International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Identification and Analysis of Partial Discharge Origin using Xgboost Algorithm

[1]Dr. Priyanka M. Kothoke, [2]Dr. Praveen B. M.

Submitted: 20/10/2023 **Revised**: 10/12/2023 **Accepted**: 18/12/2023

Abstract: Partial Discharge (PD) patterns serve as a valuable diagnostic tool for assessing the condition of High Voltage (HV) insulation systems. Human experts are capable of identifying potential insulation flaws in different representations of PD data. Phase-resolved partial discharge (PRPD) Patterns are frequently employed as a means of conveying information. In order to determine the type of defect, it is necessary to establish a correlation between the statistical properties of partial discharges (PDs) and the characteristics of the defect in high-voltage (HV) equipment reliability. For instance, an empty space, a flat surface, or a luminous halo. Partial discharge is observable on the Graphical User Interface (GUI) of the model, which was developed using the Xgboost Method in Python on Google Colab.

Keywords: *Partial discharge, Xgboost, Google Colab, Python*

1. Introduction

In the process of predicting optimal future outcomes for given inputs, neural networks demonstrate a limited degree of flexibility. These artificial neural networks are highly recognized and valued as a highly effective tool for addressing a variety of issues related to characterization, clustering, regression, and design. This is because they enable the representation of nonlinear techniques, which leads to their widespread recognition and appreciation.

As a consequence of this, we have noticed a decrease in measurement, a reduction in expectations, a systematic interpretation of the machine, and other outcomes that are comparable. Within the scope of this investigation, we propose the utilization of Backpropagation through Time (BPTT) of Artificial Neural Networks (ANN) as an alternative approach. Once the disparity in emphasis between the two sets of variables reaches zero, BPTT will be utilized until the situation is satisfied. Measurable parameters such as mean, standard deviation, change, skewness, and kurtosis were provided by the Python procedures that were used to prepare the data. Python programming and Matlab programming have both benefited from its utilization, which has led to an increase in accuracy in both of these applications. Through the utilization of the Xgboost Technique, it is possible to recognize releases that are occurring at a specific level in multiple sources of protection.

PD is said to play a significant part in the maturation and breakdown protection of high voltage electrical mechanical assemblies, as stated by Akimasa Hirata et al. (2006). The performance of the defense sector is affected in a variety of ways by the various sources of professional development. The occurrence of electrical discharges, the presence of curved sections, and sudden bursts of light are all indicators that there may be a problem with the safety measures employed. When determining the extent of the damage caused by the release, understanding how PD is classified is of the utmost importance. PDO is primarily concerned with identifying releases whose provenance is unknown.

Recently, a number of different methods including "*neural networks, master frameworks, fluffy classification and wavelet analysis*", have been utilized in order to identify instances of Partial Discharge. During the past few years, there has been a substantial rise in the utilization of neural networks for the purpose of constructing recognition and identification systems.

The utilization of a neural system in the nursery's "spatial fluctuation proof system", the current transformer PD design identification system, and the gas protected substation PD checking method are all topics that are discussed in the research that was conducted by S.H. Park et al. (2003). The application of neural systems has reached a widespread level of significance. The research process for multilayer neural systems is frequently excessively time-consuming and requires thorough and flawless preparation. This is despite the fact that neural systems have the inherent capability to perform continuous actions with almost perfect accuracy. The Master framework technique, on the other hand, is responsible for collecting information regarding the human capacity to construct information collections.

[1]*Post-Doctoral Fellow, Srinivas University, Managalore, India*
priyankakothoke@gmail.com
[2]*Research Director, Srinivas University, Mangalore, India*
researchdirector@srinivasuniversity.edu.in

Despite the fact that it is essential to construct and maintain a foundation through the application of diligent efforts. It has been demonstrated that algorithms that use machine learning have the capability to effectively identify the abnormalities that are responsible for Partial Discharge diagnosis. Especially when dealing with shallow structures like artificial neural networks (ANN) and support vector machines (SVM), the process of defining a component vector for utilization by multiple layers of fundamental computer units can be time-consuming in advance. This is especially true when multiple layers of fundamental computer units are involved.

Throughout the course of our lives, we have been exposed to a wide variety of experiences, some of which we have assimilated, whether we were aware of it or not. Because of the capacity of the human mind to acquire new information, we are able to acquire skills such as speaking, behaving, composing, and computing. There are a great number of organic neurons that make up the brain, and these neurons are connected to every part of our body through a sensory system. The operation of this system involves sending an electric impulse to the brain, which serves as information. This impulse causes the brain to move in the direction that corresponds to the information that it receives, prompting the brain to move in the corresponding direction. In a similar manner, we were able to acquire the ability to recognize a variety of objects, such as a journal, a vehicle, a pen, and so on. The operations of artificial neural systems are entirely dependent on the operations of biological neural systems. Although biological neural systems are less complex than the human sensory system, they are still capable of comprehending a wide variety of complex and challenging topics. As a consequence of this, it is not possible to differentiate between the various fractional discharges, crown discharges, and other vocal indications with greater precision. In order to differentiate between the various PD designs with a minimum of effort, it is now necessary to come up with an innovative creation. In accordance with the findings of Shan Ping et al. (2002), the models have successfully accomplished a number of objectives and fulfilled their intended purpose.

