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Systematic Review

Partial Discharge Source Classification in Power Transformers: A Systematic Literature Review

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Featured Application: Development of intelligent and real-time monitoring systems for transformer health diagnostics and condition monitoring.

Abstract: Power transformers, like other High-Voltage (HV) electrical equipment, experience aging and insulation degradation due to chemical, mechanical and electrical forces during their operation. Partial discharges (PD) are among the most predominant insulation breakdown mechanisms. Monitoring partial discharges has proven to provide valuable information on the state of the insulation systems of power transformer, allowing transformer operators to make calculated decisions for maintenance, major interventions and plan for replacement. This systematic literature review aims to systematically examine the use of machine learning techniques in classifying PD in transformers to present a complete indicator of the available literature as well as potential literature gaps which will allow for future research in the field. The systematic review surveyed a total of 81 research literatures published from 2010 to 2023 that fulfilled a specific methodology which was developed as part of this study. The results revealed that supervised learning has been the most widely used Artificial Intelligence (AI) algorithm, primarily in the form of Support Vector Machine (SVM). The collected research indicated 20 countries represented in the publications, with China carrying out 32% of the research, followed by India with 10%. Regarding PD, the survey revealed that most researchers tend to investigate numerous types of PD and compare them to one another. Furthermore, the use of artificial PD defect models to simulate the occurrence of PD is widely used versus the use of actual power transformers. Most of the literature tends to not specify the physical characteristics of PD, such as the magnitude of PD, PD inception voltage and PD extinction voltage.

Keywords: partial discharge; transformer; machine learning; artificial intelligence

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1. Introduction

Insulation systems play a pivotal role in the proper functioning and long-term operation of high-voltage electrical equipment such as transformers, cables, switchgear, motors and generators [1,2]. Insulation systems in transformers are divided into liquid and solid insulation [3]. Oil makes up the liquid insulation [3–5], while solid insulation in transformers includes kraft paper [6,7], Nomex [8,9] and pressboard [9]. PD develops within the insulation systems of HV electrical equipment. These are localized electric discharges that can degrade the dielectric capability and lead to premature failure of the transformer [10,11].

While PD is a phenomenon that impacts all HV electrical equipment, such as gas-insulated switchgear, cables, motors, generators, etc., this systematic literature review places focus on electrical transformers. Transformers make up an essential part of an electrical reticulation or network, as they allow for efficient long-range interconnection of transmission lines while also ensuring that the voltage is transformed to the levels required by end users. The failure of a transformer results in the loss of power supply to portions of the electrical network, with potential costly damage as well as a loss of production or income for customers. Losses may also lead to long downtime as the manufacturing process of a large transformer can take more than 24 months. Monitoring PD in electrical transformers forms a great basis for planning essential preventative maintenance, which can prevent costly failures before they occur and allow the transformer owner to plan adequately and execute the most ideal maintenance during planned outages.

The emergence of Artificial Intelligence (AI) has allowed scholars to research possible means of improving the condition monitoring of equipment. The use of AI has been shown to greatly improve the time taken to analyze and classify PD in the monitored equipment, while also improving the accuracy of detection compared to manually performed analysis. Studies in the use of Machine Learning (ML) techniques for PD classification in transformers have been around for some time; however, this Systematic Literature Review (SLR) will be limited to the literature published between the years 2010 and 2023. Further restrictions were applied by discounting the literature about any HV electrical equipment other than electrical transformers, as well as disregarding other faults occurring in transformers but considering only partial discharge faults. The SLR presented a series of Research Questions (RQ) with the aim of identifying possible literature gaps within the study of automatic transformer partial discharge classification using machine learning algorithms, as well as to offer context to be utilized by the reader to develop future studies. The RQ are as follows:

1. RQ1: Which resource publication sources have been predominantly utilized in the literature to study the use of machine learning in monitoring electrical transformer partial discharge?
2. RQ2: From which countries do the publications on transformer partial discharge monitoring with the use of machine learning originate?
3. RQ3: How has the research on the automatic classification of transformer partial discharge using machine learning evolved over the period under review?
4. RQ4: Which partial discharge types does the collected literature investigate?
5. RQ5: From which sources were the partial discharge data used in the literature collected?
6. RQ6: Which PD measuring methods are used in the sampled literature?
7. RQ7: Which measuring equipment is used in the measuring of PD in the literature?
8. RQ8: Which national and international standards are referenced in the literature?
9. RQ9: Which feature extraction methods are mostly utilized in the collected literature?
10. RQ10: Which machine learning algorithms are the most utilized for monitoring partial discharge in electric transformers?
11. RQ11: What are the challenges that are experienced when utilizing machine learning in classifying transformer partial discharge as documented in the literature?
12. RQ12: What are the possible future research opportunities highlighted in the literature?

Additionally, the techniques utilized in this paper provide awareness to the reader on the different forms of PD occurring in transformers and how these are predominantly studied to aid in their own research. It further highlights the machine learning concepts currently being studied in transformer PD monitoring to aid in further development in this field.

2. Conceptualization of Partial Discharge in Transformers

The IEC 60270 standard defines partial discharge as a localized breakdown of the transformer solid or liquid dielectric material, which moderately bridges the conductors and may or may not occur close to a conductor [11]. PD mainly occurs due to nearby voltage stresses within the insulation or even on the surface of solid insulation, which results in a slow deterioration of the insulation material and reduces the life of the insulation in the transformer, which may ultimately cause complete insulation breakdown and premature failure of a transformer. It emerges as current pulses lasting much shorter than 1 μs; this is due to electric fields that are larger than the limit of the insulation and thus induce a partial breakdown of the local dielectric material [12]. The characteristics of PD result in the production of light, heat, sound, electromagnetic and chemical reactions [13] which contribute to further deterioration of the insulation material, but also provide means for sensing and monitoring the source and level of PD within a transformer by methods such as acoustic emission, optical, ultra-high frequency and electrical.

Three essential definitions related to PD as defined in [14] are apparent charge, PD inception voltage and PD extinction voltage. Apparent charge ‘q’ of a PD pulse amounts to the charge which, if introduced between the connections of the test object within a short duration of time, would yield the same voltage measurement across the terminals as the PD pulse itself, and is expressed in pico-coulombs (pC). The PD inception voltage (PDIV) is the smallest voltage at which the magnitude of a partial discharge pulse value is equivalent to or greater than a given low value. The PD extinction value (PDEV) is the smallest voltage at which the magnitude of a chosen PD pulse value is equivalent to or lower than a given low value. Furthermore, an equivalent circuit representing the PD activity is formulated using the premise of PD inception in a void. The PD results in a spark occurring inside the void, thus initiation the flow of current in the conductor. This equivalent circuit is represented by a capacitor ‘C3’, which is parallel to two other capacitors, ‘C1’ and ‘C2’, as shown in Figure 1. ‘C1’ and’C2’ form a voltage divider, with ‘C1’ representing the capacitance of the void while ‘C2’ is the capacitance in series with the void. ‘C3’ is the capacitances within the insulation.

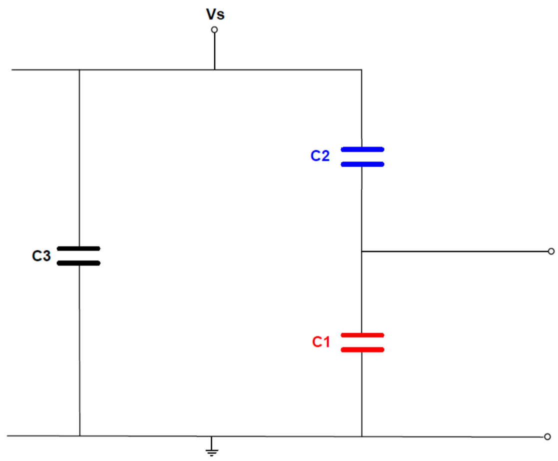

Figure 1. Partial discharge equivalent circuit.

The nature and form of electric transformers is that they are made up of a variety of insulation materials. Internally the transformers are filled with insulating oil which makes up the liquid insulation material. Solid insulation materials inside a transformer come in the form of Kraft paper which is primarily wrapped around the conductors to provide electrical insulation strength. Pressboard is also extensively utilized as insulation between layers of conductor, as well as to provide both electrical insulation and mechanical support for the transformer internals. Externally transformers have bushings; some house busbars within ducts while others utilize spacing as a form of isolation between phases. This broad variety of dielectric materials mean that transformers are also exposed to many forms of PD. Ref. [15] classifies PD occurring in transformers into five types, namely corona, surface discharge, internal discharge, electrical treeing and barrier discharge. Corona discharge occurs due to sharp live points which ionize a fluid dielectric such as air or oil. This can occur inside or outside the transformer on bare conductors or terminations. Surface discharge occurs in close proximity to the dielectric material, which is a result of a difference in electric field strength between the insulation and the barrier of the insulation material. Surface discharges are further influenced and propagated by pollution or contamination on the insulation material such as dust or water on bushing insulators. Internal discharges are created due to voids or cavities inside solid insulation material. These voids are generally formed during the manufacturing process and are impossible to eliminate. Electrical treeing is a form of defect propagation which occurs within solid insulation. These generally originate as insulation defects such as voids and spread through the material under high electric fields. The degradation of transformer cellulose insulation under the chemical processes of pyrolysis, hydrolysis and oxidation further results in the breakdown of compounds which are trapped in the transformer oil and thus tend to fast track other failure modes due to tracking.

The mechanisms used for detecting and monitoring PD are premised on the properties and physical characteristics that PD exhibit. Various detection methods and sensors have been developed with the aim of identifying the sounds, electromagnetic waves, optical waves and electrical pulses that are generated by the onset of PD. Some of the PD detection methods which are widely used include acoustic emission, electrical, optical, electromagnetic and ultra-high frequency. Acoustic emission entails the conversion of pressure waves—which can or may not include sound and are created by the mechanical force at the location of the PD pulse [16]—into electrical signals which can be detected via a dedicated acquisition system. Benefits of the acoustic emission method are that it can be used for PD detection both inside and outside a transformer by means of multiple acoustic sensors placed at strategic locations. It is capable of detecting multiple PD sources, as well as detecting the location of the PD by the use of Time Delay of Arrival difference between the sensors. Electrical detection method is the most widely used method and involves the detection of the current pulse generated by the PD. This method employs either a direct probing or RF emission. Direct probing requires capacitive couplers to be connected to the phase terminals of the transformer, while RF uses antennas for the detection. Both these detection methods are highly susceptible to noise, and require careful setup and calibration in industrial use. The optical detection method relies on the presence of light created due to a spark. This method works well for detecting corona discharge but falls short when it comes to internal discharge. The method utilizes optical sensors, with advancement in these sensors allowing for PD detection both in air and oil [16].

3. Materials and Methods

This systematic literature review (SLR) commences by defining the topic, then developing clear research questions with an emphasis on answering pertinent literature gaps. A search methodology to collect the literature which falls within the defined topic then ensues, which is followed by developing an inclusion and exclusion criterion which will be used to form a decision regarding the literature to be considered. The required data is collected from the literature. This data is utilized to assess the research development in the field at hand. The flow diagram shown in Figure 2 details the steps of the SLR as compliant to [17].

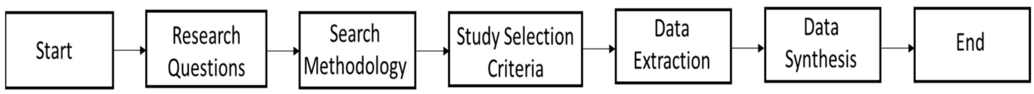

Figure 2. SLR flow diagram.

Proposed Inclusion and Exclusion Criteria

Table 1 sets out the criteria used to determine which of the literature from the publication sources would be included and which would be excluded from the review. This is to ensure that the literature utilized for the review aligns with the focus of this research.

