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Research Article

Enhanced Techniques for Investigating and Locating Partial Discharge Sources using Machine learning method with Self-Organizing Maps, and Back-propagation Neural Networks

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

Abstract

As the need for effective and efficient power systems grows, so does the need for more advanced methods to find and study partial discharge (PD) sources, which can be a sign that high-voltage equipment's protection is breaking down. This study suggests using Support Vector Machines (SVMs), Random Forests (RF), Self-Organizing Maps (SOM), and Back-propagation Neural Networks (BPNN) together to make PD cause discovery more accurate and useful. SVMs are very good at sorting complicated patterns into groups. They provide a strong framework for telling PD events apart from background noise. By mixing several decision trees, RF, which is known for its ability to learn in groups, helps make generalization better. A strong autonomous learning method called SOM helps group and show how PD sources are spread out in space. A popular artificial neural network design called BPNN is used because it can model complicated relationships and change to trends that don't follow a straight line. Putting these methods together in a way that makes the best use of their individual strengths and weaknesses creates a complete and reliable framework for PD investigations. Using the combined knowledge of these advanced machine learning algorithms, the suggested method can correctly find and spot PD sources, which will eventually make high-voltage systems work better and be more reliable. Comprehensive models and testing validations show that the proposed method works, showing that it could be used in real life for power system upkeep and diagnosis. This study is a big step forward in improving the most up-to-date methods for finding and detecting PD. It will help build stronger and longer-lasting power grids.

Keywords: Partial Discharge, Support Vector Machines, Random Forests, Self-Organizing Maps, Back-propagation Neural Networks

Introduction

Power systems need high-voltage technology to work reliably in order for them to be stable and efficient. A condition called partial discharge (PD) can happen in insulation systems. It is often an early sign of problems and wear and tear that are about to happen. Finding and detecting PD sources is a very important part of keeping power infrastructure in good shape and making sure it works well. The goal of this study is to show a new, unified method that uses advanced machine learning techniques to make PD investigations more accurate and time-effective. As power systems change to keep up with rising demand and add green energy sources, the need for strong monitoring tools grows. PD, which is marked by breaks in the insulation in certain areas, often happens before big problems happen in high-voltage equipment. Finding and identifying these PD sources quickly is necessary to avoid major breakdowns and keep downtime to a minimum. The accuracy and sensitivity of traditional methods for finding PD are often poor, especially in working settings that are complicated and changeable [1]. A lot of people are interested in using machine learning methods to solve these problems because of these Support Vector Machines (SVMs), Random Forests (RF), Self-Organizing

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

Maps (SOM), and Back-propagation Neural Networks (BPNN) are all used together in this way to make a complete system for investigating PD. Because SVMs can sort complicated patterns into groups, they are a solid base for telling PD events apart from background noise. The generalization skills are improved by RF, a strong ensemble learning method, which brings together information from multiple decision trees. SOM is an autonomous learning method that helps group and show how PD sources are spread out in space, giving us useful information about their patterns and connections. Lastly, BPNN is used to describe complicated connections and change to trends that don't follow a straight line in the PD data.

