optimization method (ROM)).

The monitoring system is comprised of three sections, namely data pre-processing, feature extraction, and development of the classification model. In the data pre-processing module, the data acquired from the sensors is cleaned from inconsistent measurements, missing data points, and outliers to sidestep any possible false interpretations in the subsequent steps [32,33]. Next, data encoding, correlation analysis, and data normalization are implemented to feed in the required data into the AI model used. The normalized data is then fed into the data-split module, in order to separate the data into training, validation, and testing. Moreover, data optimization incorporates algorithms that can improve the overall model accuracy. In the classification module, the AI model chosen is trained by applying n-fold cross-validation. This is the procedure followed in the paper.

The main contribution in this paper is also to improve the PD identification and classification in power cable insulation. The same experiment was conducted in [34], however, due to the complex nature of PDs and the high number of classes (number of different voids), an accuracy of approximately 77% was observed. In [5], the maximum classification accuracy acquired was 92.2% but with decreased number of classes. Therefore, this paper attempts to keep the same number of classes or voids investigated in [34] and maintain a reasonably high classification accuracy. This task is challenging due to a certain degree of similarities in the PD characteristics of the different voids [35]. Hence, in order to achieve this task, additional features were extracted other than the statistical and polarity-based distribution features used in [5] and [34]. The Weibull distribution features were introduced in this paper as well. The Weibull distribution features are represented by the pulse height analysis (PHA) pattern where the data obtained from the sensor can be visualized using a probability distribution graph. Features such as the scale parameter and shape parameters can be acquired from Weibull distribution to feed into the AI model selected. Moreover, there were features that had a weak correlation with the output class, decreasing the accuracy of the overall classifier used, ergo, they were removed in this study. The succeeding sections of this paper explains the experimental setup, the analysis of the results, and the significant improvement observed relative to the research articles mentioned.

## III. Experimental Setup

The considered HVAC extruded cable has an XLPE insulation with a thickness of 5.5 mm. The cable rated voltage is 20 kV, and the voltage between the conductor and screen is 12 kV. The HVAC cable geometry is shown in Fig. 2, with dimensions shown in Table 1. The sample is placed in silicone oil and observed with an optical microscope. Silicone oil is a synthetic liquid insulating medium that possesses exceptional dielectric properties [10]. Therefore, silicone oil can block external discharges and flashovers. The circuit constructed is shown in Fig. 3.

TABLE I
DIMENSIONS OF THE HVAC EXTRUDED CABLE INVESTIGATED.

| Component | Radius [mm] | Material of component | Relative Permittivity $\varepsilon_r$ |
|---|---|---|---|
| Conductor | $R_c$=9.5 | Aluminum | 1 |
| Conductor Screen | $R_{cs}$=9.9 | Graphite screen | 1 |
| Insulation | $R_{ins}$=15.4 | XLPE | 2.3 |
| Insulation Screen | $R_{is}$=15.8 | Graphite screen | 1 |
| Wired Screen | $R_{ws}$=16.3 | Copper | 1 |
| Metallic Sheath | $R_{ms}$=17.5 | Lead | 1 |
| PVC Jacket | $R_{pj}$=20 | PVC | 2.9 |

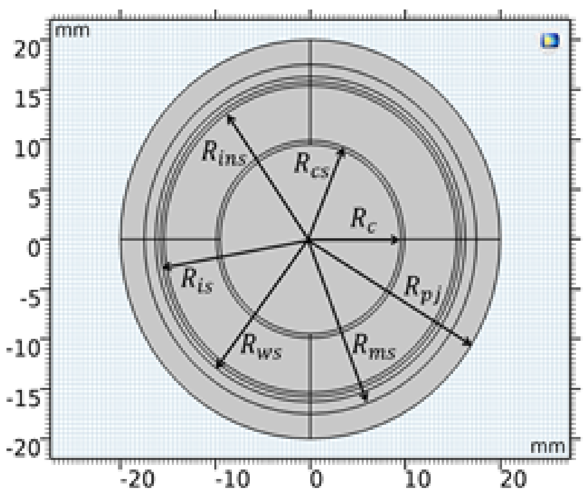


Fig. 2. Geometry of the HVAC extruded cable investigated.

The circuit in Fig. 3 has an autotransformer T1 employed as a supply for the circuit with a step-up transformer, a 50 kΩ resistor R connected in series for protection reasons, a high voltage divider connected to the input of the oscilloscope to acquire the AC voltage behavior. The other input of the oscilloscope is connected for the capturing the current pulse emitted from the PDs instigated. The PD measurements were conducted in compliance with the IEC 60270 standard. The PD characteristics were monitored with a PD sensor, the LDS-6 meter, which can be processed by the LDIC program (LDS-6).