Table 1. Inclusion and Exclusion Criteria.

Criteria	Inclusion Criteria	Exclusion Criteria
Topic	Scholarly work must be about the use of machine learning in the classification of partial discharge in electric transformers.	Articles that do not relate to machine learning, partial discharge or electric transformers, and do not include machine learning.
Research Framework	Work must include a research framework or methodology.	Articles without a clear research framework.
Language	Articles are written in English.	Articles written in any other language other than English
Publication Period	Articles published between 2010 and 2023.	Articles published before 2010
Publication Type	Articles published by reputable publishers.	Work that is not formally published.
Topic	Scholarly work must be about the use of machine learning in the classification of partial discharge in electric transformers.	Articles that do not relate to machine learning, partial discharge or electric transformers, and do not include machine learning.

4. Recent and Related Research Works

Employing machine learning techniques has proven to greatly improve the classification and recognition of different types of partial discharge mechanisms occurring in different parts of power transformers, both inside and outside, and in oil or air. Table 2 shows a collection of literature analyzing the use of machine learning algorithms to classify PD in power transformers.

Table 2. Transformer PD Literature.

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[18]	2016	Energies Journal	Artificial Neural Network	Artificial PD Defect Model	Focuses on reviewing the published literature on the use of ANN for partial discharge pattern recognition and proposes improvements such as establishing the optimal training weights, use of extensive PD data for training, recognition of different levels of PD degradation as well as techniques to shorten training time.
[19]	2022	Energies Journal	Support Vector Machine, K-Nearest Neighbors, Naïve Bayes, Classification, Random Forest, Probabilistic Neural Network	Not specified	Analyses eight partial discharge classes occurring in transformer solid and liquid insulation systems in a laboratory setup measured with the use of acoustic emission techniques. PD data is analyzed with five different classification algorithms and the results are compared against one another.
[20]	2015	IEEE Electrical Insulation Conference	Deep Neural Network	Not specified	Illustrates the improvements in partial discharge diagnostic accuracy which can be attained by the application of deep neural networks.
[21]	2020	Energies Journal	Convolutional Neural Network	PD images	Presents the application of a neural network based on the CNN architecture to partial discharge images to diagnose the aging of electrical insulation.
[22]	2010	International Symposium	Support Vector Machine, Probabilistic Neural Network	Experimental setup	Compares the performance of two partial discharge classification methods, namely SVM and PNN, on four PD sources to determine the classification accuracy.
[23]	2019	IEEE Transactions on Power Delivery	Deep learning	Artificial PD Defect Model	Explores a novel approach of using PD current as input signal from four kinds of PD defects, while implementing two dimensionality reduction techniques, PCA and T-SNE, to the data to improve classification accuracy.
[24]	2019	IEEJ Transactions on electrical and electronic engineering	Support Vector Machine	Solid insulation	Utilizes a Weibull distribution-based method on the PD of a power transformer oil–paper insulation to determine the remaining service life of the transformer.
[25]	2019	Energies	Deep neural network, Convolutional Neural Network	Scholarly works	Reviews the progress made on the use of deep learning artificial intelligence methods for the automatic identification of partial discharge in transformers over the period between 2015 to 2023.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[26]	2014	IEEE Transactions on Power Delivery	Neuro-Fuzzy Technique	Power transformer	Introduces a neuro-fuzzy PD recognition technique on a medium voltage transformer to enhance the recognition accuracy compared to orthogonal transforms and calibration line methods for the main types of PD.
[27]	2020	IEEE Transactions on Dielectric and Electrical Insulation	Probabilistic Neural Network, Support Vector Machine	Scholarly works	Presents a review of the literature on conventional machine learning algorithms applied to PD diagnostics, with a focus on input signals, sampling rates, core methodologies and recognition accuracies.
[13]	2021	IEEE Access	Artificial Neural Network	Transformer bushing	Reviews PD detection, localization and severity with the use of machine learning techniques, then draws on the advantages and disadvantages of the various PD detection methods.
[28]	2020	Alexandria Engineering Journal	Artificial Neural Network	Experimental setup	Employ several acoustic sensors, strategically positioned at pre-specified locations of a transformer, and the time difference of arrival (TDOA) of the signals to enhance determining the location or source of PD.
[29]	2017	BDCAT Conference	Support Vector Machines, Random-Forest, Logistic Regression, Fussy Support Vector Machine, Gradient Boosting	Experimental setup	Introduces a stacking ensemble strategy to four types of PD data and illustrates the accuracy improvement from 99.31% to 99.61% over existing classification methods.
[30]	2014	IET Generation, Transmission and Distribution	Probabilistic Neural Network	Experimental setup	Researches the use of a multivariate denoising tool to enhance the overall correctness of single and multiple partial discharge sources where PD data is collected with the use of a UHF sensor.
[31]	2013	Conference on Electrical Insulation and Dielectric Phenomena	Support Vector Machine	Artificial PD Defect Model	Develops a hybrid discrete wavelet transform algorithm to target the classification of multiple PD sources occurring in the same data sample.
[32]	2019	IEEE Transactions on Power Delivery	Support Vector Machine	Artificial PD Defect Model	Employs Local Binary Pattern (LBP) and Histogram of Oriented Gradient (HOG) techniques to extract image features from greyscale images which are used for PD pattern recognition.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[33]	2015	IEEE Transactions on Dielectrics and Electrical Insulation	Support Vector Machine	Experimental setup	Addresses the issue of classifying varying PD types collected via acoustic emission under differing measurement conditions such as PD source location, oil temperatures and barrier insertion.
[34]	2017	Energies Journal	Artificial Neural Network, Fuzzy Logic	Artificial PD Defect Model	Compares the accuracy of artificial neural networks and Fuzzy logic in recognizing different partial discharge sources.
[35]	2013	Electrical Power and Energy Systems	Support Vector Machine	Experimental setup	Utilizes multiple optical sensors inside a steel tank in a laboratory setup to develop a method of identifying single and multiple partial discharge sources.
[36]	2011	Energies	Improved Bagging Algorithm, Support Vector Machine, Back Propagation Neural Network	Experimental setup	Introduces an Improved Bagging Algorithm (IBA) which enhances the generalization capability and improves the accuracy of the Backpropagation neural network.
[37]	2013	IEEE Transactions on Dielectrics and Electrical Insulation	Bayesian networks, k-nearest Neighbors, Multi-layer perceptron, Fuzzy Support Vector Machine	Artificial PD Defect Model	Investigates three challenging issues linked to the automatic classification of artificial PD sources, namely acquiring symbolic characteristics using feature extraction, identifying different types of PD using pattern recognition algorithms and identifying multiple PD sources.
[38]	2018	IET Science, Measurement and Technology	Kernel partial least squares regression (KPLS)	Artificial PD Defect Model	Introduces the variable predictive model-based class discrimination (VPMCD) method which is based on kernel partial least squares (KPLS) regression to exploit the inter-relations of extracted features of PD signals.
[39]	2018	Energies	One Class Support Vector Machine	Power Transformer	Researches the use of a One-Class Support Vector Machine (OCSVM) as an alternative to the binary SVM for PD assessment, indicating the benefit of noise-eliminating capabilities for PD assessment.
[40]	2018	IET Science, Measurement and Technology	Support Vector Machine	Test transformer	Develop a method of identifying unknown partial discharge patterns utilizing an improved Support Vector Data Description (SVDD). This method produces higher recognition accuracy, is more efficient and can be used to recognize unknown PD types where regular supervised algorithms fall short.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[41]	2021	Energies	Artificial Neural Network	Artificial PD Defect Model	Adopts the use of long short-term memory neural networks to solve the issue of overlapping partial discharge types, achieving 99% accuracy on single class recognition and 43% for multiclass.
[42]	2017	Entropy	Artificial Neural Network	Transformer bushing	Proposes a new feature extraction method which is derived from Ensemble Empirical Mode Decomposition (EEMD) and Sample Entropy (SamEn) achieving satisfactory recognition results experimental data.
[43]	2022	International conference on power and energy systems engineering	Not specified	Artificial PD Defect Model	Manufactures an optical PD detection device for the detection of PD occurring inside a transformer, thus evaluating the advantages of optical detection over other PD detection methods such as UHF, ultrasonic, etc.
[44]	2022	Energies	k-Nearest Neighbors	Experimental setup	Utilizes four different types of UHF antennas to research their influence on the efficacy of partial discharge classification in a transformer.
[45]	2023	Applied Science	Convolutional Neural Network	Artificial PD Defect Model	Develop a novel partial discharge recognition algorithm which deals with the shortfalls of common artificial intelligence systems, such as complexity, high power requirements, high memory use and cost.
[46]	2010	International Conference on Machine Learning and Cybernetics	Artificial Neural Network	Power Transformer	Proposes a novel PD pattern recognition tool utilizing 3D patterns and PD fingerprints that can be easily implemented on MATLAB software (https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5580736, accessed on 25 October 2023). The novel system achieves better recognition rates than current methods.
[47]	2016	IET Science, Measurement and Technology	Decision Tree	Experimental setup	Studies the use of Acoustic sensors for measuring and distinguishing between different types of partial discharges occurring in transformer oil–paper insulation. Classification is improved however the sensors still have limitations due to the environment.
[48]	2020	IEEE Access	Convolutional Neural Network	Artificial PD Defect Model	Applies a Convolutional Neural Network method to six transformer-based partial discharge faults and achieves an improvement of 18.78% over the performance of SVM.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[49]	2021	Applied Science	Support Vector Machine	Experimental setup	Offers a novel MobileNets Convolutional Neural Network method for recognition of partial discharges in transformers, reduces complexity, increases speed and obtains improved classification performance.
[50]	2020	Energies	Convolutional Neural Network, long-term, short-term memory network	Transformer model	Develops a PD pattern recognition tool predicated on convolutional neural network and long short-term memory (LSTM) network to achieve better overall performance on recognition of PD patterns for floating defects, metal protrusion, void and surface discharge compared to the common CNN.
[51]	2018	IEEE/PES Transmission and Distribution Conference and Exposition	Online sequential extreme learning machine (OS-ELM)	Power Transformer	Tackles the limitations of traditional partial discharge recognition algorithms by producing a novel Online Sequential Extreme Learning Machine (OS-ELM) which can produce faster learning speed, higher recognition accuracy and improved stability for large data samples.
[52]	2016	Expert Systems with applications	Support Vector Machine	Transformer parts	Investigate the use of a support vector machine to distinguish between multiple types of partial discharge in a noisy environment.
[53]	2019	Conference on Dielectric Liquids	Random Forest, Support Vector Machine, Linear Discriminant, k-nearest Neighbors	Experimental setup	Presents the use of Random Forest algorithm for transformer partial discharge recognition which is compared to classification performed by other machine learning techniques. Random Forest achieved the highest accuracy with 94.44% followed by cubic SVM and LD at 83.33% and 77.78%, respectively.
[54]	2021	IET Generation, Transmission and Distribution	Support Vector Machine	Experimental setup	Utilizes an image-based feature extraction method based on upright speed-up features resulting in increased accuracy and better noise handling.