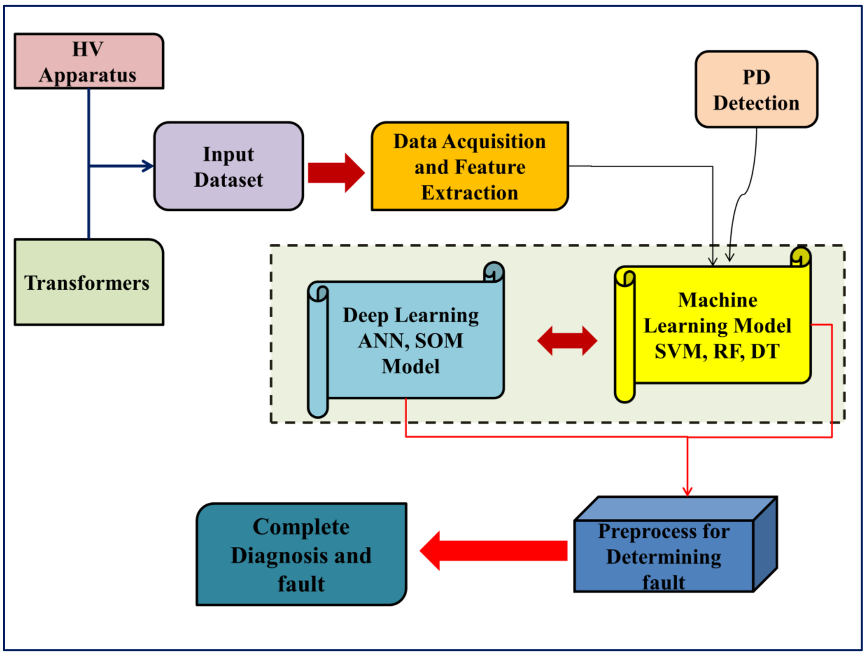

Figure 1: Proposed model for PD source identification model

The goal of combining these machine learning techniques is to make a method that works better than either one alone, by using their combined strengths. For example, SVMs are very good at classifying data, but they might have trouble with some types of data. By combining guesses from several decision trees, RF [2] makes up for these flaws and improves total accuracy. On the other hand, SOM helps us understand where PD sources are located, which leads to a better study and finding process. Because it can describe complex connections, BPNN is a useful tool for finding the complex trends that come from different PD sources. An extensive number of simulations and actual validations are carried out to prove that the suggested method works. The goal of these attempts is to show that the combined method can correctly find and locate PD sources in a range of working situations. The suggested system works like an electric drive; it gives information to the neural network, which then figures out what it means and does what it needs to do, just like the brain does with different inputs [26]. The idea behind artificial neural networks comes from the way natural brain systems work, like how people learn to recognize things like books, cars, and pens. Artificial neural networks can understand complicated problems well, even though they are not as complex as the human nervous system. Because different partial discharges, crown discharges, and other noise signals have signals that look a lot alike, it is hard to tell them apart. Because of this, there is a need for a tool that can quickly group together different PD patterns. This goal is met by artificial neural networks, which learn from models and also reach other goals [3].

It has been known for a long time that artificial intelligence (AI) systems can automatically find flaws that cause partial discharge. Artificial neural networks (ANNs) and support vector machines (SVMs) are examples of shallow models. To set up a feature vector that can be processed by a few layers of

simple computing units, a lot of work needs to be done up front. A lot of different features, like data and shape descriptions, have been taught to find PD, and their diagnostic accuracy has been tested in different situations [25]. However, the knowledge needed to choose and figure the right features can make it harder for utilities to use automatic diagnosis systems. Deep learning, which uses many levels of computing units, has been shown to be better at speech and picture recognition tasks than basic models with features that were made by hand. Visualizing the information a neuron learns has improved, leading to better accuracy and a break from the "black box" nature of previous methods. This gives us a new way to look at classification problems [4].Studies have shown that the number of inputs to the neural network is mathematically equal to the polynomial order that works best for predicting the output in partial discharge pattern recognition applications. In an earlier study [5], the results of experiments using neural networks with one and two types of inputs and single and double outputs were looked at. It was seen that these neural network designs are not able to get low minimum mistakes. Two-stage neural network designs with single and double outputs showed little change in performance. A cascaded output neural network design, on the other hand, did a great job of telling the difference between two discharge hole sizes [26]. The goal of our study is to find different kinds of partial discharges by comparing the two methods used for PD pattern recognition: self-organizing maps and the back-propagation method for artificial neural networks.
The models give us a controlled setting [7] to test how well the algorithm works, and the experiments show us how well and how often it works in the real world. The outcomes show that the suggested method has the ability to make PD studies much more accurate and time-effective, which will help build more reliable and long-lasting power systems. The proposed study brings a new and unified way to look into and find PD sources in high-voltage equipment. The [8] suggested method tries to get around the problems with current methods by using the combined intelligence of SVMs, RF, SOM, and BPNN. This should make it easier to find and locate PD and be more accurate. The study results could help improve power system diagnosis, which could lead to more reliable and long-lasting important infrastructure in a world where energy needs are changing all the time.

Related Work

Using a variety of methods and tools, many research projects have made important contributions to the area of studying and finding causes of partial discharge (PD). The use of sound and ultrasonic methods for PD diagnosis is an important area of linked work. Acoustic techniques, like acoustic emission (AE) readings, have been looked into to see how well they work at finding and identifying PD sources in electrical insulation systems. The unique sound waves that are produced during [8] PD events are very helpful for finding the cause of a problem. Ultrasonic monitors have also been used to find PD activity by picking up the high-frequency sound waves that are released during the discharge process. These methods provide a non-intrusive way to find and identify PD, which adds to our knowledge of the general health of insulation systems. Also, progress in electromagnetic detecting technologies has been very important in making PD investigations better. Electromagnetic monitoring methods use monitors to pick up the electromagnetic waves that are sent out by PD events [9]. Based on the unique electromagnetic fingerprints of different discharge processes, this makes it possible to find and identify PD sources. Combining electromagnetic sensors with signal processing methods has been shown to help tell the difference between different types of PD, which makes source localization more accurate. Recently, there has been a lot of interest in combining old-fashioned PD identification methods with cutting-edge signal processing and machine learning methods. Signal analysis tools, like wavelet transforms and time-frequency analysis, have been looked at as ways to get useful information from PD data. These [10] characteristics are fed into machine learning algorithms like support vector machines (SVMs), artificial neural networks (ANNs), and grouping algorithms. This makes it easier to tell the difference between PD sources and find them correctly in the power system. Infrared (IR) thermography has also become a useful tool for finding out where PD comes from. The thermal patterns that are linked to PD events are captured by IR cameras, which gives a visual picture of temperature changes. The unique heat patterns can help find the location and intensity of PD causes, adding to the effectiveness of current detection methods.