For a considerable amount of time, artificial intelligence systems have demonstrated their capacity to diagnose the fundamental defects that are associated with Partial Discharge. An example of this would be “Artificial Neural Networks” (ANN) and “Support Vector Machines” (SVM), both of which are designed to have a restricted level of depth or complexity. Before a component vector is discovered by multiple layers of fundamental computer units, a considerable amount of effort is required to characterize it. This is prior to the discovery of the component vector. In order to determine whether or not Partial Discharge is present, a set of measurable and descriptive criteria has been developed. Additionally, an attempt has been made to evaluate the respective capabilities of these criteria to indicate the presence of the disease in particular circumstances, as stated by E. Gulski et al. (2001). It is possible that the implementation of computerized inferential frameworks within utilities will encounter challenges due to the required level of expertise that is required to select and determine features that are suitable. Deep systems, which are comprised of multiple layers of computing units, have been shown to outperform shallow models with manually designed features in a variety of tasks, including communication and image recognition, according to the research conducted by S. Ghosh et al. (2002). According to the progress that has been made in understanding the capacity that is acquired by a particular neuron, it has been determined that neurons are not merely a method of discovery as was previously believed; rather, they have the potential to offer a new perspective on a problem that is associated with characterization.

When fractional release design acknowledgment applications are utilized, the quantity of inputs to the neural system can be utilized to determine the polynomial that is greatest suitable for forecasting yield. This can be accomplished by utilizing the neural system. An investigation into the exploratory results obtained from neural systems were carried out by Gagan Deep Meena et al. The researchers used single and twofold yields in their research. However, it was discovered that there is no neural network architecture that is capable of achieving the lowest possible number of errors. These neural-arrange structures that produce both single and double outputs are also the subject of investigation in this study. It seems as though they have a negligible impact on operational efficiency. It has been demonstrated by M. Catterson et al. (2012) that a neural network system is capable of producing outstanding results when it comes to distinguishing between two distinct sizes of releasing cavities. The Xgboost Technique was utilized in order to accomplish the goal of our investigation, which was to identify PD design acknowledgements that occurred in the middle of releases.

Methods of analysis based on statistical principles. The GNB Technique utilizes the phase-resolved data approach, which falls under one of the three categories. According to K. P. Bennett, phase resolved data is utilized because it can generate 2D patterns that show variations in phase angle and charge, phase angle and number of pulses, or phase angle and charge. This use of phase resolved data leads to improved accuracy in the outputs by comparing these patterns.

Currently, a buzzer is employed exclusively to notify the primary source of power in any given industry. Regarding the repair of insulation flaws, a buzzer can solely indicate the location of the discharge, without providing information about the specific type of discharge. The method proposed in this study enables accurate identification of the PD type, facilitating the elimination of insulation faults from high-voltage equipment through specific approaches that minimize the risk of a supply failure. The phase angle, q, and pulse count, n, are the most crucial attributes of PDs. The basis of PD distribution patterns is formed by these three characteristics.

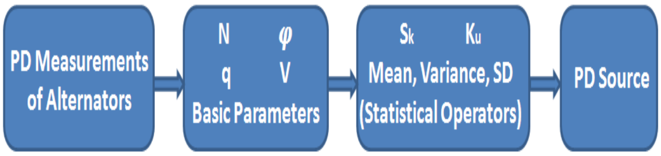

Fig 1. Block diagram of discharge analysis for (n-q)[15-17]

Where, S.D = "standard deviation", Sk = "skewness", Ku = "kurtosis",

The GUI for this application (GUI) is created using Google Colab integrated Python model. Inputting statistical variables, the discharge type can be identified by inputting statistical measures such as mean, standard deviation, variance, skewness, and kurtosis into a graphical user interface (GUI).

Initially, in our investigation, we employed statistical metrics. The discharge type can be identified by inputting statistical measures such as "mean, standard deviation, variance, skewness, and kurtosis" GUI.Regarding the results of the PD source, a preliminary draft was prepared as mentioned in Figure 1 for the (n-q) case. Upon inputting the five statistical parameter values, the Python model in Google Co-laboratory will exhibit the discharge type.