[55]	2018	IEEE International Conference on Industrial and Information Systems	Support Vector Machine	Artificial PD Defect Model	Develops a Time-frequency classification method with the use of UHF PD signals collected from transformer oil and accuracy tested with different barriers and spacing between sensors.
[56]	2019	2nd International Symposium on big data and applied science	Deep Forest	Artificial PD Defect Model	Proposes the use of deep learning methods for automatic feature learning and pattern recognition as a replacement for classical feature extraction required when using shallow neural networks.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[57]	2019	IP Conference series	Random Forest	Scholarly works	Examines the application of Random Forest algorithm for transformer PD recognition which achieves higher recognition accuracy compared to SVM and kNN when tested using the tenfold method.
[58]	2021	IET Science, Measurement and Technology	Support Vector Machine	Artificial PD Defect Model	Extracts partial discharge adaptive features by employing a stacked auto-encoder algorithm to address the obstacles facing pattern recognition of multisource partial discharges.
[59]	2021	Energies	Convolutional Neural Network	Artificial PD Defect Model	Researches the use of single-source PRPD patterns to train a convolutional neural network model and tests the model on single and multi-source PD patterns which results in an improvement from 77.3% to 99.6% for multi-source PDs over traditional CNN architecture.
[30]	2014	EIT on Transmission and Distribution	Support Vector Machine	Scholarly works	Focuses on the use of UHF signals to detect single and multiple PD sources of the void and floating metal types, then applies denoising methods before extracting the appropriate features. Then proves this as a capable technique which can be used for classification.
[60]	2020	IEEE Transactions on Instrumentation and Measurement	Isolation Forest	Experimental setup	Introduces a PD separation methodology using linear prediction analysis (LPA) and isolation forest algorithm (IFA) which proves successful in distinguishing between multisource PD signals in a 35 kV transformer during testing.
[61]	2020	International Automatic Control Conference	Clustering Decision Tree	Power Transformer	Proposes a PD identification system which integrates the decision tree and the clustering scheme for use in cast-resin transformers. The performance of the new system is compared to the Weka method and attains superior classification error rates.
[62]	2019	Sensors	Support Vector Machine, k-Nearest Neighbors	Power Transformer	Develops a method of classifying different fault signals, including PD inside a transformer with the use of data collected via acoustic emission signals. The developed algorithm achieves classification accuracies above 98%.
[63]	2018	2nd Conference on Energy Internet and Energy System Integration	Extreme Learning Machine, Sparse self-encoder	Artificial PD Defect Model	Achieves improved PD pattern recognition accuracy as well as increased training speed by utilizing sparse self-coding and extreme learning machine networks.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[64]	2018	Energies	Least Squares Support Vector, Random Forest	Solid insulation	Investigate the characteristics of PD occurring in the oil-pressboard of converter transformers under both AC and DC voltage, then utilize random forest for defect recognition and ultimately discuss the comparison in performance between LSSV and RF.
[65]	2018	Electric power systems research	Multiple Linear Regression	Experimental setup	Proposes new methodologies for generating and locating high-frequency experimental PD current pulses based on multiple linear aggression models.
[66]	2012	IEEE Transactions on dielectrics and electrical insulation	Not specified	Experimental setup	Utilizes an inductive loop sensor to analyze wave energy distribution and differentiate between two PD sources occurring in transformer oil–paper insulation systems.
[67]	2020	International journal of emerging trends in Engineering Research	Not specified	Not specified	Demonstrates the performance of the acoustic emission method for recognition and classification of three different PD sources produced in a prototype transformer, then utilizes spectral analysis to show the frequency range of each PD source.
[68]	2016	IEEE Transactions on Dielectrics and Electrical Insulation	fuzzy k-nearest Neighbor, Back-propagation neural network, Support Vector Machine	Artificial PD Defect Model	Utilizes image-oriented feature extraction and selection algorithms on PD data thereby improving the classifier accuracy by an average of 5% to 7% compared phase resolved partial discharge patterns of the same PD data.
[69]	2016	IET Science, Measurement and Technology	Support Vector Machine	Artificial PD Defect Model	Simulates five partial discharge sources inside a transformer model and extracts features via PCA which are applied to the SVM algorithm for classification. The results indicate an accurate classification of the five PD patterns.
[70]	2012	IET Science, Measurement and Technology	Modified binary partial swarm optimization	Power Transformer	Develops a novel modified binary partial swarm optimization (MBPSO) method used to localize PD sources of an arc furnace transformer from a steel company. The efficiency of the algorithm is found to be comparable to existing algorithms.
[71]	2018	Condition Monitoring and Diagnosis	Deep Neural Networks, Convolutional Neural Network	Simulation	Proposes new transformer PD fault identification methods, with PD data collected via ultrasonic testing, and features classified by Recurrent Neural Network, Deep Neural Network and Convolutional Neural Network. CNN achieves the best average accuracy of 99.82%.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[72]	2019	IET High Voltage	Artificial Neural Network	Experimental setup	Uses Artificial Neural networks to Classify different discharges on outdoor insulators which were tested with the use of acoustic sensors. The results are compared to controlled samples tested in a laboratory and both achieve recognition rates higher than 85%.
[73]	2018	IET Science, Measurement and Technology	Support Vector Regression, Artificial Neural Network	Experimental setup	Examines the use of a system of low-cost radio sensors for continuous partial discharge monitoring and develops models based on support vector regression and least squares support vector regression (LSSR), with LSSVR being the recommended algorithm due to its low complexity.
[47]	2018	Analytics for Renewable Energy Integration	Convolutional Neural Network, Random Forest, Decision Tree, Support Vector Machine	Experimental setup	Compares the classification performance of deep learning to traditional methods on three different partial discharge types which were collected using acoustic emission sensors on a transformer.
[74]	2023	IEEE Transactions on Power Delivery	Ridge Regression	Artificial PD Defect Model	Investigates partial discharges due to repetitive impulse excitation occurring in power electronic devices. The PD data is measured with the use of UHF sensors and processed with a ridge regression classifier improving accuracy to 98.6% over classical deep learning models.
[75]	2013	IEEE 1st International Conference on Condition Assessment Techniques in Electrical Systems	Support Vector Machine	Artificial PD Defect Model	Utilizes PCA to extract features from phase-resolved partial discharge patterns which are used as input to support vector machine algorithm for classifying PD data of six PD types. The highest classification results are achieved on corona discharge, discharge in oil and particle movement discharge, each at 100% accuracy.
[46]	2010	Proceedings of the ninth international conference on machine learning and cybernetics	Artificial Neural Network	Power Transformer	Suggests a four-layer artificial neural network model for transformer partial discharge pattern recognition which is applied to field transformers. The proposed pattern recognition approach improves the overall recognition rate from 88.25% to 95.25% over current methods.
[76]	2023	8th International Conference on Control and Robotics Engineering	Convolutional Neural Network, Support Vector Machine	PD images	Evaluates the use of a convolutional neural network for PD recognition versus traditional methods which include feature extraction steps. The results indicate that the proposed method can classify different types of PD.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[77]	2022	4th International conference on Applied machine learning	Deep learning	Power Transformer	Presents the use of a deep learning model for transformer partial discharge fault identification thus achieving classification accuracy of up to 99.31%, 97.92% and 93.75% on the training set, validation set and test set, respectively.
[78]	2022	6th International conference on condition assessment techniques in electrical systems	Artificial Neural Network, Support Vector Machine, Random Forest	Artificial PD Defect Model	Analyzes four different types of PD and classifies it using artificial neural network, support vector machine and random forest. 100% accuracy is achieved for corona defects with SVM and RF.
[79]	2021	Electrical insulation conference	Generative adversarial network	Artificial PD Defect Model	Develop digital twins with the use of generative adversarial networks to identify incipient discharges occurring within defects in transformer insulation systems. The UHF signal discharges can simulate the digital twin of the transformer however more studies are required to understand the classification accuracy.
[80]	2023	IEEE Transactions on Plasma Science	Deep learning	Experimental setup	Looks into the detection and identification of poor PD signals in noisy environments by utilizing implantable optical detection tools, optical emission spectroscopy and ultraviolet monitoring. The collected PD data is fed to a deep learning model to determine the recognition and classification accuracy. The Developed model achieves a precision of 100% and an accuracy of 99%.
[81]	2022	Security and Communication Networks	Convolutional Neural Network	Simulation	Combines the benefits of artificial neural networks with accurate feature extraction to produce a novel transformer PD pattern recognition model and proves the value of applying the model to practice.
[82]	2022	Intelligent Automation and soft computing	Convolutional Neural Network	Artificial PD Defect Model	Proposes a deep learning-based partial discharge classification algorithm which addresses the disadvantages of traditional algorithms, which include the generation of high dimensional data as well as the need for additional steps required in the processing which results in high memory requirements as well as slower process times and higher costs.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[83]	2023	Energies	Support Vector Machine, k-Nearest Neighbor	Power Transformer	Suggests the use of kNN and SVM techniques for imputing missing DGA data of a PD source, resulting in enhanced accuracy and precision when contrasted to methods lacking data imputation.
[84]	2021	IEEE Access	Random Forest, k-Nearest Neighbors, Support Vector Machine, Artificial neural network, Naïve Bayes, AdaBoost	Dissolved Gas Analysis	Applies several artificial intelligence algorithms to tackle the shortcomings of handling data uncertainty in the transformer health index. Random Forest models provide a higher accuracy at 97%.
[85]	2014	IEEE Transactions on Instrumentation and Measurement	Support Vector Machine	Experimental setup	Proposes a novel multichannel instrumentation system of PD location in transformers based on acoustic emission detection with the use of piezoelectric and optic sensors.
[74]	2014	IEEE Transaction on Dielectrics and Electrical Insulation	k-Nearest Neighbors	Power Transformer	Utilizes copper coil radio frequency sensors to detect PD in a transformer which provides a simple and reliable online PD detection and localization method.
[86]	2018	IET Science, Measurement and Technology	Artificial Neural Network	Transformer model	Places focused on the catadioptric phenomenon of acoustic emission wave propagation do develop the reduction of PD localization errors in power transformers.
[87]	2023	ResearchGate	Convolutional Neural Network, Support Vector Machine	Artificial PD Defect Model	Introduces a multi-dimensional intelligent state model composed of CNN-SVM mode to overcome the low recognition accuracy of single intelligent state recognition models. The accuracy and consistency of the model are improved by 3.33% and 16.66%, respectively.
[88]	2012	2018 Condition Monitoring and Diagnosis	Artificial neural network	Artificial PD Defect Model	Utilizes waveform parameters and PD patterns from four artificial PD sources collected with the use of the types of sensors to develop an artificial neural network algorithm for the classification of PD sources in a transformer, achieving recognition rates between 90% and 96%.
[89]	2022	Journal of Soft Computing Paradigm	Support vector machine, Convolutional neural network	Simulation	Employs the phase-amplitude response of PRPD patterns which are classified using a convolutional neural network to diagnose partial discharge of a 132/11 kV and a 132/25 kV transformer.