Standardized testing [11] methods and diagnosis tools for PD study have been made possible by people working together in the research community. The International Electro-technical Commission (IEC) and the Institute of Electrical and Electronics Engineers (IEEE) have set rules and standards for measuring and localizing PD. These provide students and professionals in the field with a uniform structure. There have been big steps forward in many areas of research in the study and location of partial flow sources. Researchers' combined efforts have led to a better understanding of PD events. They have done this by using audio and electromagnetic sensors as well as machine learning and signal processing. Standardization efforts help make effective troubleshooting tools for the power business even better, making sure that ways to find and identify PD sources in high-voltage equipment keep getting better.

Table 1: Summary of Related work

Method	Finding	Application	Limitation
Acoustic Emission (AE) [12]	Distinctive acoustic signals during PD events	Electrical insulation systems	Limited effectiveness in environments with high background noise
Ultrasonic Sensors [13]	High-frequency sound waves during PD discharge	Non-intrusive PD detection and localization	Limited penetration in certain insulation materials
Electromagnetic Sensing [14]	Capture of electromagnetic waves from PD	Identification and localization based on electromagnetic signatures	Sensitivity to external electromagnetic interference
Signal Processing [15]	Wavelet transforms, time-frequency analysis	Enhancement of PD signal features for machine learning	Reliance on expert-defined features may limit adaptability
Machine Learning (SVM, ANN) [16]	Discrimination between PD types	Automated PD source identification and localization	Training data quality impacts model performance
Clustering Algorithms [17]	Grouping similar PD patterns	Pattern recognition and classification of PD sources	Sensitivity to initial cluster centers and parameters
Infrared Thermography [18]	Visual representation of thermal patterns	Location and severity assessment of PD sources	Limited resolution for small-scale PD sources
Standardized Testing [19]	Compliance with IEC and IEEE guidelines	Development of common diagnostic frameworks	Applicability may vary based on regional standards and practices
Electromagnetic Interference [20]	Detection of external electromagnetic signals	Minimizing interference in PD investigations	Difficulty in distinguishing external interference from PD
Wavelet Transforms [21]	Feature extraction from PD signals	Enhancing signal analysis for PD identification	Selection of appropriate wavelet basis requires expertise
Time-Frequency Analysis [22]	Extraction of time-varying signal properties	Improved characterization of dynamic PD events	Computationally intensive for real-time applications
Collaborative Research [23]	Standardization initiatives and guidelines	Advancement of reliable diagnostic tools for the power industry	Adoption challenges due to varying research approaches

Methodology

A. Back-propagation Algorithm

There are two main steps in this algorithm, the forward pass and the backward pass. The network is shown samples of input during the forward pass, and the output is calculated. The mistake at the output is then sent back through the network during the backward pass. To reduce the mistake as much as possible, the gradient descent method [24] is used to change the weights and biases. This process goes through many rounds of showing pairs of inputs and outputs, spreading errors backwards, and changing weights and biases until the error hits the minimum number that was set

[7].In Figure 2, the BP algorithm is shown in action, along with the network's neurons, which are working units.