2. Literature Review

Ensuring the reliability and safety of power infrastructure requires the critical detection and analysis of partial discharges (PD) in high-voltage systems. Recently, researchers have utilized sophisticated methods like machine learning (ML) and deep neural networks (DNN) to improve the precision and effectiveness of diagnosing Partial Discharge (PD). The objective of this literature review is to succinctly analyze and contrast multiple papers that contribute to the expanding field, offering valuable perspectives on the identification, categorization, and pinpointing of Partial Discharge.

Chan et al. (2023) specifically examine the advancements made in techniques for localizing Partial Discharge (PD) in their recent review. The paper provides valuable insights into different techniques for precisely localizing PDs, which is a critical factor in guaranteeing focused maintenance and repair.

Kalaivani et al. (2023) present a new method for identifying the positions of water droplets on high-voltage insulators. This approach utilizes a convolutional neural network (CNN) that has been optimized using the bacterial foraging algorithm. The study aims to improve the precision of PD identification, specifically in difficult environmental circumstances.

The study conducted by Borghei et al. (2023) centers around the empirical examination, formulation of a theoretical framework, and analysis of data pertaining to partial discharges. The work is expected to enhance the comprehension of PDs by employing a blend of experimental and analytical methodologies.

Sahoo et al. (2023) examine the characteristics of electrical tree growth and analyze the pattern of partial discharges using a deep neural network. The paper offers valuable insights into comprehending the correlation between electrical tree growth and PD patterns, employing advanced deep learning techniques for thorough analysis.

Boczar et al. (2022) utilize machine learning methods to detect fundamental categories of partial discharges that occur in paper-oil insulation. The study demonstrates the effectiveness of using acoustic emission measurements in combination with machine learning for precise identification of partial discharge.

Balouji et al. (2022) present a classification technique for PDs that arise from multilevel pulse-width modulation (PWM) systems. The paper utilizes machine learning methodologies to demonstrate the versatility of these algorithms in handling intricate PD sources.

Samaitis et al. (2021) investigate the identification and positioning of Partial Discharges (PDs) in connectors of air power lines through the utilization of ultrasonic measurements and artificial intelligence models. The study likely highlights the incorporation of ultrasonic data into AI models for accurate detection and localization of PD.

Lu et al. (2020) present a thorough examination of machine learning techniques used in condition monitoring for PD. The paper examines different machine learning techniques, providing a comprehensive overview of the current advancements in condition monitoring for PD.

Barrios et al. (2019) provide a comprehensive overview of the latest advancements in methods for detecting PD. Although the title is concise, it is highly probable that the paper provides a thorough examination of various methodologies and advancements in the field.

Balouji et al. (2019) introduce a paper that focuses on the classification of PD in power electronics applications through the utilization of machine learning techniques. The study is expected to investigate applications that are specifically related to power electronics, providing valuable insights into customized solutions for this field.

The research on partial discharge detection and analysis has undergone substantial advancements, with scholars utilizing sophisticated machine learning and deep learning methods to improve precision and effectiveness. The reviewed papers provide valuable insights into the ongoing efforts to ensure the reliability and safety of high-voltage systems, covering topics such as the recognition of partial discharges in challenging environments, as well as their classification and localization. Scientists are still investigating new techniques, optimization algorithms, and application-specific approaches to deal with the complexities of partial discharge phenomena.

3. Naive Bayes Model

a. Understanding Independence: Naive Bayes assumes independence between features, meaning the presence of one feature is independent of the presence of any other feature given the class variable (normal or partial discharge). Assess whether this assumption is reasonable for your dataset. In the context of electrical signals, independence might be a simplifying yet acceptable assumption.

b. Choosing the Variant: There are different variants of Naive Bayes, and the choice depends on the nature of your features and data distribution:

c. Gaussian Naive Bayes: Assumes that the continuous features follow a Gaussian distribution. Suitable for features that are normally distributed.

d. Multinomial Naive Bayes: Appropriate for discrete features, often used in text classification.

e. Bernoulli Naive Bayes: Suitable for binary features, assuming features are binary (0 or 1).

f. Parameter Estimation: Estimate the parameters of the chosen Naive Bayes model based on the training data. This involves calculating the mean and standard deviation for Gaussian Naive Bayes or probability distributions for discrete features.

g. Class Priors: Calculate the prior probabilities of each class (normal and partial discharge) based on the training set.

h. Testing Set: Apply the trained Naive Bayes model to the testing dataset to predict the class labels.

i. Performance Metrics: These metrics provide insights into how well the model is classifying instances.

j. Iterative Process: If the model performance is not satisfactory, iterate over the preprocessing steps, adjust feature selection, or consider other variants of Naive Bayes.

k. Hyperparameter Tuning: Depending on the variant chosen, you may have hyperparameters to tune. For example, the smoothing parameter in Gaussian Naive Bayes.

l. Integration: Once satisfied with the model's performance, integrate it into your monitoring system for real-time or periodic analysis.

m. Continuous Monitoring: Implement a monitoring system to track the model's performance over time and update it as necessary.