Table 2. *Cont.*

Ref. Year	Year	Data Source	ML Algorithm	PD Source	Summary
[90]	2023	Sensors	Convolutional neural network	Power Transformer	Analyses partial discharges occurring within bubbles in transformer insulation mineral oil with the use of a CMOS image sensor. Developing a classification method which achieves a classification accuracy of 95% for the validation set and 82% for the test set.
[91]	2020	IEEE Conference on Electrical Insulation and Dielectric Phenomena	Support Vector Machine	Artificial PD Defect Model	Proposes the classification of different partial discharges occurring in outdoor electric insulators with the use of different machine learning algorithms and achieves a 93% recognition rate for five PD defects using SVM with RBF kernels consistently achieving the highest recognition rates.
[92]	2010	IEEE Transactions on Dielectrics and Electrical Insulation	Support Vector Machine	Artificial PD Defect Model	Studies the use of a wide bandwidth PD measurement system which includes a radio frequency current transducer sensor to perform online automatic PD source identification.
[93]	2021	International Conference on Artificial Intelligence and Smart Systems	Support Vector Machine	Artificial PD Defect Model	Demonstrates a new technique for partial discharge prediction with the use of a Deep Learning algorithm and tests it on void, corona and surface discharges occurring in transformer insulation systems.

Table 2 possesses a collection of the recent literature in the research of automatic transformer PD classification using machine learning algorithms. The table provides a background of each of the collected literatures together with a summary of the research contents and the primary focus placed by the researchers. However, the literature of Table 2 provided much more knowledge, data and findings into available gaps in the literature from the research, employing different classes of machine learning algorithms. While great strides have been made regarding the use of ANNs for PD classification, ref. [18] expresses the lack of research on the utilization of ANNs for discerning the source positioning of PD. This introduces a literature gap, as the characteristics of PD sources may vary based on their position and whether it is a single- or multiple-source PD [18]. Most of the investigated literature utilizes PD data from experimental setups performed over a limited amout of time. This results in a lack of generality as PD patterns change over time. This therefore provides an opportunity for researchers to classify and compare the development of PD over much longer periods of time. Further to this, there is a greater need for use of onsite PD data taken under normal conditions in the presence of noise and electromagnetic disturbances in order to further upgrade the developed models. A common shortcoming of deep neural networks is that they are time-consuming due to their dependence on the back propogation algorithm. There is a necessity for improved and easier approaches to be developed which will result in reduced training times [18,20].

The literature indicates research to further improve the performance of traditional machine learning algorithms. These include combining multiple ML algorithms as indicated by [83], where kNN is combined with SVM to input missing values. Ref. [50] constructs a convolutional neural network and a long–short memory hybrid method which is tested on UHF PD signals, while [32] combines local binary pattern and histogram of oriented gradient to extract features form PD images. These are proving to be promising methods, for which the literature proposes further research.

4.1. Literature Sources and Search Techniques

The literature to be reviewed was collected from reputable online research repositories. An extensive search was conducted on scholarly works published on the following online repositories: Google Scholar, IEEE Explore, Science Direct, Springer Link, Wiley Online Library, Academia, Research Gate and Multidisciplinary Digital Publishing Institute (MDPI). A set of keywords relating to the SLR research topic was utilized to maximize the relevant results while also reducing the return of unnecessary or unrelated literature. Table 3 presents the list of keywords employed in searching for the literature.

Table 3. Proposed Keyword Search.

Keyword Search
"Machine learning"
"Transformer" "Transformer condition monitoring"
"Partial discharge" "PD"
"Artificial intelligence"

Bearing in mind that the search keywords produce the basis for obtaining the applicable literature, the appropriate selection of keywords is crucial for the collection of literature in the SLR. A custom range is applied to the search to limit the results to the period between 2010 and 2023. This search brought forward a total of 21,812 scholarly works across the seven online repositories. Of these, 21,668 research papers were automatically eliminated on initial screening; therefore, 144 research papers were downloaded as part of the survey. Applying the inclusion and exclusion criterion shown in Table 1 to the 144 research papers resulted in the elimination of 63 papers and a total of 81 scholarly works qualified to be used in this survey. Table 4 shows the list of online repositories that were utilized as well as the total number of results achieved before the initial screening.

Table 4. Results achieved from literature search.

No.	Online Repository	Number of Results
1	Google Scholar	16,529
2	Multidisciplinary Digital Publishing Institute (MDPI)	260
3	IEEE Explore	233
4	Springer Link	3904
5	ResearchGate	43
6	Science Direct	715
7	Wiley Online Library	128
Total		21,812

The process used for performing this SLR is a Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) flowchart, shown in Figure 3.

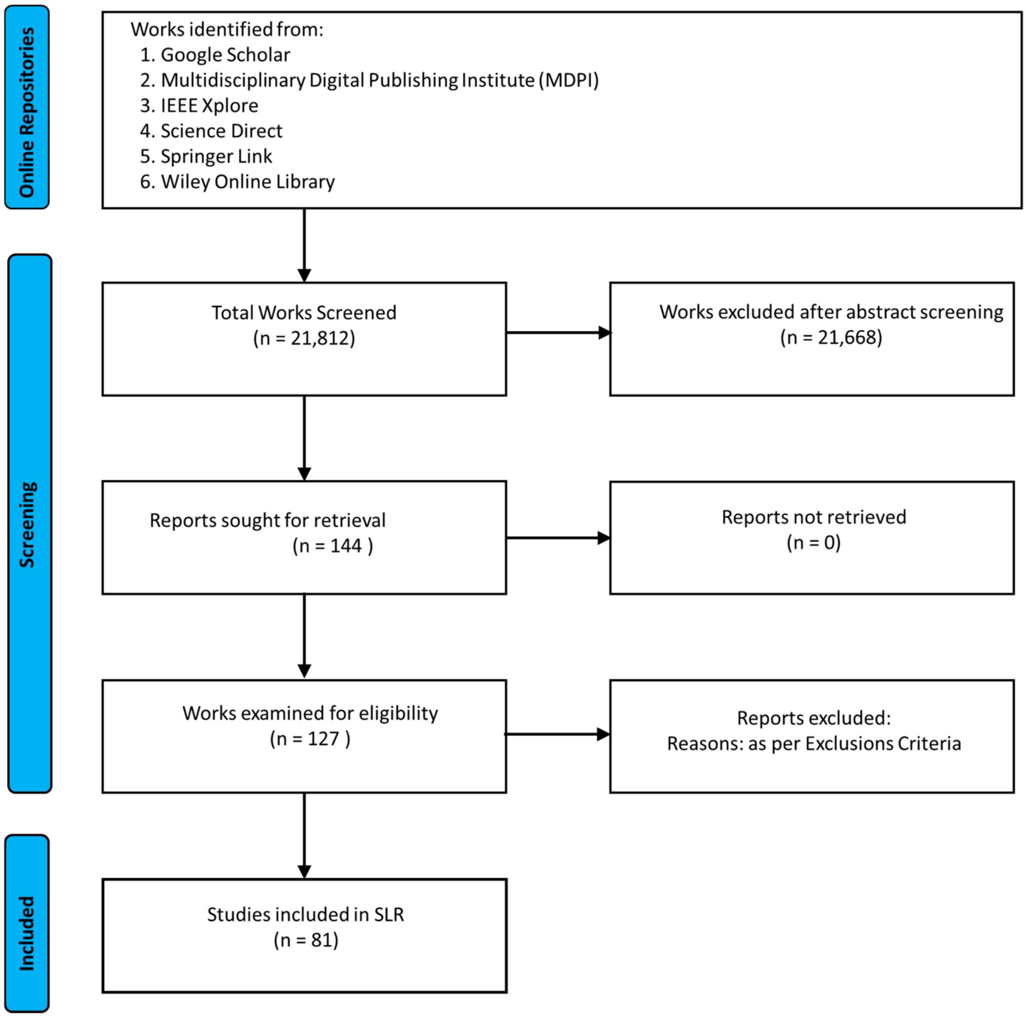

Figure 3. Suggested PRISMA flowchart.

4.2. Quality Assessment

The collected literature was subsequently evaluated on criteria based on a set of five quality assessment (QA) checks as listed below:

QA1: Is the aim of the research explicitly stated?
QA2: Does the research clearly specify the data collection methods?
QA3: Is the PD classification process clearly stipulated?
QA4: Is there a clear research methodology utilized in the research?

QA5: Do the research findings contribute to improvement of the literature?

The responses to the QAs are rated on a scale between zero (0) and one (1), with a 'No' response assigned '0' points, a score of '0.5' given where the criteria is 'Partially' met and '1' point assigned to a 'Yes'. All five QAs are scored using this criterion. Each of the literature under review can receive a between 0 and 5 points. The results of the QA for the collected literature are tabulated in Table 5 below.

Table 5. Collected Literature Quality Assessment Results.

Study	QA1	QA2	QA3	QA4	QA5	Total	%
1	1	0.5	0	1	1	3.5	70
2	1	1	0	1	1	4	80
3	1	1	1	1	1	5	100
4	1	1	1	1	1	5	100
5	0.5	1	1	1	1	4.5	90
6	0.5	1	1	1	1	4.5	90
7	0.5	1	0	1	1	3.5	70
8	0.5	1	1	0.5	0.5	3.5	70
9	0.5	1	1	1	0.5	4	80
10	1	0.5	0.5	1	0.5	3.5	70
11	1	0.5	0.5	1	1	4	80
12	1	1	1	1	0.5	4.5	90
13	0.5	0.5	0	0.5	0.5	2	40
14	1	1	1	1	0.5	4.5	90
15	1	1	0.5	1	0.5	3.5	70
16	1	1	1	1	1	5	100
17	1	1	1	1	0.5	4.5	90
18	0.5	1	1	1	1	4.5	90
19	1	1	1	1	1	5	100
20	0.5	1	0.5	1	0.5	3.5	70
21	0.5	1	1	1	0.5	4	80
22	1	1	1	1	0.5	4.5	90
23	1	1	1	1	1	5	100
24	1	1	1	1	1	5	100
25	0.5	1	1	1	0.5	4	90
26	0.5	1	0.5	1	0.5	3.5	70
27	1	1	0	1	0.5	3.5	70
28	0.5	1	0.5	1	0.5	3.5	70
29	1	1	1	1	0.5	4.5	90
30	0.5	1	1	1	1	4.5	90
31	1	1	0.5	1	0.5	4	80
32	1	1	1	1	0.5	4.5	90
33	0.5	1	1	1	0.5	4	80
34	0.5	1	1	1	0.5	4	80
35	1	1	0.5	1	0.5	3.5	70
36	1	1	0.5	1	1	4	80
37	0.5	1	1	1	0.5	4	80
38	1	1	0.5	1	0.5	4	80
39	0.5	1	1	1	0.5	4	80
40	1	1	0.5	1	0.5	4	80
41	0.5	0.5	1	1	0.5	3.5	70
42	1	1	1	1	0.5	4.5	90
43	0.5	1	1	1	1	4.5	90
44	0.5	0.5	1	1	0.5	3.5	70
45	1	1	0.5	1	0.5	4	80
46	1	0.5	1	1	0.5	4	80
47	1	1	0.5	1	1	4.5	90
48	1	1	1	1	0.5	4.5	90
49	0.5	1	1	1	1	4.5	90
50	1	1	1	1	1	5	100

Table 5. *Cont.*

Study	QA1	QA2	QA3	QA4	QA5	Total	%
51	0.5	1	0.5	1	0.5	3.5	70
52	0.5	1	0.5	1	0.5	3.5	70
53	1	0.5	1	1	1	4.5	90
54	0.5	1	1	1	0.5	4	80
55	0.5	1	1	1	0.5	4	80
56	1	1	1	1	0.5	4.5	90
57	1	1	1	1	0.5	4.5	90
58	1	1	1	1	1	5	100
59	1	1	1	1	1	5	100
60	1	1	1	1	1	5	100
61	0.5	1	1	1	0.5	4	80
62	1	1	1	1	1	5	100
63	1	0.5	1	1	0.5	4	80
64	1	1	1	1	0.5	4.5	90
65	0.5	1	1	1	0.5	4	80
66	1	1	0.5	1	0.5	4	80
67	1	1	1	1	1	5	100
68	1	0.5	1	1	1	4.5	90
69	0.5	1	1	1	0.5	4	80
70	1	0.5	1	1	0.5	4	80
71	1	0	0.5	1	0.5	3	60
72	1	1	0.5	1	0.5	4	80
73	1	1	0.5	1	0.5	4	80
74	1	1	0.5	1	0.5	4	80
75	0.5	1	1	1	1	4.5	90
76	0.5	1	1	0.5	0.5	3.5	70
77	1	1	1	1	1	5	100
78	0.5	1	1	1	0.5	4	80
79	0.5	0.5	1	1	0.5	3.5	70
80	1	1	1	1	0.5	4.5	90
81	0.5	1	1	1	1	4.5	90

5. Results

The literature collected after the PRISMA flowchart is used to formulate the responses to the twelve research questions developed in Section 1 concerning transformer partial discharge classification using machine learning algorithms.

RQ1: Which resource publication sources have been predominantly utilized in the literature to study the use of machine learning in monitoring partial discharge in electrical transformers?

Figure 4 shows the literature published in journals to greatly dominate the publications of scholarly works on using machine learning algorithms for the classification of partial discharge in electric transformers. From analysis of the collected literature, 56 of the 81 literatures under review were journal papers; this makes up more than double the number of conference papers, which account for only 25 publications in the period under review. This indicates a vast preference for scholars to publish their works in journals.

