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KNOWLEDGE EXTRACTION TECHNIQUES FOR POWER TRANSFORMER MAINTENANCE DATA: REVIEW

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ABSTRACT

The maintenance of power transformers is time or condition-based and at the end of this one, analysis reports are produced to give its status. These different reports produced over time form a large database called the transformer maintenance asset bank. Extracting knowledge from this power transformer maintenance data is now an important subject for the scientific community given the importance of the transformer in the electric power generation chain. The science of data mining finds a field of application for its analysis techniques, the most used in preventive maintenance are predictive techniques. This work reviews knowledge extraction techniques from power transformer maintenance data. For this purpose, 80 articles from a platform are identified and 7 of them are retained at the end after meeting the criteria. Among the predictive analysis techniques namely regression, classification, and prediction, classification is the most used with its ANN (Artificial Neural Network) algorithm. On the other hand, association rule mining (ARM) has the highest accuracy, 98.21% in 2020. In addition, the combination of a classification algorithm preceded by the descriptive one, namely the principal component analysis (PCA), could offer higher accuracy than when they are used individually.

Keywords: Classifier, Data Mining, Predictive Analysis, Maintenance, Transformer

1. INTRODUCTION

According to the report of Transfo Elec and OKSMAN Seraphin Laboratory in 2017, transformer losses cause 50% of operating losses in the power generation sector, 10% in the chemical industry, 7% in paper mills, and 6% in commercial enterprises Transfo Elec (2017). Predictive maintenance, widely used today for its predictive aspects, reduces operating costs, ensures continuity of service, and thus improves productivity in industry. At the end of the maintenance, data analysis, reports are made to the status of the transformer. These different reports, produced over time, constitute a voluminous data bank. The principle of predictive maintenance is to analyze the data to predict failures and thus maintain production equipment and infrastructure systems more effectively and efficiently than the so-called traditional or conventional approaches, such as corrective maintenance (CM) and preventive maintenance (PM) Lu et al. (2009), Zhao et al. (2017). Prediction of a fault consists of analyzing the relevant information received and reporting it to the prevention mechanism. Therefore, this new approach to thinking about maintenance will involve data science, which makes it possible to process large amounts of information. The authors Bouroche & Gilbert (1980), Rouanet & Lepine (1976), are among the pioneers of data science. Long before the use of data science in transformer maintenance data, Wang et al. (2002) presents traditional methods for monitoring and diagnosing transformers. In 2015, Amy et al. developed an intelligent engineering asset management system for power transformer maintenance questions to prevent faults and detect potential transformer failures under various operating conditions. For this purpose, they used principal component analysis (PCA) to transformer dissolved gas data and an artificial neural network Trappey et al. (2015). In 2009, Jahromi et al. used the health index (HI) based on data analysis for transformer asset management Jahromi et al. (2009).

The success of this discipline lies in its graphical representations highlighting relationships that are difficult to capture through direct data analysis; but more importantly, these representations are not tied to an "a priori" opinion about the laws of the analyzed phenomena, unlike the methods of classical statistics. The mathematical foundations Kogan et al. (1988) of data analysis began to develop at the beginning of the 20th century, but it is computers that have made this discipline operational, and that has allowed its generalization.

This paper presents a general review of the existing literature on current data mining techniques used in the prediction of power transformer failures. Similarly, this paper will serve as a compass for future directions of researchers in power transformer data mining techniques. It allowed me to browse 80 articles and make a referral that resulted in selecting 7 articles whose relevance followed rigor in a multicriteria analysis based on time, citation, and accuracy. The accuracy of the prediction model is essential in taking reasonable measures to anticipate and avoid potential internal failures of power transformers. This paper is organized into four parts, an introduction in the first part, then the second part the presentation of the failures related to power transformers and the classifiers commonly used, the third part presents the methods used and the fourth part allows us to conclude this work.

2. FAILURES RELATED TO POWER TRANSFORMERS AND DATA MINING

In this section, we will identify the common failures of power transformers and the data mining algorithms used to extract knowledge from maintenance data.

2.1. FAILURE RELATED TO POWER TRANSFORMERS

The evolution of the failure rate of a product in general and of the transformer in particular during its whole life is characterized by what is called in reliability analysis the "bathtub" curve. The failure rate is high at the beginning of the device's life. Then, it decreases quite rapidly with time (decreasing the failure rate), this phase of life is called the youth period. Afterward, it stabilizes at a value that is desired to be as low as possible during a period called the useful life (constant failure rate).