4. Gaussian Mixture Model (Gmm)

a. Visual Inspection: Initially, visually inspect the data to get a sense of how many clusters might exist. This could involve plotting histograms or scatter plots of the features.

b. Information Criteria: Utilize information criteria such as the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) to guide the selection of the number of components. These criteria balance the goodness of fit with the complexity of the model.

c. Cross-Validation: Perform cross-validation on different numbers of components to assess the model's generalization performance.

d. Mean and Covariance Initialization: Initialize the mean and covariance matrices for each component. This can be done randomly or using a method like k-means clustering to provide a good starting point.

e. Mixing Coefficients: Initialize the mixing coefficients, representing the proportion of data assigned to each component. These coefficients should sum to 1.

f. E-step (Expectation): Calculate the likelihood of each data point belonging to each component using the current parameter estimates.

g. Use Bayes' theorem to compute the posterior probability (responsibility) of each component for each data point.

h. M-step (Maximization): Update the model parameters based on the weighted sum of data points' values, where weights are the responsibilities from the E-step.

i. Update the mean, covariance, and mixing coefficients to maximize the expected log-likelihood.

j. Log-Likelihood: Monitor the log-likelihood of the data during each iteration. The goal is to maximize the log-likelihood, indicating that the model is becoming more likely given the observed data.

k. Convergence Criteria: Define a convergence criterion, such as the change in log-likelihood or the change in model parameters, to determine when the EM algorithm has sufficiently converged. If the changes are small, the model has reached a stable state.

l. Iteration: Repeat the E-step and M-step until the convergence criterion is met. Each iteration brings the model closer to accurately representing the underlying data distribution.

5. Xgboost Technique

a. Gradient Boosting Framework:

XGBoost builds a series of weak learners (usually decision trees) sequentially, with each new tree aiming to correct errors made by the ensemble of existing trees.

b. Regularization Techniques:

XGBoost incorporates L1 (Lasso) and L2 (Ridge) regularization terms into its objective function, helping prevent overfitting and improving model generalization.

c. Tree Pruning:

XGBoost employs a depth-first tree growing strategy and prunes trees during the construction process. This enhances computational efficiency and prevents the model from becoming too complex.

d. Handling Missing Values:

XGBoost can effectively handle missing data during training and prediction, eliminating the need for imputation or preprocessing steps.

e. Parallel and Distributed Computing:

XGBoost is designed for parallel and distributed computing, making it highly scalable and suitable for large datasets.

f. Cross-Validation:

XGBoost includes a built-in cross-validation function, allowing users to assess model performance during training and optimize hyperparameters.

g. Feature Importance:

XGBoost provides a feature importance score, helping users understand the contribution of each feature to the model's predictions.

h. Gradient-based Optimization:

XGBoost employs a gradient-based optimization technique to update model parameters, enhancing the speed and efficiency of the training process.

6. Experimental Results

On the diagram, "0" represents for known discharge, "1" for surface discharge, and "2" is for void. Figure 2 shows a comparison of all the variables.

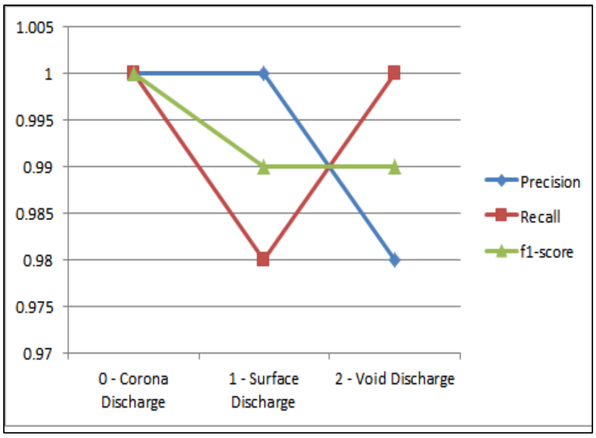

Fig.2. Plots showing Precision, Recall, and f1-score for the three known discharges