RQ2: From which countries do the publications on transformer partial discharge monitoring with the use of machine learning originate?

The representation of countries in the study of using machine learning techniques for classification of partial discharge in transformers was found to be wide, with 20 countries being represented in the collected literature published between 2010 and 2023. This indicates that this is a field of study that has gained interest worldwide, but also indicates the importance that scholars and users have placed on monitoring and understanding the health of their transformers. The motivation for these countries to invest in research can be related to the need to reduce costly transformer failures, extend the life of their assets, improve condition monitoring, adequately improve planned maintenance and eliminate grid failures which can have massive economic impacts.

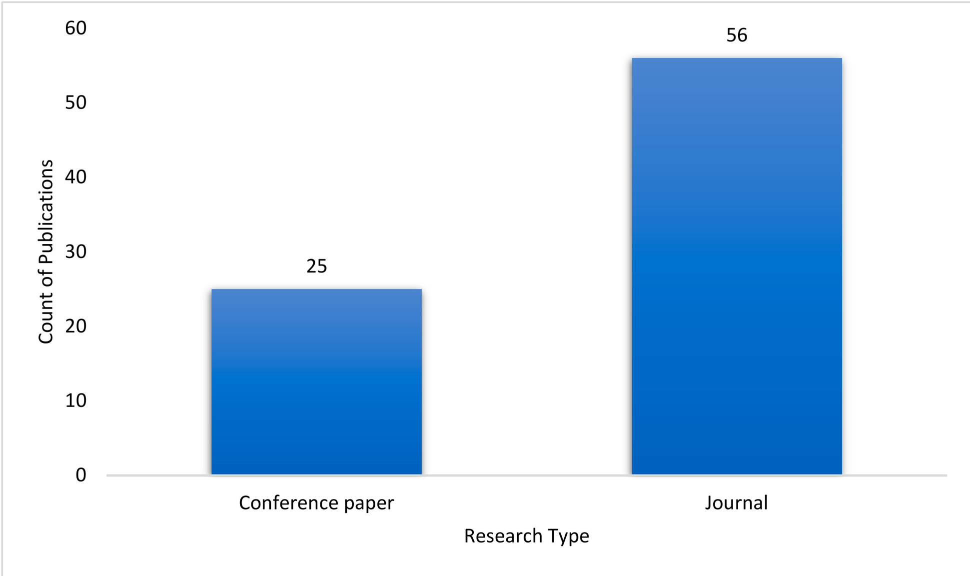

Figure 4. Research publication sources.

From the 20 countries represented in the literature, it can be seen in Figure 5 that China has contributed most of the literature at 32%. The superiority of China in this research indicates a continued sign of China's active investment and contribution to the advancement of technology in the field of artificial intelligence. When it comes to the field of power transformers and partial discharge, it can be attributed to the large landscape of China, the economy which has been one of the fastest growing in recent years and the economy's reliance on a reliable electrical grid. China is currently the largest producer of electricity with 8534 TerraWatt-hours of electricity produced in 2021 according to [94]. This made up 30% of the entire world's electricity production in 2021. The research places India in second position with 10% of the publications, Spain in third with 7% and closely followed by Indonesia with 6%. Although India only produced 6% of the total electricity in 2021, the electricity production grew by 10% in that year, which was equal to China's growth.

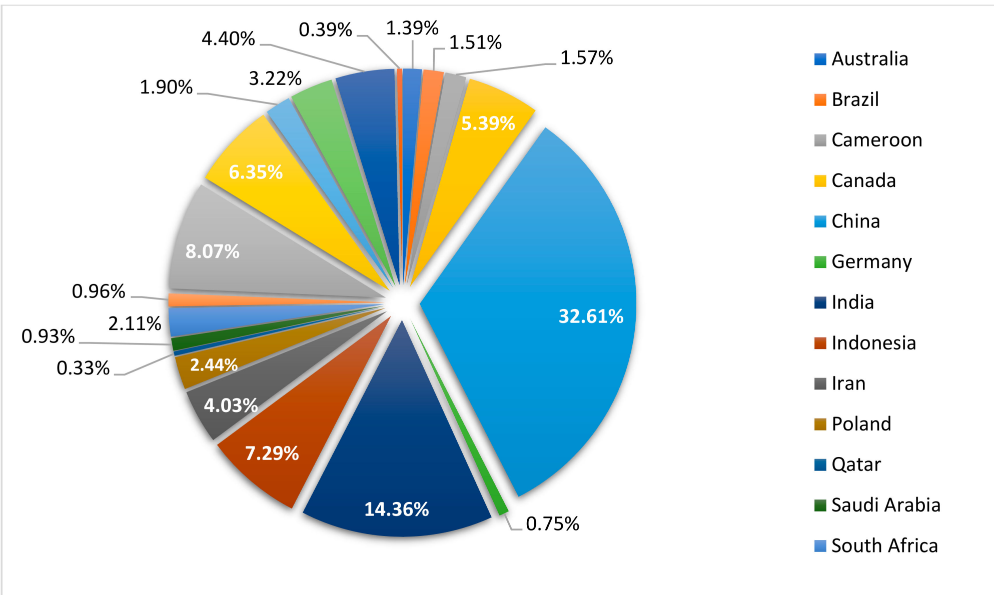

Figure 5. Countries represented in the literature.

RQ3: How has the research on the automatic classification of transformer partial discharge using machine learning evolved over the period under review?

Publications of partial discharge source classification using machine learning algorithms have shown very steady and consistent growth over the period from 2010 to 2023, as shown in Figure 6. While four papers were published in the year 2010, the following year saw a decline to the lowest publications in the period under review, with only one documented paper published in 2011. The years from 2012 to 2017 consisted of publications of three or five papers per year. The greatest documented studies came in the year 2018, which peaked at 13 publications in that year. The interest in this study has remained post-2018, with publications remaining consistently higher than the preceding years.

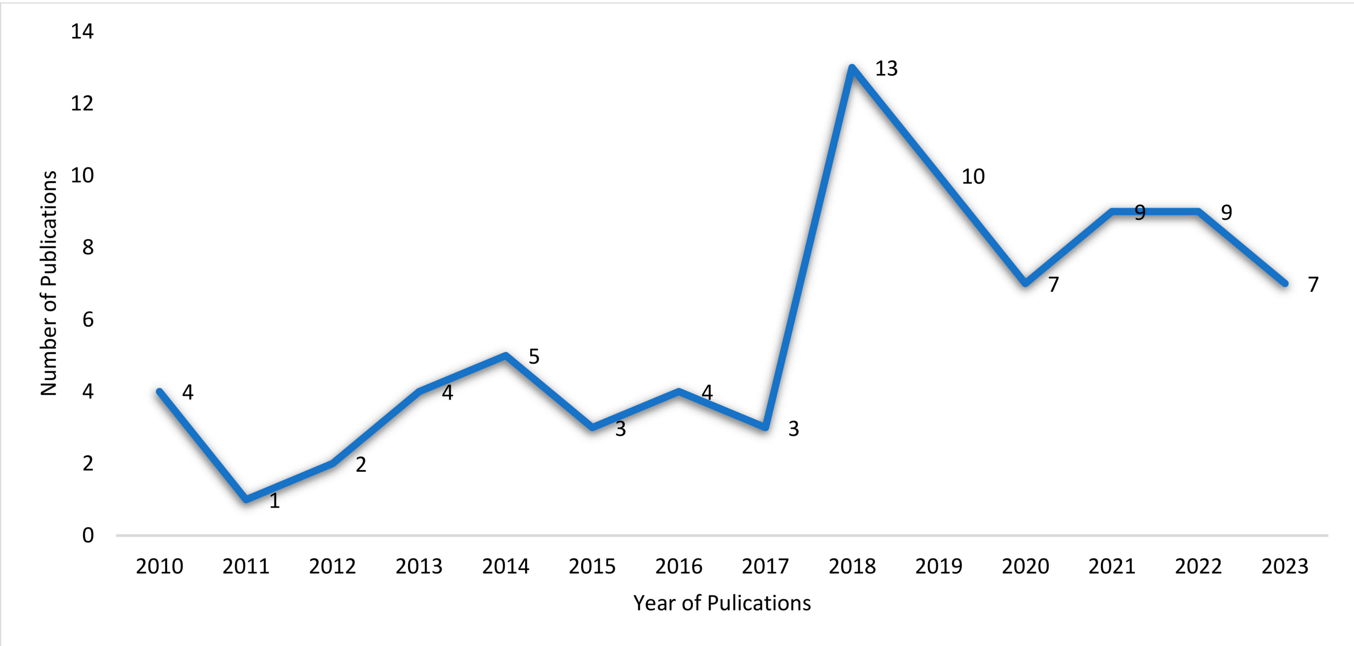

Figure 6. Timeline of literature publications.

The number of documented papers in the years up to 2017 indicates persistent interest in developing the knowledge base and research in the field. The huge increase in 2018 can be related to an increased understanding attained in the field from the research of the years thus far. The results of years post-2018 can be attributed to further development and building on the successes and research attained thus far.

RQ4: Which partial discharge types does the collected literature investigate?

A total of 231 partial discharges were analyzed in the 81 publications under review, as can be seen in Figure 7. Corona and surface discharge are the two predominantly tested types of PD in the research in transformer partial discharge classification using machine learning algorithms. Corona discharge was investigated in 55 research papers, while surface discharge was investigated in 50 of the research papers and 75.3% of the research papers under review investigated multiple partial discharge types in one publication. The benefit for researchers to investigate multiple PD types is that transformers are constructed with solid and liquid insulation systems. These insulation systems are susceptible to a variety of degradation mechanisms due to their chemical compositions. Investigating multiple PD allows the researchers to develop classification models for different types of PD while also comparing the accuracy of the model for each PD type.

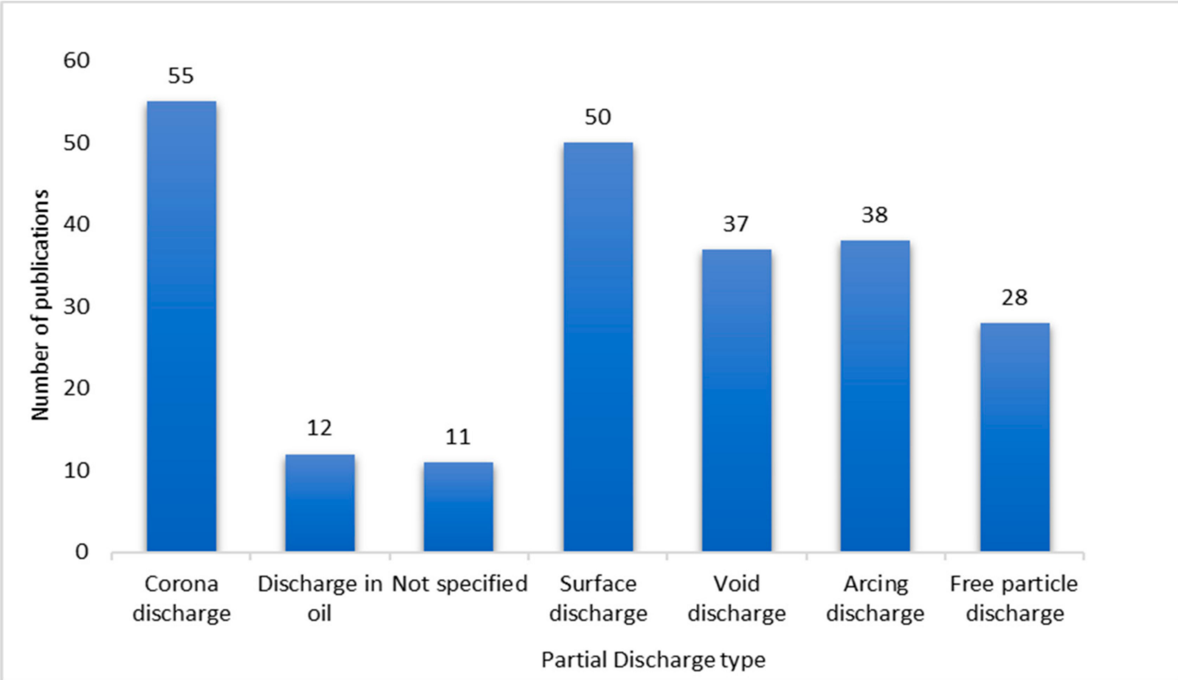

Figure 7. Types of partial discharges.