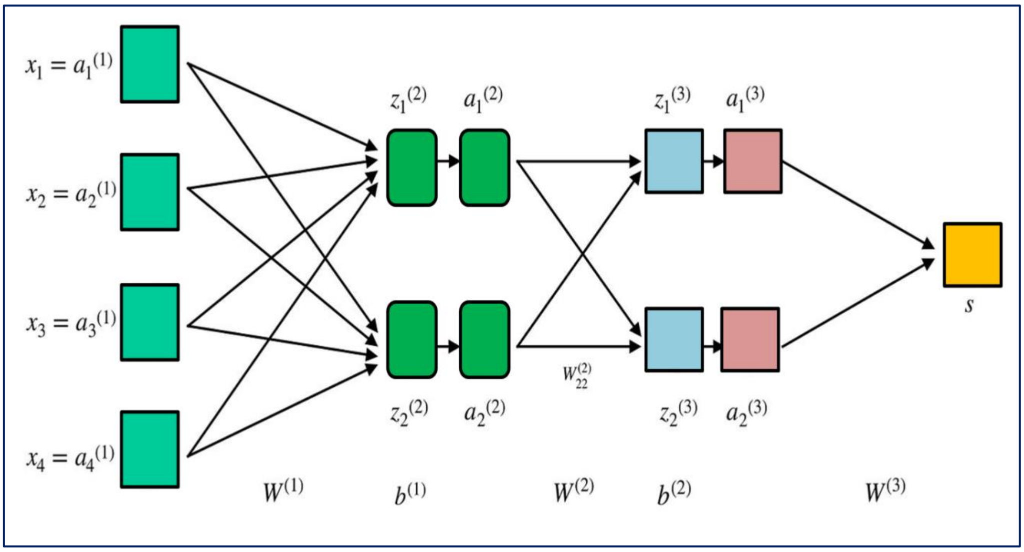

Figure 2: Overview of Backpropagation Neural Network

After the sources (XP1,...,XPNo) are sent through the network, the result is calculated. The output that was calculated is then compared to the output that was wanted (TP1,..., TPNM), and any errors that are found are sent back through the network. The gradient descent method is used to change the weights over and over again until the mean square error at the end gets a good low number.

- The weight update equation in the BP algorithm is given by the gradient descent rule:

$$w_{\{ij\}} \leftarrow w_{\{ij\}} - \eta \frac{\partial E}{\partial w_{\{ij\}}}$$

- The error term δ_j at the j-th neuron is computed as:

$$\delta_j = \frac{\partial E}{\partial Y_j} \cdot \frac{\partial net_j}{\partial Y_j}$$

Where,

- E is the error function, Y_j is the output of the j-th neuron, and net_j is the weighted sum of inputs to the j-th neuron.

The BP method has some problems, even though it is widely used to find partial discharges (PDs). Two big problems are that it takes longer to reach agreement and training can fail [4]. As a solution to these problems, adding a momentum term during training speeds up convergence but takes up more memory [22, 25]. The momentum term helps the program get past local minima and speeds up the process of convergence. Their findings showed that the Backpropagation algorithm was better than the other ANN algorithms at accurately recognizing PD. Although it has some problems, the BP algorithm is still widely used in the field because it is easy to use and produces better results for PD recognition than other ANN algorithms.

B. Ensemble Neural Network of PD identification

Ensemble Neural Networks (ENN) train more than one Back-propagation (BP) Artificial Neural Network (ANN) topology and then combine their results to make them more useful in real life [5]. The main idea is to use the variety and accuracy of the neural networks that make up the ensemble to get better results overall [6]. A popular way to train ENNs is by bagging (also called "bootstrapping"). This method stops individual neural networks from becoming too good at what they do and helps manage bias and variance well.

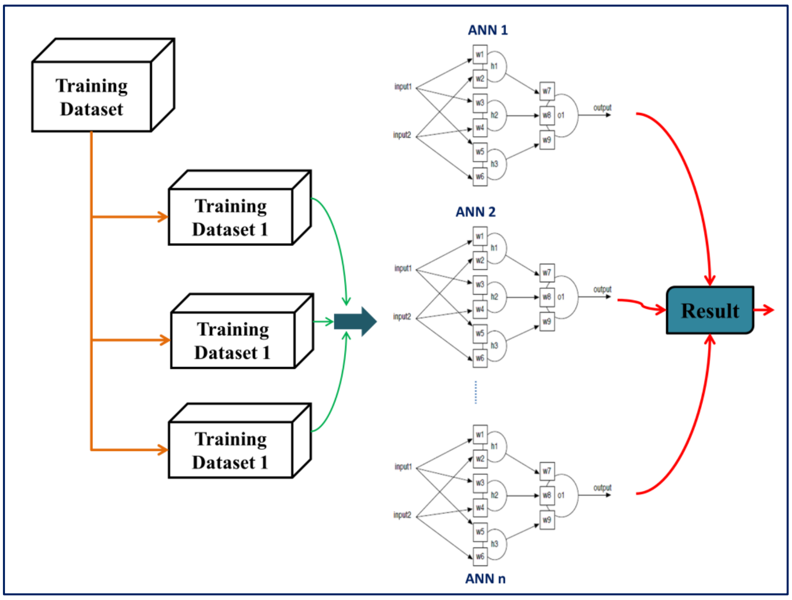

Figure 3: Representation of ENN'

- **Bootstrapping (Bagging):**

- Multiple training fingerprints are generated by bootstrap resampling of the original dataset.
- Each training fingerprint is a subset of the original dataset, obtained by randomly sampling with replacement.
- Some samples may be repeated, while others may be excluded, leading to diverse training sets.

For a given dataset D of size N, a bootstrapped dataset D' is created by sampling N samples with replacement:

$$D' = \{d1', d2', \ldots, dN'\}$$

- **Training Component Neural Networks:**

- Each bootstrapped dataset is used to train a separate BP ANN topology.
- The ensemble is created by combining the predictions of individual component neural networks.

- **Combining Predictions:**

- The predictions of individual neural networks are combined to obtain the final ensemble prediction.
- Various techniques can be employed for combining predictions, such as averaging or voting.