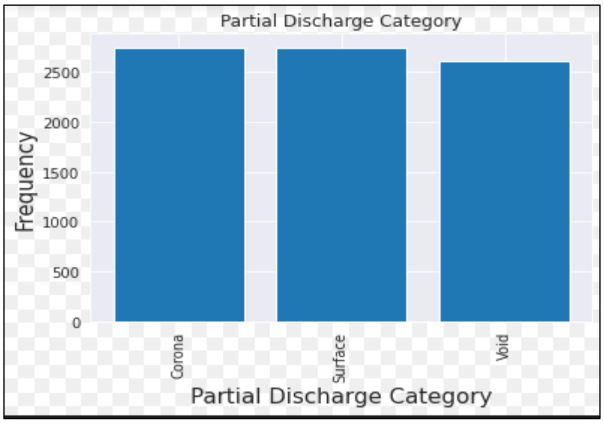

Fig.3. Comparison of void, surface and corona wrt frequency

Fig.4. Xgboost method execution on Google co-lab window

The subsequent action involves transferring pre-processed data from the server. To execute the program and observe the results on the graphical user interface (GUI), employ a statistical methodology that involves following the three steps depicted in the aforementioned image. This process is further elucidated by Figures 2, 3, and 4.

Table 1. Comparison of various methods

Methodology	Accuracy	Precision	Recall	F1 Score
Naive Bayes	94.5	95.8	95.4	95.2
Gaussian Mixture Model (GMM)	96.7	97.6	96.4	96.1
XGBoost	98.9	98.5	98.6	98.7

XGBoost, the accuracy is 98.9%, indicating that the model correctly classified approximately 98.9% of the instances. [Figure 4]

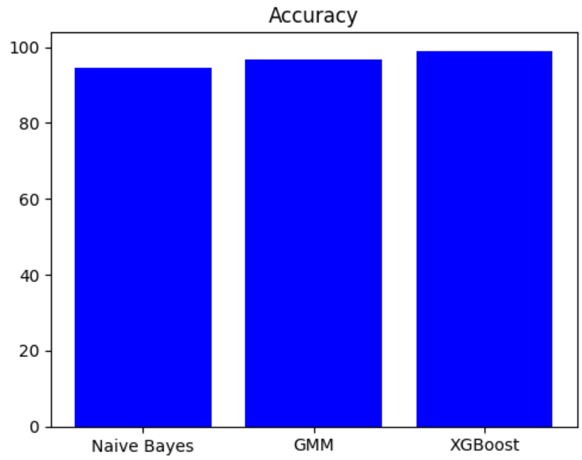

Fig 4. Accuracy Comparison Plot

Naive Bayes, the precision is 95.8%, suggesting that when Naive Bayes predicts a positive instance, it is correct about 95.8% of the time. [Figure 5]

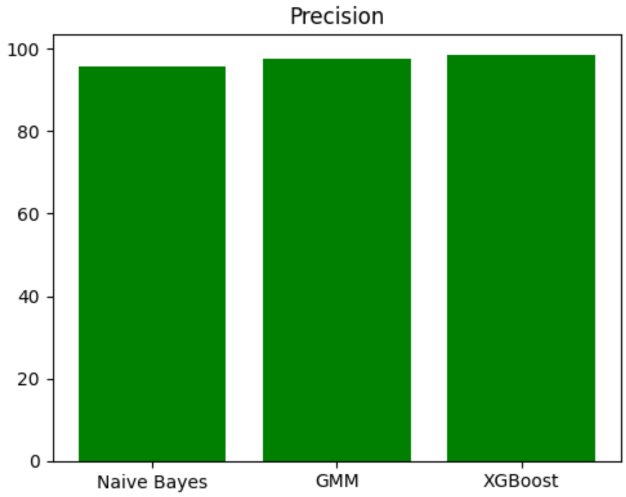

Fig 6. Precision Comparison Plot

For instance Recall, for GMM, the recall is 96.4%, indicating that GMM identified approximately 96.4% of the actual positive instances. [Figure 7]

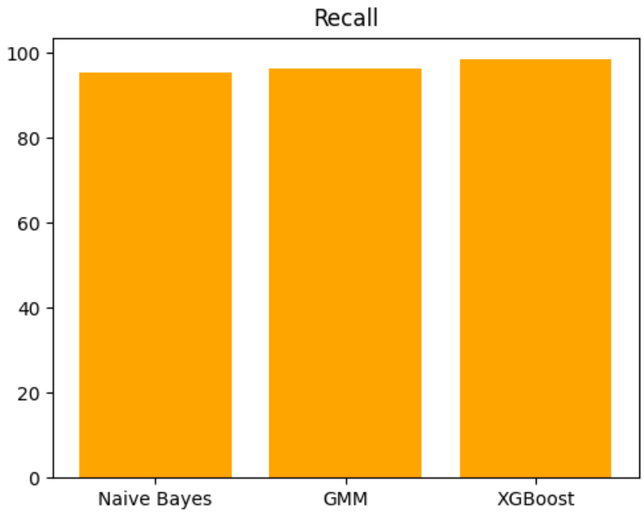

Fig 7. Recall Comparison Plot

A higher F1 score indicates a better balance between precision and recall. For XGBoost, the F1 score is 98.7%. [Figure 8]