Corona discharge is the most common type of discharge occurring in HV electrical equipment, while surface discharge is considered to be the most destructive type of PD [95]; therefore, their prevalence in the literature indicates the investment provided to understand and possibly mitigate or reduce their long-term effect. The rather low number of publications relating to discharges in oil brings forth some prominent observations. It indicates a research gap in the literature, considering the various developments in transformer insulating oils which include mineral oil, vegetable oil and synthetic oil. The development of PD in various insulating oils and their propagation introduce an available opportunity for further research and development of automatic classification models as well as providing input to enhancing the compositions of the oils. Secondly, the low publications are possibly a result of reliance on transformer dissolved gas analysis, which has proven to be a very effective tool for detecting degradation of solid insulation via the gases trapped in the transformer oil.

RQ5: From which sources was the partial discharge data used in the literature collected?

The study of the sources used to collect partial discharge data to be used in the context of transformer partial discharge classification using machine learning techniques opens some notable information. The leading source of PD data is collected from artificial PD defect models. This makes up 35% of the results from the literature reviewed. Artificial defect models are laboratory-constructed models of different designs and sizes. These models are specifically set up to simulate a particular PD defect type. Figure 8 illustrates an example of four PD defect models used in the classification of multiple PD defects using machine learning algorithms. In Figure 8, defect model (a) is an air gap defect model, (b) is a floating defect, (c) is a surface defect and (d) is a tip defect model.

Artificial defect models are preferred by researchers as they can model the specific PD defect that they are looking for. In a machine learning algorithm, this data allows for better training of the algorithm and permits fewer outliers as the data collection is specific to the defect. The testing phase of the algorithm is also improved, as the algorithm is trained with specific data and can deal better with outlying data points.

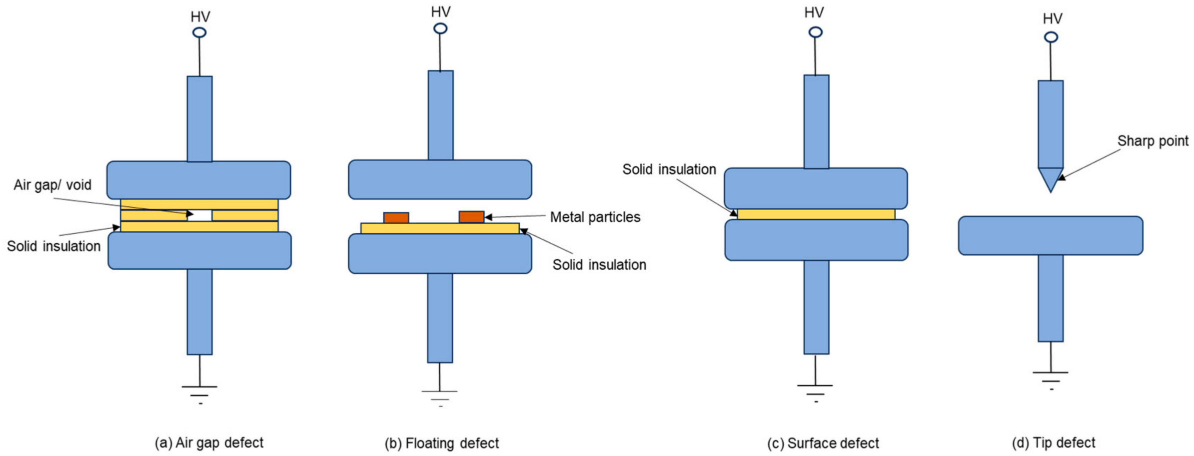

Figure 8. Artificial PD defect models.

PD experimental setups came second with 25% of the publications as can be seen in Figure 9, while data collected from actual transformers came third with 16% of the publications in the period between 2010 and 2023.

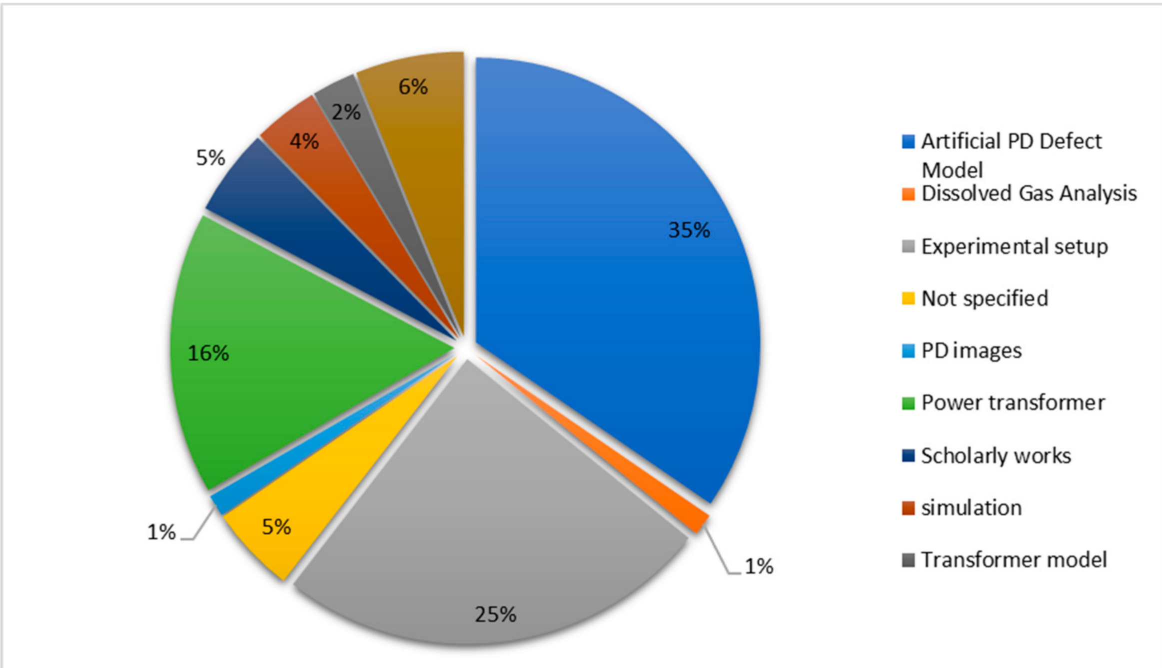

Figure 9. Sources of Partial Discharge.

RQ6: Which PD measuring methods are used in the sampled literature?

Partial discharge is a complex physical process with random distribution properties [10]. The discharges produce phenomena such as sound, light and electromagnetic waves and release electric charges. These phenomena are used in the detection and measurement of PD within a transformer. Within the literature reviewed for transformer partial discharge classification using machine learning algorithms in the period between 2010 and 2023, the most used detection methods were Ultra-High Frequency (UHF) and Electric with 30% and 27%, respectively as shown in Figure 10. The UHF method is mostly preferred due to its high resistance to external Disturbances such as electromagnetic interference, which can be expected in industrial areas where PD testing takes place [96]. It further has a high signal-to-noise ratio as well as good signal detection sensitivity [97]. The electrical method also has its advantages, which include excellent PD signal recording in laboratory environments, high sensitivity, low noise levels, low signal attenuation and high precision measurements [98].

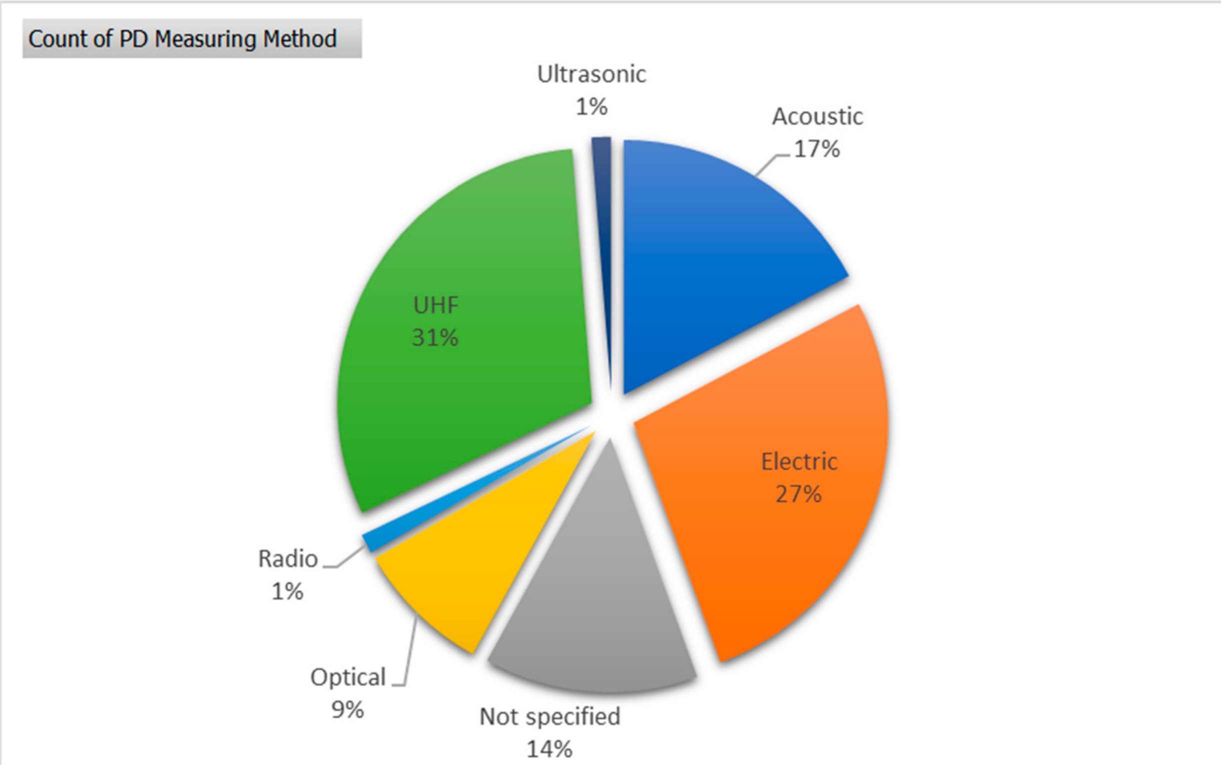

Figure 10. Partial Discharge Measuring Techniques.

Acoustic emission came third with 17% of the publications, while optical emission had 9%. Acoustic emission benefits from noise resistance, which makes it an asset for online measurements, and since sensors can be placed at different locations of the test device, it provides better discharge position information [99]. In 15% of the reviewed literature, the researchers did not specify the technique they utilized to measure the PD. This is a gap in the literature on which researchers can further improve.

The PD measuring techniques noted in Figure 10 are not without their drawbacks. While the UHF method has exceptional sensitivity, it cannot be calibrated. The electrical method is mainly used in laboratory environments and is not for onsite or online use. It is also highly sensitive to electromagnetic interference. Acoustic emission has low sensitivity, adds complexity to data handling and processing and requires additional costs due to the requirement of multiple sensors [98].

RQ7: Which measuring equipment is used in the measuring of PD in the literature?