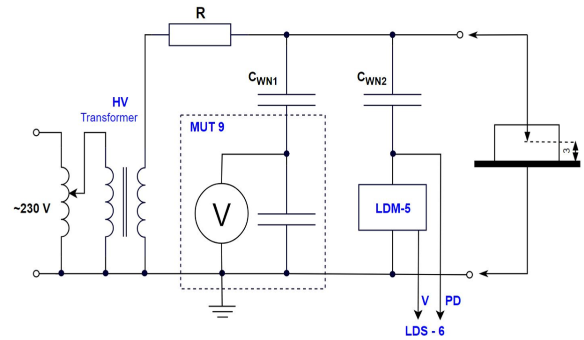


Fig. 3. Circuit depicting the PD acquisition procedure under AC voltages.

TABLE II
DESCRIPTION OF THE SAMPLES INVESTIGATED.

| Void Type | Void Size |
|---|---|
| Spherical | 1mm, 2mm (diameter) |
| Cubic | 2mm (sides) |
| Cuboidal | 2mm (edges) |
| Cylindrical | 2mm (diameter), 10mm (length) |

The experiment entails PD tests with different applied high AC voltages (7, 8, 9, and 10 kV) on spherical, cubic, cuboidal, and cylindrical voids in cross-linked polyethylene (XLPE) insulation systems as shown in Table II. The phase-resolved partial discharge (PRPD) and time-resolved partial discharge (TRPD) patterns are acquired for classifying the severity of the defect present in the XLPE insulation. The PD patterns were detected by a PD sensor and the feature extraction of the PD activities was implemented. The features extracted were statistical, Wavelet Decomposition, and Weibull distribution features. Due to excessive noise present in the system, a bandpass filter was applied along with Wavelet Decomposition to denoise the signal. Then unwanted features were removed to avoid inconsistency in the data obtained. Lastly, different ML algorithms were implemented to classify the different types of defects tested

## IV. Results and Discussion

The results acquired show high classification accuracies for ML algorithms such as Ensemble methods and support vector machine (SVM). This study also showed the importance of feature engineering in industrial applications due to the amount of data reduced for achieving faster and accurate computational results. Classifying the type of defect will allow engineers to determine the severity of the fault taking place in order to take the proper countermeasures against its effects.

As shown in Figure 4, the PD magnitude is in the range of picocoulombs (pC). The highest magnitude obtained was approximately 0.5pC. To make sense out of this complicated behavior, feature engineering was applied to extract the relevant features and classify each defect mentioned in the previous section. After the feature extraction Decision Tree

(DT) and Support Vector Machine (SVM) was used to classify the defects tested. The highest accuracy achieved was 90.4%

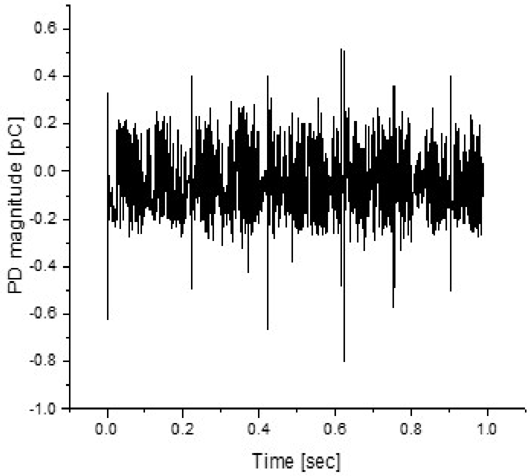


Fig. 4. PD signal of the spherical void present in the XLPE insulation.

for DT, where the training time took 77 seconds, the maximum number of splits was 2927, and the number of learners was 30. However, for SVM the accuracy acquired was 83.9%, where the training time took 18 seconds, and the kernel function was quadratic. The accuracies acquired were quite exceptional because the defects investigated have similar characteristics so this decreased the classification accuracy. In addition, multi-classification problems tend to have lower accuracies due to the amount of given parameters. The confusion matrices for SVM and DT, and the ROC curve for DT are shown in Figures 5, 6, and 7 respectively. If defects with different characteristics were investigated then higher accuracies could have been achieved. Fig. 5 clearly shows that the misclassification was