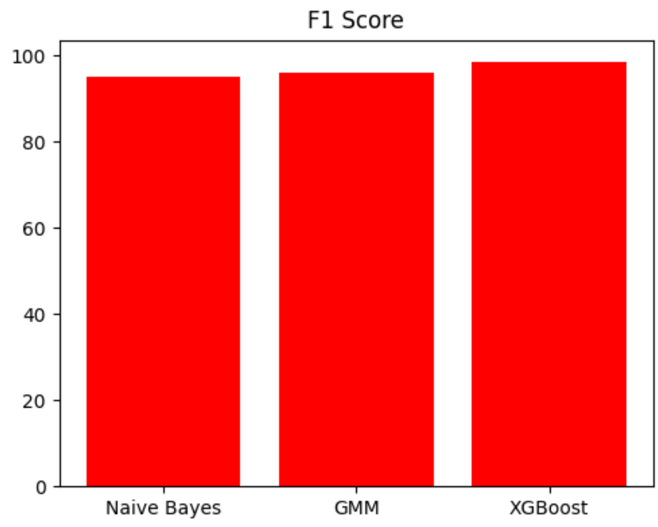

Fig 8. F1 Score Comparison Plot

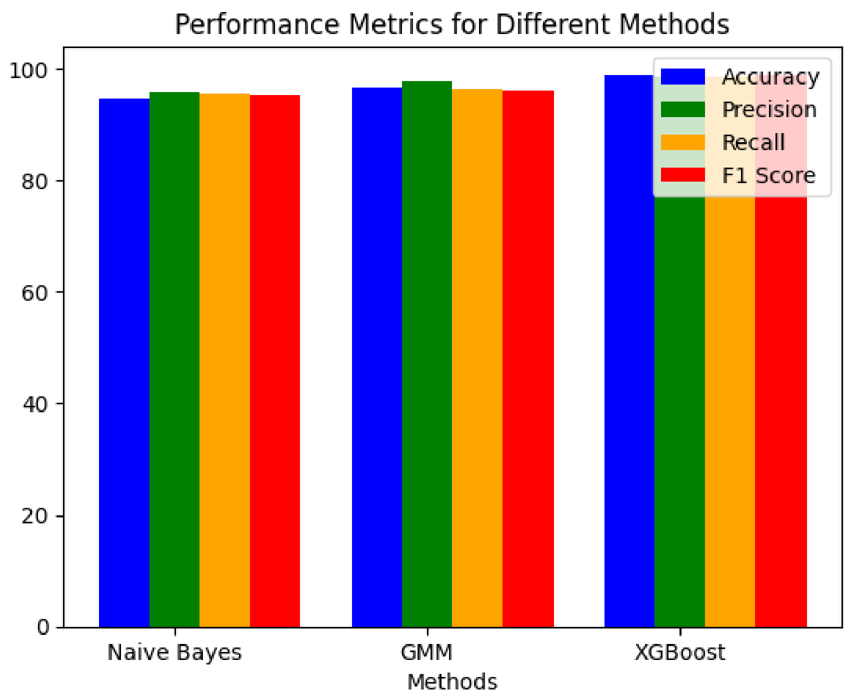

Fig 9. Methodology Comparison Plot

7. Conclusion and Recommendations

Our investigation revealed that the statistical algorithm implemented in the MATLAB software was incapable of accurately discerning the source of the discharge, whether it originated from a void or the surface. Using Python software, it can now be determined that data2 represents a surface discharge. By employing a conventional model, we successfully determined the specific classification of Partial Discharge. Precise results can be acquired by utilizing Google Colaboratory. By utilizing Google's co-laboratory in Python, the occurrence of errors can be rapidly diminished to zero. To mitigate power supply issues in the industrial sector, XGBOOST proves to be an exceptional tool. In conclusion, it is advisable to utilize the Xgboost methodology for the purpose of discerning the specific type of partial discharge. The work provided presents the performance metrics for three different categorization methodologies: Naive Bayes, Gaussian Mixture Model (GMM), and XGBoost. These metrics are evaluated on a specific task. XGBoost stands out as the top performer, achieving the best accuracy (98.9%), precision (98.5%), recall (98.6%), and F1 score (98.7%). This indicates that XGBoost demonstrated superior performance in accurately categorising cases, maintaining a high level of precision, and successfully catching pertinent positive occurrences. Nevertheless, both GMM and Naive Bayes exhibited impressive performance across the criteria, highlighting its appropriateness for the classification task. The Gaussian Mixture Model (GMM) demonstrated exceptional performance in capturing intricate patterns within data distributions, with an accuracy of 96.7% and an F1 score of 96.1%. The findings emphasise the trade-offs between precision and recall, where XGBoost attains an ideal equilibrium demonstrated by its elevated F1 score. The selection of the best appropriate methodology is contingent upon specific application requirements and factors, including interpretability and computing efficiency. Although XGBoost is currently the best performance in this situation, continuous improvement and examination of misclassifications are crucial for maximising the practical efficiency of any model. Ultimately, the table presents a thorough summary of the advantages and relative effectiveness of Naive Bayes, GMM, and XGBoost, providing essential knowledge for making well-informed decisions in classification tasks.