The analysis of measuring equipment used in the collection of PD activity for the research into transformer partial discharge classification using machine learning techniques indicates a lack of variety. Figure 11 indicates the oscilloscope as the preferred measurement device with 29 research papers citing its use. This high preference for using the oscilloscope can be attributed to its availability in research laboratories. This is also the case with the data received in Figure 9 of RQ5 where it was determined that 60% of the sources of PD data in this literature were collected from artificial PD defect models and experimental setups. Since most of the research has been done in laboratories, it is more cost-effective to utilize the available equipment where it can achieve the results. Of the 81 scholarly works reviewed, 27 publications did not specify the equipment used to measure the data which was utilized. This is because the primary focus of this research is developing machine algorithms which can classify transformer partial discharge at a very high accuracy. The works on experimental setups and data collection are already well-developed and the literature is well-publicized. The use of various types of PD detectors was the third most utilized means of measuring PD in this collected literature. The PD detectors were cited in 17 publications in the period between 2010 and 2023. The PD detectors are generally used by companies who specialize in performing PD tests on actual power transformers and on tests which occur outside the laboratories.

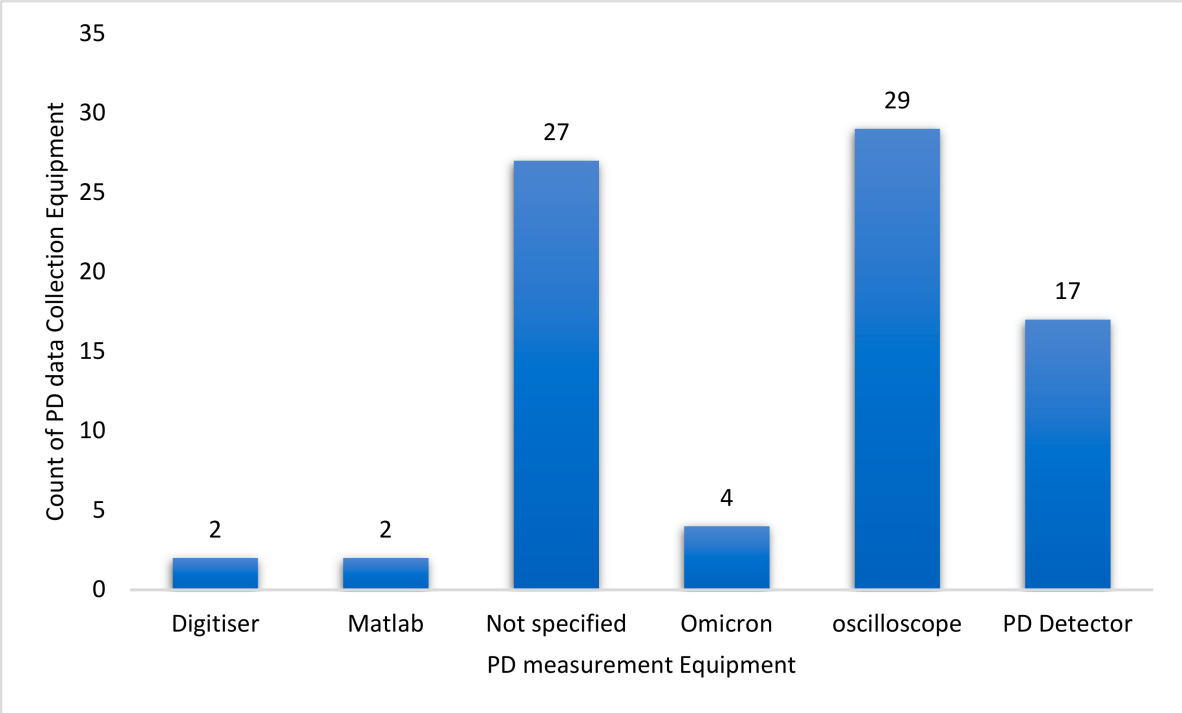

Figure 11. Partial discharge data collection equipment.

RQ8: Which national and international standards are referenced in the literature?

The analysis of the international standards used in the research on transformer partial discharge classification using a machine learning algorithm is as expected, with the IEC 60270 dominating the literature with 35 publications citing this standard as seen in Figure 12. The IEC 60270 is the high-voltage test technique for partial discharge measurements. It defines the requirements for PD measurements, the measuring systems, measurement techniques, types of tests, circuits, etc. Therefore, it is expected that researchers will utilize this standard for guidance. Other international standards that feature in the literature include IEC 60076.3 [100], IEC 60034-27 [101], IEC 60112 [102], IEC 60296 [103], IEC 62478 [104] and IEC 60060-1 [105].

IEC 60076.3 concerns power transformers (insulation levels, dielectric tests and external clearances in air), IEC 60034-27 concerns rotating electric machines (measurement of insulation resistance and polarization index of winding insulation of rotating electric machines), IEC 60112 concerns the method for the determination of the proof and the comparative tracking indices of solid insulating materials, IEC 60296 concerns the fluids for electrotechnical applications (unused mineral insulating oils for transformers and switchgear) and IEC 60060-1 concerns high-voltage test techniques (general definitions and test requirements). As can be seen, the above standards all refer to high-voltage electrical tests or insulation tests. These standards are all valid for the research on transformer partial discharge as PD is a high-voltage discharge that occurs in the insulation systems of transformers.

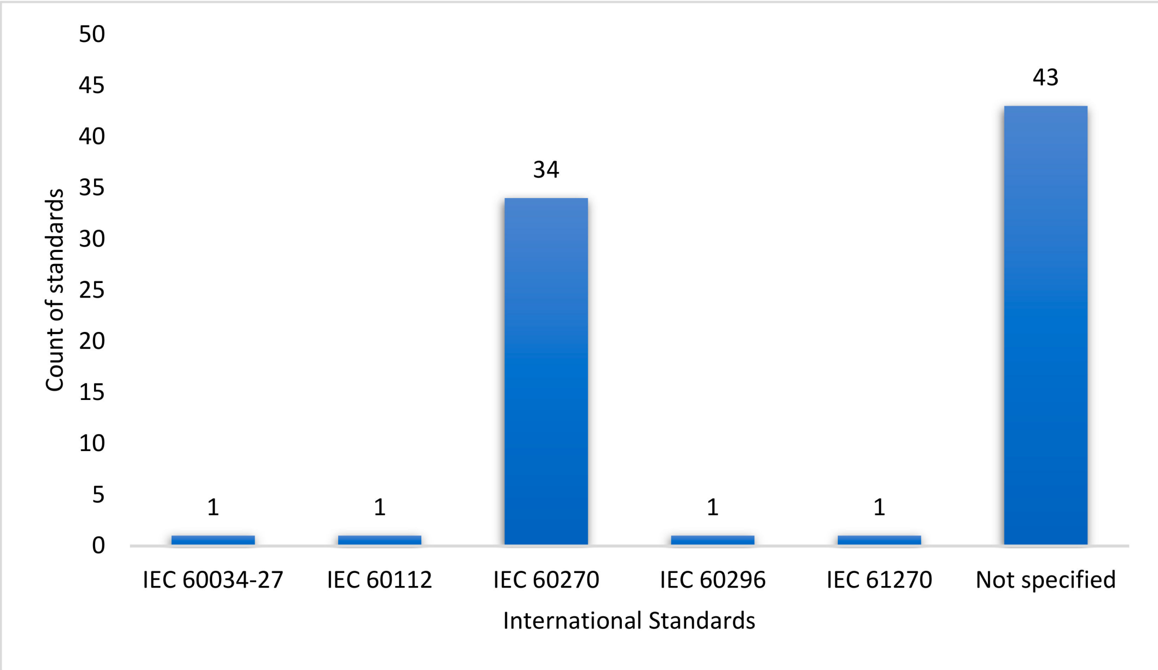

Figure 12. Partial discharge employed standards.

RQ9: Which feature extraction methods are mostly utilized in the collected literature?

Feature extraction is a process of extracting relevant features from the raw data used in machine learning. It reduces the amount of data without losing vital information required for developing the algorithm. Feature extraction therefore reduces the memory required, reduces computation time and improves the efficiency and the accuracy of the developed model. The analysis of the feature extraction techniques used in the literature for transformer partial discharge classification using machine learning algorithms indicates that researchers are open to utilizing a large variety of techniques; however, most of the scholarly works published between 2010 and 2023 indicated a preference for utilizing statistical features. These far outweighed the rest of the techniques, with 35% of publications indicating their use. Figure 13 shows the breakdown of the feature extraction techniques in the collected literature.

Principal Component Analysis (PCA) came in second with only 19% of the publications. PCA is a linear technique with the advantage of reducing dimensionality and identifying key variables; this makes its use very attractive to researchers. A total of 18 feature extraction techniques were found in this study, which indicates a wide variety of choices and willingness for scholars; however, 21% of publications did not specify the technique utilized. The possible reasons for not specifying are that for that data the researchers did not use a feature extraction technique, or that the authors chose to place a major focus on the primary objective of the research. This indicates a likely gap in documenting from the perspective of those research papers.

RQ10: Which machine learning algorithms are the most utilized for monitoring partial discharge in electric transformers?

A remarkably noticeable variety of artificial intelligence (AI) algorithms can be identified in the literature for transformer partial discharge classification using machine learning algorithms (Figure 14). Support vector machine (SVM) stands out as the most abundantly utilized algorithm with 26% of researchers in the literature opting for it. SVM is a powerful and very popular supervised learning algorithm that is highly effective for use in a two-dimensional space as it determines an ideal hyperplane for classifying data. The preference of researchers to use SVM indicates the likelihood of mostly linear data being prevalent in transformer PD samples. Another rationale is on the basis of most researchers opting for data collected from artificial defect models as elaborated in RQ5, resulting in data that is clearly defined and has clear separation. Linear SVM is limited by the data size as well as the presence of noise. This limitation is generally overcome with the use of kernels.

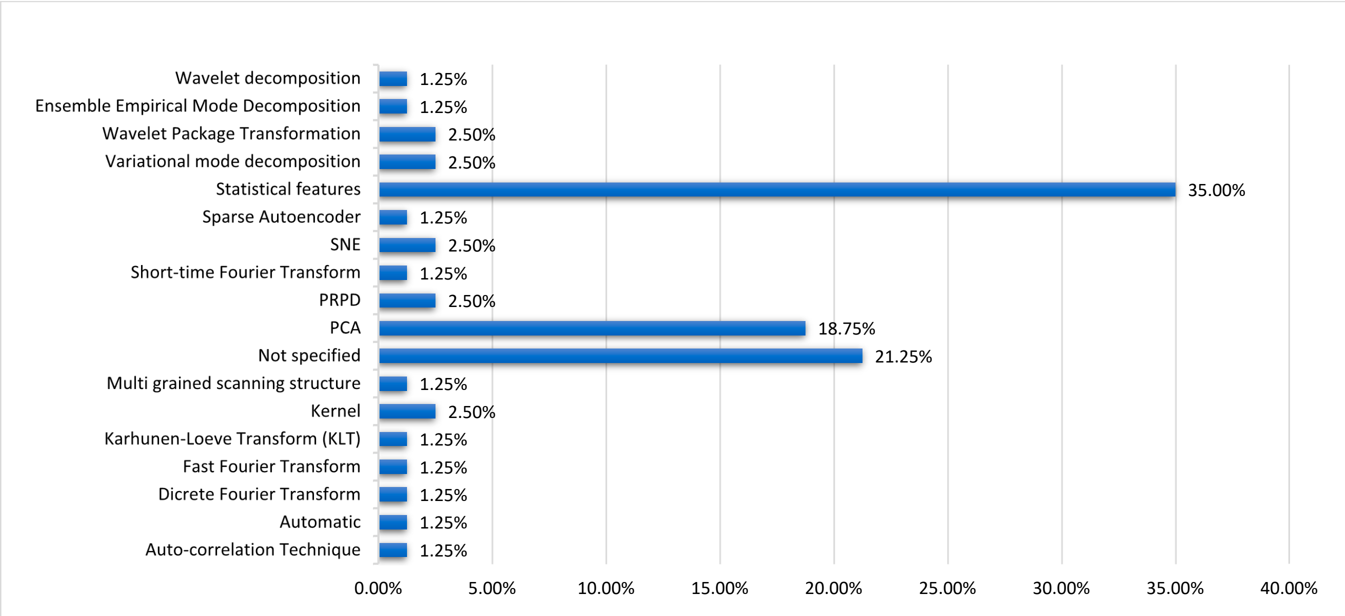

Figure 13. Feature Extraction Techniques.