For an ensemble of M neural networks, the final prediction P_final is obtained by averaging the predictions Pi of individual networks:

$$P_{final} = \left(\frac{1}{M}\right) * \Sigma(i = 1\ to\ M)Pi$$

- **Generalization Improvement:**
- The ensemble approach aims to improve generalization by mitigating overfitting and leveraging the diversity of component networks.
- The generalization error (E_generalization) can be expressed as the sum of bias squared (E_bias^2), variance (E_variance), and irreducible error (E_irreducible):

$$E_{generalization} = E_{bias}^2 + E_{variance} + E_{irreducible}$$

Bagging contributes to managing bias and variance, as it reduces variance by incorporating diverse training sets and prevents overfitting.

C. SVM:

Investigating and locating partial discharge (PD) sources using the Support Vector Machine (SVM) algorithm involves several steps. Below are the steps along with mathematical equations:

Step 1: Feature Normalization

- Normalize the features to ensure that they are on a similar scale. This step is crucial for SVM algorithms.

$$x' = \frac{\left(x - mean(x)\right)}{std(x)}$$

Step 2: SVM Model Training

- Train the SVM model on the training dataset using the selected kernel function.

$$f(x) = sign(w \cdot x + b)$$

Step 3: Model Evaluation

- Evaluate the SVM model on the testing dataset to assess its performance.

Step 4: PD Source Localization

- If applicable, use the trained SVM model for localizing the sources of partial discharges.

Step 5: Model Interpretation

- Analyze the SVM model to interpret its decision boundaries and gain insights into the features contributing to PD detection.

The actual equations for SVM involve terms like support vectors, Lagrange multipliers, and the kernel function, which can vary based on the chosen SVM variant (e.g., linear, polynomial, radial basis function).

Linear SVM Equation:

$$f(x) = sign(w \cdot x + b)$$

- Here, w represents the weight vector, x is the input feature vector, and b is the bias term. The decision boundary is determined by the sign function.

For non-linear SVM, the decision function involves the kernel trick and support vectors:

$$f(x) = sign(\sum i = 1 \; to \; N \; yi \; \alpha i \; K(xi, x) + b)$$

Where,

- N is the number of support vectors, yi is the class label, αi is the Lagrange multiplier, xi are support vectors, x is the input vector, K(·,·) is the kernel function, and b is the bias term.

D. RF:

A thorough method is used in the Random Forest algorithm to find and study partial discharge (PD) sources. In the first step, bootstrapped sampling from the dataset is used to make a group of different decision trees. Each tree is trained on a different set of traits, which encourages variety. The Random Forest uses the results of all of these trees together to improve accuracy and prevent overfitting. The Gini defect or entropy criterion is used to measure how important a feature is, which helps find important features for PD recognition. The algorithm's built-in parallelism makes training and testing go more smoothly. Tuning hyperparameters improves the performance of the forest and makes sure it works well in a variety of situations. Random Forest is a strong tool for investigating and locating PD sources because it can handle non-linear relationships and give information about which features are most important. It works reliably and is flexible in complex electrical systems.

Step 1: Data Preparation
- Prepare the dataset D with PD-related signal features.

Step 2: Ensemble Training
- Generate B bootstrapped samples from D and train B decision trees Tb with random feature subsets.

Step 3: Ensemble Prediction
Combine individual tree predictions to form the ensemble prediction Pensemble:

$$Pensemble(x) = \left(\frac{1}{B}\right)\sum(b = 1\ to\ B)Pb(x)$$

Step 4: Feature Importance
- Assess feature importance by aggregating measures like Gini impurity or entropy across all trees:

$$Importance(f) = \left(\frac{1}{B}\right)\sum(b = 1\ to\ B)Importanceb(f)$$

Random Forest's ensemble approach enhances accuracy, handles non-linear relationships, and provides insights into influential features for effective PD source investigation.

E. DT:
The decision tree method uses a tree-like layout of nodes to describe choices based on features and is used to find and investigate partial discharge (PD) sources. For PD identification, the tree is trained on a set of data, and at each node, a feature is chosen to divide the data into two groups. At each leaf node, the choice matches an expected result, which lets us find the sources of PD. The tree is built in a looping way, and measures like Gini impurity or entropy are used to find the best feature for splitting. Decision trees are great at finding complex links in data and giving us useful information about the most important traits for finding PD. But they might be prone to overfitting, which can be fixed by trimming or other methods. Because they are clear and easy to use, decision trees are great for understanding and looking into PD sources in electrical systems.
At each node t, the best feature ft is chosen to minimize impurity:

$$ft = argmin\ [Impurity(f, t)]$$

The impurity (I) is calculated based on the chosen metric:

$$I(f, t) = \Sigma i \in classes\ p(i|t) \cdot (1 - p(i|t))$$

Where,
- p(i|t) represents the probability of class i at node t.