References

[1] Akimasa Hirata, Syou Nakata, and Zen-Ichiro Kawasaki, “Toward Automatic Classification of Partial Discharge Sources With Neural Networks”, IEEE transactions on power delivery, vol. 21, no. 1, january (2006).

[2] J. R Hyde and I. J. Kemp, “Partial Discharge Pattern Recognition and Associated Technologies”, IEEE Colloquium on Monitoring Technologies for Plant Insulation,(1994).

[3] S.H.Park, K. W.Leel, K.J.Lim. andS.H.Kang, “Classification of External and Internal PD Signals Generated in Molded Transformer by Neural Networks”, Proc. of the 7th Int. Conf. on Properties and Applications of Dielectric Materials June 1-5 Nagoya P2-41,(2003).

[4] Shan Ping', XuDake', Wang Guolil, Li Yanming, “Application of Neural Network with Genetic Algorithm to UHF PD Pattern Recognition in Transformers”, Annual Report Conference on Electrical Insulation and Dielectric Phenomena, (2002).

[5] E. Gulski and F. H. Kreuger, “Computer-aided recognition of Discharge Sources”, IEEE Trans. on Electrical Insulation Vol. 27 No. 1, February, (2001).

[6] S. Ghosh and N.K. Kishore, “Modelling Of Partial Discharge Inception And Extinction Voltages Of Sheet Samples Of Solid Insulating Materials Using an Artificial Network”, Proc. Of IEE Volume: 149 , Issue: 2 (2002).

[7] Gagan Deep Meena, Dr. Girish Kumar Choudhary, Manoj Gupta, "Neural Network Based Recognition Of Partial Discharge Patterns", International Journal of Advanced Engineering Research and Studies. Vol. I/ Issue II/January-March, (2012).

[8] V. M. Catterson, B. Sheng, "Deep Neural Networks for Understanding and Diagnosing Partial Discharge Data", Institute for Energy and Environment, University of Strathclyde, Glasgow, United Kingdom (2012).

[9] M. M. A. Salama, and R. Bartnikas," Determination of Neural-Network Topology for Partial Discharge Pulse Pattern Recognition", IEEE Transactions On Neural Networks, Vol. 13, No. 2, March (2002).

[10] K. P. Bennett, and C. Campbell, “Support vector machines: hype or hallelujah,” ACM SIGKDD Explorations Newsletter, vol. 2, no. 1, pp. 1-13, (2000).

[11] M. Junshui, T. James and P. Simon, “Accurate On-line Support Vector Regression", Neural Computation, vol. 15, no. 11, pp. 2683—2703,(2003).

[12] Shikha Agarwal, Balmukumd Jha, Tisu Kumar, Manish Kumar, Prabhat Ranjan, " Hybrid of Naive Bayes and Gaussian Naive Bayes for Classification: A Map Reduce Approach", International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8, Issue-6S3, April (2019).

[13] Dana Bani-Hani, Pruthak Patel & Tasneem Alshaikh, " An Optimized Recursive General Regression Neural Network Oracle for the Prediction and Diagnosis of Diabetes", Global Journal of Computer Science and Technology: D Neural & Artificial Intelligence Volume 19 Issue 2 Version 1.0 Year (2019).

[14] Namrata Bhosale, Priyanka Kothoke Amol Deshpande, Dr. Alice Cheeran, “Analysis of Partial Discharge using Phase-Resolved(φ-q) and (φ-n) Statistical Techniques”, International Journal of Engineering Research and Technology, Vol. 2 (05), (2013), ISSN2278-0181.

[15] Priyanka Kothoke, Namrata Bhosale, Amol Deshpande, Dr. Alice Cheeran, “Analysis of Partial Discharge using Phase-Resolved (n-q) Statistical Techniques”, International Journal of Engineering Research and Applications.

[16] Yogesh R. Chaudhari, Namrata R. Bhosale, Priyanka M. Kothoke, “Composite Analysis of Phase Resolved PD Patterns using Statistical Techniques”, International Journal of Modern Engineering Research (IJMER) Vol. 3, Issue. 4, pp-1947-1957, (2013).