Artificial neural networks (ANN) and convolutional neural networks (CNN) came in second and third place, with 12% and 11% of the publications, respectively. ANN and CNN are neural networks which lean towards deep learning algorithms. Neural networks have gained increased interest in the field of artificial intelligence as a viable alternative to traditional machine learning. They are capable of performing automatic feature learning, thus eliminating the step of manual feature extraction; they can also handle much larger datasets compared to traditional algorithms. These benefits make neural networks very pleasing for researching a variety of different PD types occurring in transformers.

RQ11: What are the challenges that are experienced when utilizing machine learning in classifying transformer partial discharge as documented in the literature?

Some challenges and constraints on transformer partial discharge classification with machine learning algorithms which have been recorded in the reviewed literature are as follows:

- PD mechanisms of multiple defects have not yet been fully understood; the development of machine learning techniques has.
- Determining the effect of frequency on degradation induced by PD.
- The effect of nanostructured insulators on PD resistance and how coarse a surface is.
- PD mechanisms in the presence of space charge resulting from cavity discharge.
- The correlation between PD breakdown under DC voltage.

RQ12: What are the possible future research opportunities highlighted in the literature?

The possible future research opportunities that have been highlighted in the literature include the following:

- Understanding of the propagation of PD signals inside transformers. Current machine learning models and the research has primarily placed focus on detecting the present state of PD, as well as improving the accuracy, speed and reducing memory. Developing models which will allow for understanding the propagation of PD within a transformer can provide further insight to grow the knowledge base within the research space.

- The optimization of the design of PD sensors. The use of optical and acoustic sensors for multiple PD source detection and localization is currently limited by the cost of multiple sensors required. Optimizing on the design of these can reduce cost and size, therefore allowing for further research and use in a variety of locations.
- Proper calibration techniques for PD charge. The current PD detection techniques and application thereof in multiple locations are limited as some techniques cannot be calibrated as prescribed in IEC 60270. The development of accredited calibratable sensors and calibration techniques can aid in the uptake of newer techniques.
- Research into surface tracking and flashover due to static electrification in the interface of oil and pressboard. The research into surface discharge and tracking occurring on pressboard and oil together with the degradation mechanisms and the results thereof can be highly beneficial in understanding the long-term effect of PD on transformer insulation systems.
- Further research into the interpretation of automated classification of PD formed under the presence of conducting particles, moisture, temperature, etc.
- The collection and automatic classification of PD over a much longer period. The study indicated that PD data has primarily been collected from artificial defect models in a laboratory. The literature could benefit from long-term PD collection from on site transformers to test the effectiveness and efficiency of the developed models.
- Utilizing a combination of machine learning algorithms to overcome the shortfalls and improve the ultimate classification performance of the model. This concept has been initiated; however, it still requires further refinement to test and improve its effectiveness.

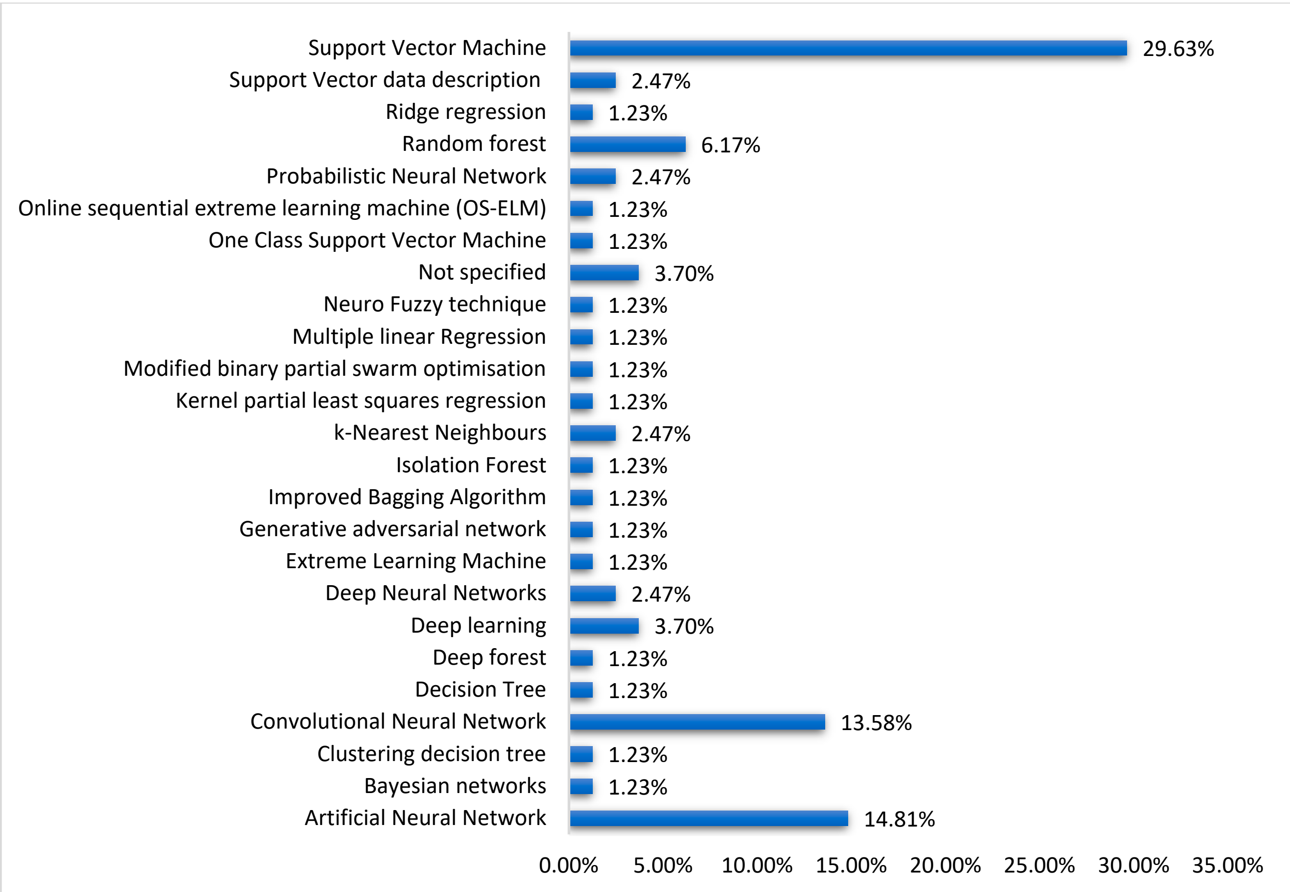

Figure 14. Employed Machine Learning Algorithms.

6. Limitations of the Study

The systematic literature review was performed within the confines of the aim of the study, which was further bounded by the determination of an inclusion and exclusion criteria. This method ensures that the research methodology is clear; however, it may also introduce some limitations to the study. Some of the limitations include that the literature was collected only from well-known, reputable publications. This methodology guarantees that the research works used are of an acceptable standard and have been peer-reviewed for correctness. Therefore, there may be other works contributing to the subject matter which may not have made it into the set criteria. Another limitation is that the subject matter placed a boundary on only PD. The effect of heat, mechanical forces, transformer loading and chemical forces that contribute to the deterioration of insulation, which may further exacerbate PD, have not been taken into account. Lastly, it would benefit

7. Contribution of the Study

The significance of this SLR is in contributing to the advancement of the technology area relating to the automated classification of partial discharge in power transformers. Its contribution is in providing an extensive and discerning review of the research and development undertaken in this field in the last decade. The SLR analyses the literature in question and studies in detail the landscape of the literature, revealing the most preferred publication sources for scholars and researchers, the countries engaged in the research and the evolution of the research over the period under consideration. The SLR further analyses the role of PD in transformers by divulging the types of PD that have been researched, indicating improvement in the field where single-source PD analysis has largely been replaced by multisource analysis and classification. The source of PD data collection indicates the preference for collecting data from artificial PD models and the SLR also unveils the types of PD measuring methods that are preferred as well as the PD measuring equipment that have been used. Moreover, it delves into the use of artificial intelligence in classifying PD in transformers by analyzing the feature extraction techniques used by researchers and the most favored machine learning algorithms. Lastly, the SLR identifies the challenges experienced by researchers and scholars in the field of transformer PD classification using machine learning algorithms and further establishes possible opportunities or research gaps that can further improve the advancement of this research area. Therefore, this SLR offers a platform to indicate the present state of the research on transformer PD classification using machine learning algorithms, and thus provides a basis for further development and growth.

8. Conclusions

This paper provides an in-depth analysis and review of the existing research and literature in the field of transformer partial discharge classification with the use of machine learning algorithms. The foundation of this paper introduces the electrical transformer, with particular emphasis on the solid and liquid insulation systems. This is then accompanied by a focus on the explanation of partial discharge, its development within transformer dielectric and its effects on the transformer, as well as how it can be used to monitor the health of the transformers. The use of artificial intelligence in monitoring and classifying PD activity is then introduced, together with the advantages it provides.

This systematic review included a robust methodology developed using the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) flowchart. Using the PRISMA flowchart as well as a well-developed inclusion and exclusion criteria, a total of 81 research papers published on reputable research repositories between 2010 and 2023 were examined as part of this review. The study develops a series of pertinent research questions which need to be answered to provide insight into the critical elements surrounding the development in the field of utilizing AI to classify PD in electric transformers.

The review commences with the identification of the prevalent publication sources in the collected literature, indicating a substantial inclination towards journals over conference papers and research articles. After that, it studies which countries have contributed to the literature in this field. This revealed a significant range of involvement with 20 countries from diverse continents participating in this field showing worldwide interest in the development. However, China dominated the number of publications in the period under review, which is indicative of their continued investment in technology and the field of artificial intelligence as well as its practical use on electric transformers.

The paper further reviewed PD's existence in transformers in detail, starting with examining the types of PD that have been most widely researched. This highlighted the propensity for scholars to investigate multiple types of PD, training their algorithm on each type and comparing the accuracy. This reveals that researchers are moving more towards multisource PD classification algorithms rather than single-source ones which were more prevalent in the past. Secondly, it identified the types of sources used to generate the PD data, artificial defect models surpassed transformer models and actual transformers, respectively, in the top three, thus indicating that most PD data used in the literature has been collected in laboratory environments; furthermore, it indicates that this may be the most reliable form of data for training of the machine learning algorithms. The third PD assessment was that of the methods used to measure the PD activity, Ultra-high frequency, Electric and Acoustic emissions were among the most utilized methods. This assessment further indicated a wide variety of testing methods which are disposable for researchers, scholars and PD testing companies, and which can be utilized in laboratory settings, onsite, offline and online. Oscilloscopes were identified as the preferred equipment for recording PD activity. This further expounds on most of the research occurring in laboratory environments, as oscilloscopes are readily available in most electrical Engineering laboratories.

The SLR concluded by identifying the AI aspect of this research, finding that statistical features were predominant in the feature extraction space. However, a large portion of the literature did not specify the feature extraction methods used, thus leaving a sizeable gap in this space. Support Vector Machine dominated the machine learning algorithms in the literature, due to its simple nature for classifying linear data. However, the wide variety of machine learning algorithms recorded in the data indicates great future development in this space.

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