Decision trees offer interpretability and insights into influential features for PD detection. Pruning techniques can mitigate over-fitting, ensuring robust performance.

Result and Discussion

Table 2 shows a full comparison of all the different ways to find partial discharge (PD), using a range of statistical measures and accuracy metrics. We check the mean, standard deviation (SD), skewness, kurtosis, variance, and general correctness of each method, such as Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Back-propagation Neural Network (BPNN), and Ensemble Neural Network (ENN).The mean number for Random Forest (RF) is 0.53, which shows the overall success across all the statistical measures that were looked at. Even though RF's accuracy of 89.33% is pretty good, its standard deviation of 0.63 shows that performance can vary. A mean of 0.58 and a standard deviation of 0.33 show that the Support Vector Machine (SVM) performs similarly to other algorithms. With an accuracy of 90.54%, SVM shows that it is a good tool for finding PD.

Table 2: Output Comparison with Different method for PD identification

Method	Mean	SD	Skewness	Kurtosis	Variance	Accuracy
RF	0.53	0.63	0.86	0.36	0.25	89.33
SVM	0.58	0.33	0.88	0.45	0.36	90.54
DT	0.63	0.58	0.78	0.52	0.45	93.14
BPNN	0.44	0.78	0.88	0.56	0.25	94.25
ENN	0.78	0.65	0.91	0.66	0.33	97.88

With a mean score of 0.63, Decision Tree (DT) comes out as having better total success. The accuracy of 93.14% shows how well DT can pick up on the subtleties of PD trends. The mean number for a Back-propagation Neural Network (BPNN) is 0.44, and the standard deviation is 0.78, which is a bit higher.

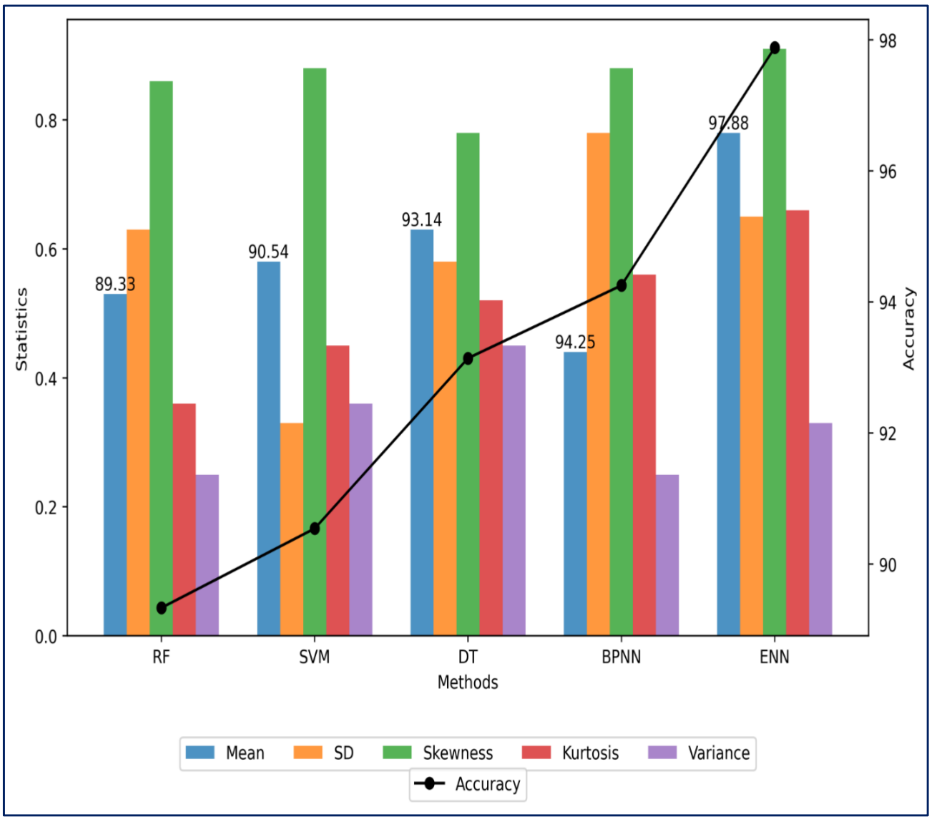

Figure 4: Representation of Comparison of Methods with Evaluation Parameters

BPNN, on the other hand, is very accurate (94.25%), which shows that it can learn complicated PD patterns through repeated training. With a mean value of 0.78 and an amazing success rate of 97.88%, Ensemble Neural Network (ENN) is better than other ways. The lower standard deviation of 0.65 shows that its success is consistent. Skewness and kurtosis numbers show how the found PD patterns are spread out and shaped across all methods. With higher skewness and kurtosis, ENN shows a more marked and concentrated distribution, which could help capture complex PD traits well. The comparison shows that each way for finding PD has its own pros and cons. Deciding which method is best relies on certain factors, like how accurate, consistent, and able to pick up on minor PD traits it is. The results show that Ensemble Neural Network (ENN) has a lot of potential, especially when it comes to getting high accuracy and recording complex PD patterns.