[17] Priyanka Kothoke, Dr. Anupama Deshpande,

Yogesh Chaudhari, "Investigation and Determination of PD source utilizing SVR and RF", International Conference on Inventive Computation Technologies (ICICT-2020), inclusion into IEEE Xplore and Scopus.

[18] Priyanka Kothoke, Dr. Anupama Deshpande, Yogesh Chaudhari, "Examination and Determination of Partial Discharge Source utilizing SOM and BPM Techniques of ANN", International Journal of Advanced Science and Technology, Vol. 29, No. 8s, (2020), pp. 3299-3306.

[19] Priyanka Kothoke, Dr. Anupama Deshpande, Yogesh Chaudhari, "Analysis and Determination of Partial Discharge Type using Statistical Techniques and Back Propagation Method of Artificial Neural Network for Phase Resolved Data;", International Journal of Engineering Research and Technology (IJERT),Vol. 08, Issue 08, August (2019).

[20] L. Kalaivani, R. V. Maheswari, B. Vigneshwaran, A. Karthick, M. Kathirvelu, and F. P. Garcia Marquez, "Partial discharge based recognition of water droplets location in high voltage insulator using convolutional neural network – Bacterial foraging algorithm based optimized machine learning classifier," Meas. J. Int. Meas. Confed., vol. 221, no. September, p. 113527, 2023, doi: 10.1016/j.measurement.2023.113527.

[21] R. Sahoo and S. Karmakar, "Investigation of electrical tree growth characteristics and partial discharge pattern analysis using deep neural network," Electr. Power Syst. Res., vol. 220, no. November 2022, p. 109287, 2023, doi: 10.1016/j.epsr.2023.109287.

[22] E. Balouji, T. Hammarstrom, and T. McKelvey, "Classification of Partial Discharges Originating from Multilevel PWM Using Machine Learning," IEEE Trans. Dielectr. Electr. Insul., vol. 29, no. 1, pp. 287–294, 2022, doi: 10.1109/TDEI.2022.3148461.

[23] S. Lu, H. Chai, A. Sahoo, and B. T. Phung, "Condition Monitoring Based on Partial Discharge Diagnostics Using Machine Learning Methods: A Comprehensive State-of-the-Art Review," IEEE Trans. Dielectr. Electr. Insul., vol. 27, no. 6, pp. 1861–1888, 2020, doi: 10.1109/TDEI.2020.009070.

[24] S. Barrios, D. Buldain, I. Gilbert, and I. Orue, "Methods — Survey of Recent Progress," no. Dl, 2019.

[25] T. Boczar, S. Borucki, D. Jancarczyk, M. Bernas, and P. Kurtasz, "Application of Selected Machine Learning Techniques for Identification of Basic Classes of Partial Discharges Occurring in Paper-Oil Insulation Measured by Acoustic Emission Technique," Energies, vol. 15, no. 14, 2022, doi: 10.3390/en15145013.

[26] J. Q. Chan, W. J. K. Raymond, H. A. Illias, and M. Othman, "Partial Discharge Localization Techniques: A Review of Recent Progress," Energies, vol. 16, no. 6, 2023, doi: 10.3390/en16062863.

[27] R. Sahoo and S. Karmakar, "Investigation of electrical tree growth characteristics and partial discharge pattern analysis using deep neural network," Electr. Power Syst. Res., vol. 220, no. November 2022, 2023, doi: 10.1016/j.epsr.2023.109287.

[28] L. Kalaivani, R. V. Maheswari, B. Vigneshwaran, A. Karthick, M. Kathirvelu, and F. P. Garcia Marquez, "Partial discharge based recognition of water droplets location in high voltage insulator using convolutional neural network – Bacterial foraging algorithm based optimized machine learning classifier," Meas. J. Int. Meas. Confed., vol. 221, no. September, pp. 1–11, 2023, doi: 10.1016/j.measurement.2023.113527.

[29] E. Balouji, T. Hammarstrom, and T. McKelvey, "Partial discharge classification in power electronics applications using machine learning," Glob. 2019 - 7th IEEE Glob. Conf. Signal Inf. Process. Proc., 2019, doi: 10.1109/GlobalSIP45357.2019.8969553.

[30] S. M. R. Borghei, "Partial Discharges: Experimental Investigation, Model Development, and Data Analytics," Diss. Virginia Polytech. Inst. State Univ., 2022.

[31] V. Samaitis, L. Mažeika, A. Jankauskas, and R. Rekuvienė, "Detection and localization of partial discharge in connectors of air power lines by means of ultrasonic measurements and artificial intelligence models," Sensors (Switzerland), vol. 21, no. 1, pp. 1–21, 2021, doi: 10.3390/s21010020.