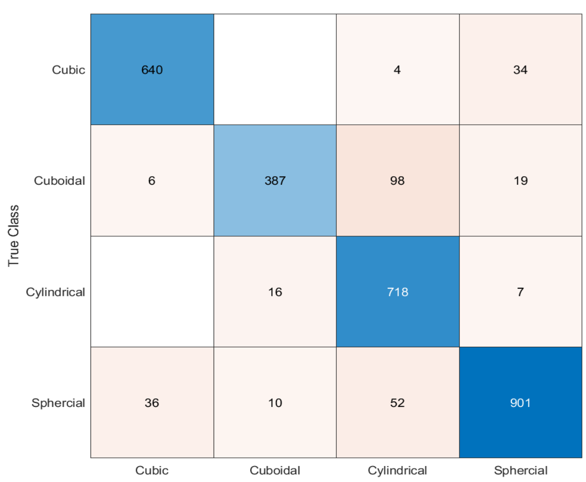


Fig. 5. Confusion matrix of the multi-classification problem using DT.

the most prominent with the cylindrical void. There were 154 misclassified values when trying to predict the cylindrical void, increasing the cost function and decreasing the overall accuracy. Having 98 misclassified values with the cuboidal void suggests that the PD characteristics of the cylindrical void and the cuboidal void are quite similar. This is also substantiated in Fig.6, where 103 misclassified values were observed when employing SVM as the ML algorithm. Hence, to overcome this effect, more data should be acquired to increase the overall accuracy of this multi-classification problem. The other solution is to optimize the features selected by eliminating unwanted features and/or extracting more features from the available data. Fig. 7 shows the AUC curve, where the area under the curve (AUC) indicates the diagnostic ability of a binary or a multi-classifier algorithm. The DT algorithm was found to be the best classifier relative to SVM for this multi-classification problem with a value of 0.99, indicating a great potential for applying it in real time operation for identifying and classifying any faults in insulating materials.

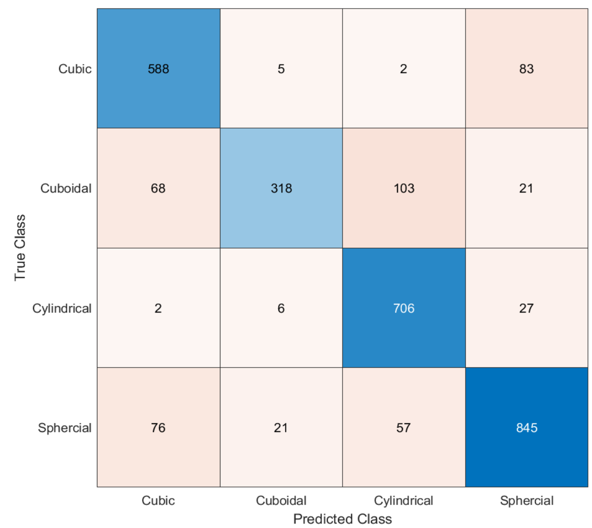


Fig. 6. Confusion matrix of the multi-classification problem using SVM.

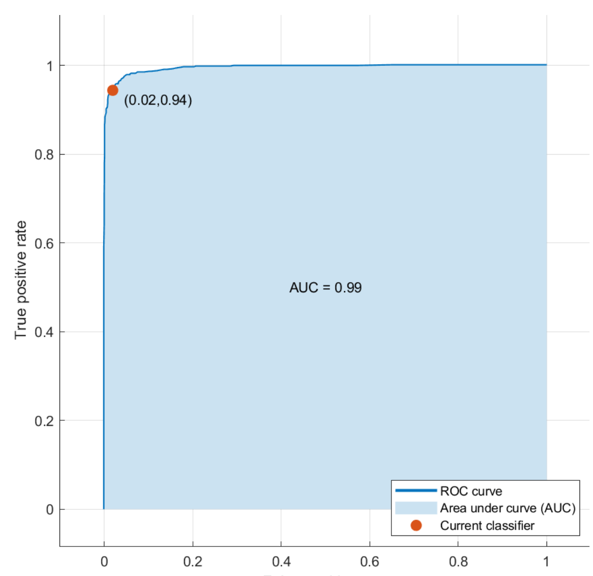


Fig. 7. AUC curve of the multi-classification problem using DT.

## V. Conclusions

A study of ML methods for the detection and classification of PDs was addressed in this paper to assess the reliability of insulation systems. A set of features were introduced and examined using selected machine learning-based algorithms. The aim was to detect and classify PDs transpiring within insulation systems. PD tests were conducted on spherical, cylindrical, cuboidal, and cubic shaped voids. The relevant PD features, for example, the PD magnitude (pC), PD repetition rate, statistical features, wavelet features, Weibull distribution features, etc., were extracted. Decision Tree and SVM demonstrated the highest classification accuracy of 90.483.9characteristics observed among the four voids. Therefore, this study demonstrated significant improvements relative to previous research done and showed the importance of classifying the type of defect as this will allow engineers to determine the severity of the fault taking place in order to take the proper countermeasures against its effects. This study also showed the importance of feature engineering and Machine Learning in industrial applications due to the amount of data reduced for achieving faster and accurate computational results.

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