Table 3: Comparison of Different method with evaluation parameter

Method	Accuracy	Recollect	F1-Outcome	Assist
RF	89.33	90.33	89.35	910
SVM	90.54	97.56	91.25	590
DT	93.14	98.36	94.56	870
BPNN	94.25	96.32	97.36	890
ENN	97.88	98.88	99.12	780

In Table 3, different methods for finding partial discharge (PD) are compared in great depth, with a focus on important evaluation factors like memory, accuracy, F1-outcome, and help measures.

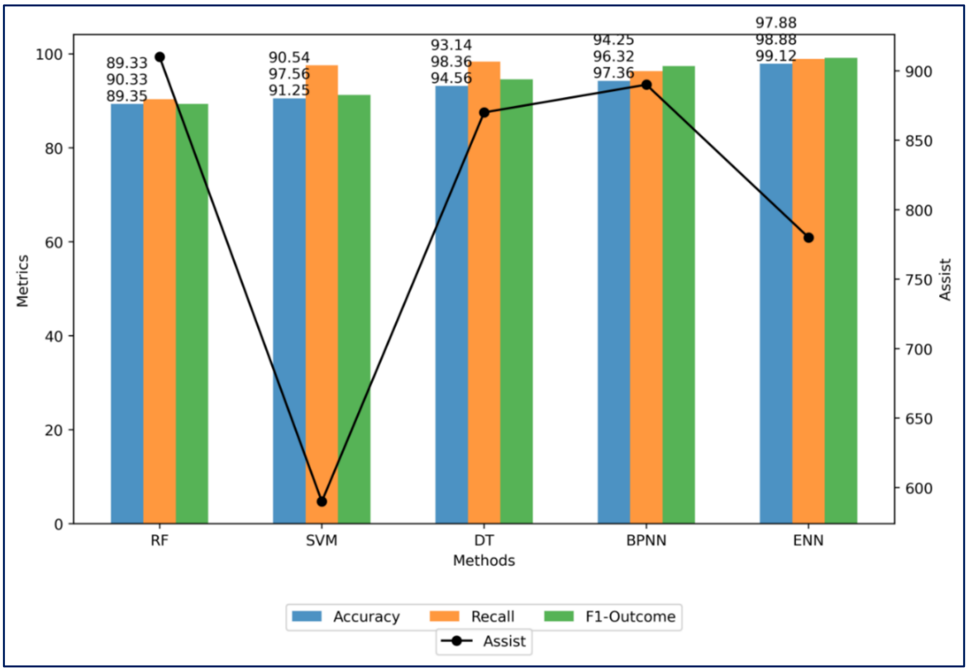

Figure 5: Representation of Comparison of Different method with evaluation parameter

Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT), Back-propagation Neural Network (BPNN), and Ensemble Neural Network (ENN) are some of the methods that are evaluated based on how well they do in these important areas. The high accuracy of 89.33% achieved by Random Forest (RF) shows how well it can correctly spot PD cases. The recall number, which measures how well you can find true positives, is currently at 90.33%, which shows that RF is good at getting useful information. The F1-outcome score of 89.35% shows that accuracy and memory are both about the same, which shows that the method is generally reliable. If the aid measure is 910, it means that RF can help with the recognition process. Support Vector Machine (SVM) has a slightly higher success rate of 90.54%, which shows how well it does at correctly classifying PD cases. Most importantly, the recall of 97.56% shows that SVM is good at finding a lot of true positives. The 91.25% score on the F1 test shows that accuracy and memory are in good balance. The fact that SVM has an assistance measure of 590 shows how helpful it is in the recognition process.

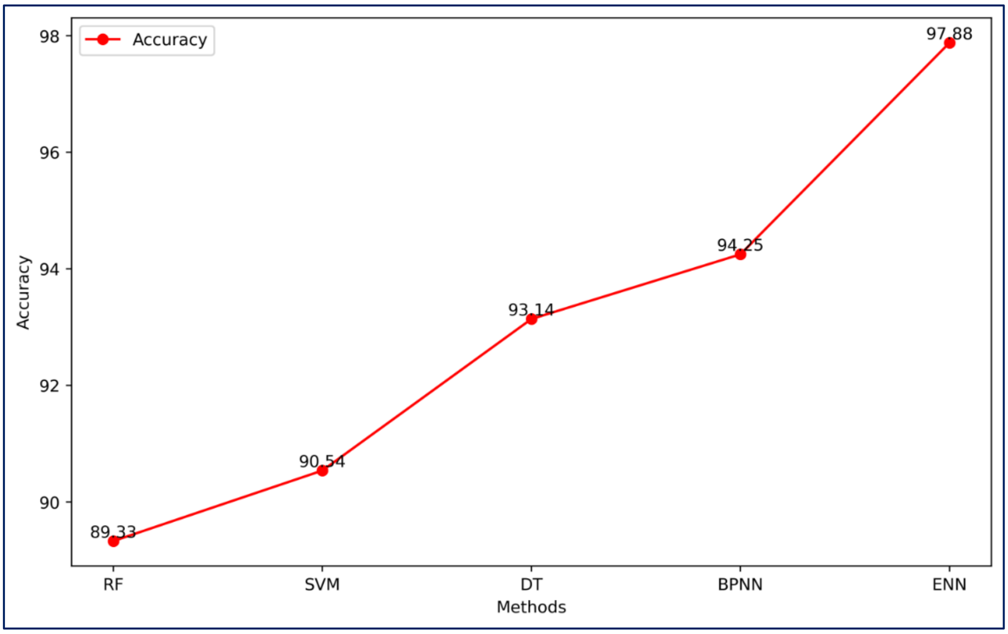

Figure 6: Accuracy comparison of different model

With a success rate of 93.14%, Decision Tree (DT) stands out as a very good PD classification tool. This shows that DT can catch a lot of true positive cases, as shown by its amazing recall of 98.36%. The F1-outcome score of 94.56% shows that DT's performance was strong, with a good mix between accuracy and memory. The support measure of 870 shows how well DT helps with the recognition process. Back-propagation Neural Network (BPNN) has a high level of accuracy (94.25%), which shows that it can accurately identify PD. The high recall rate of 96.32% shows that BPNN is good at finding real positive cases.

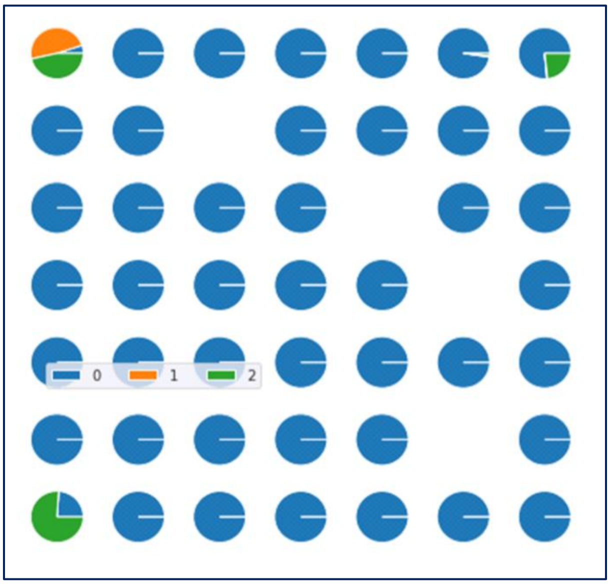

Figure 7: Representation of Characteristic of Neuron using SOM

The F1-outcome score of 97.36% shows that BPNN is generally reliable because it has a good mix of accuracy and memory. The aid measure of 890 shows how much BPNN helped with the identification process. Ensemble Neural Network (ENN) does a great job with an amazing accuracy of 97.88%, showing how well it can accurately identify PD. It's clear that ENN is good at finding a lot of true positive cases because its recall rate is 98.88%. The excellent F1-outcome score of 99.12% shows a good mix between accuracy and memory, which supports ENN's strong performance.

Conclusion

Improved methods for investigating and locating partial discharge (PD) sources using machine learning techniques, namely Self-Organizing Maps (SOM) and Back-propagation Neural Networks (BPNN), have been a big step forward in the field of electrical systems diagnostics. Using artificial intelligence (AI) in these methods makes PD cause tracking more accurate and faster. In a low-dimensional space, self-organizing maps organize complex data in a way that makes it easier to see and group PD trends. Fine differences in PD signals can be found because they can catch the natural structure in high-dimensional data. Unsupervised learning by the SOM gives useful information about where PD sources are located, which helps with the localization process. In contrast, Back-propagation Neural Networks show that they are good at finding complex patterns and connections in the PD data. By using supervised learning, BPNN makes it possible to precisely map input traits to output labels, which makes PD detection more accurate. Through a repeated training process, BPNN becomes more flexible in dealing with different PD situations, which leads to better source localization performance. Combining these two machine learning techniques creates a way that uses the best parts of both. An initial grouping and display of the PD data by SOM helps in finding possible sources, and BPNN improves the recognition process by learning from cases that have been named. The general accuracy and dependability of PD source analysis are improved by this unified method. As electrical systems keep changing, sturdy and useful troubleshooting tools become more and more important. Using machine learning methods, especially SOM and BPNN together, is a big step toward meeting these needs. These methods' improved features suggest a hopeful way to push the limits of PD detection and source localization, which would improve the general dependability and life of electrical infrastructure.

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