Table 1

Table 1 Typical Causes of Transformer Failures

Internal	External
Insulation damage	Lightning strikes
Loss of winding tightness	System switching operations
Overheating	System overload
Oxygen	System faults (short circuit)
Moisture	
Solid contamination in the insulating oil	
Partial discharge	
Design and manufacturing faults	
Winding resonance	

Finally, it rises again when wear and tear and aging take their toll, this is the period of Aging (increasing failure rate) Bellaouar (2013). Transformer failures can be classified into three main categories: electrical, mechanical, or thermal. The cause of a failure can be internal or external. Table 1 lists typical causes of failure Kogan et al. (1988), Bellaouar (2013), Agnissey (2017).

2.2. DATA MINING

The objectives of data mining methods can be grouped into five main functions: classification, estimation, segmentation, prediction, and explanation. The choice of the method will depend on the nature of the problem and the type of data available. The data mining process can be summarized as the implementation of the following tasks in information systems Figure 1: (1) identify the intervention data, (2) use data mining techniques to transform the data into useful information, (3) transform the information into concrete actions, (4) evaluate the results Lajnef et al. (2005).

Figure 1

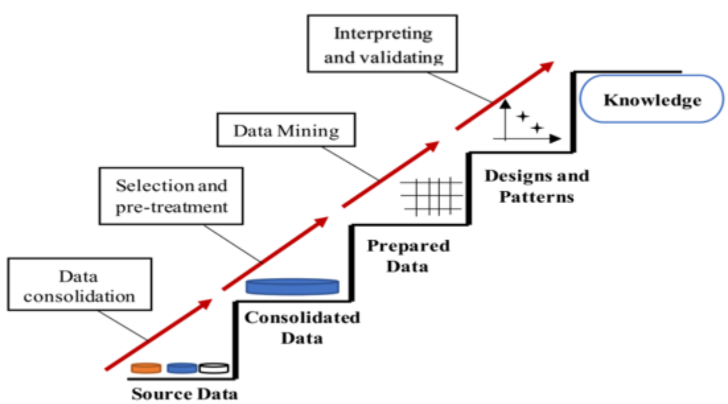

Figure 1 Data Mining Process

More precisely, data mining can be redefined as a series of data transformation and analysis operations. It consists of cleaning, integration, selection, transformation, mining, evaluation, and knowledge about the data. This knowledge allows to present to the user the information extracted from the data: tables, trees, rules, graphs, curves, and matrices.

2.2.1. DATA MINING METHODS

There is a panorama of data mining methods, of which the main ones are presented in Table 2.

Table 2

Table 2 Summary of Data Mining Techniques

Analysis	Technical	Principles	Methods
descriptive	Description	**- For a variable update the distribution of its values** **- Give the links between the distributions**	Exploratory analysis (PCA..)
	Clustering	Create subsets of data between them	-Kohonen network -hierarchical classification - Association rules.
	Link Detection (Association)	Find out which variables go together	-Apriori Algorithm -GRI (Generalized Rule Induction) Algorithm
Predictive	Regression (Estimation)	**define the link between a set of predictors and a target variable.**	- Simple/multiple linear regression; - Correlation; - Neural network
	Segmentation (supervised classification)	**Segmentation is an estimation that works on a categorical target variable.**	-Decision tree -Neural network - k-nearest neighbor method - Graphs and scatterplots
	Time series analysis		
	Forecast	**Forecasting is similar to estimation and segmentation except that for forecasting, the results are about the future.**	**That of estimation or segmentation.**

The techniques commonly used in power transformer asset management are classification, regression, and sometimes description. The corresponding algorithms include artificial neural networks, association rules, Bayesian classifier, ANOVA, and PCA.

2.2.2. CLASSIFIERS COMMONLY USED IN DATA ANALYSIS:

In the current study, the following classifiers are reviewed:

- The artificial neural network (ANN);
- Association rule mining (ARM);
- Support vector machine (SVM);
- Exploratory data analysis;
- The naive Bayesian (NB)

The notion of artificial neural networks (ANN) was developed in biology, where they play an important role in the human brain Ravi et al. (2019). The neural network is simply a network of interconnected neurons. In the neural network, the most fundamental unit of information processing is the neuron. Each artificial neuron is an elementary processor. It receives a variable number of inputs from upstream neurons. Each of these inputs is associated with a weight which represents the strength of the connection. Each elementary processor has a single output, then branches to feed a variable number of downstream neurons. Each connection is associated with a weight Touzet (2016). They are organized into three or more layers, such as the input layer, one or more hidden layers, and a single output layer Nemeth et al. (2011). ANN can be used to recognize the hidden relationships between dissolved gases and defect types through a learning process. The ANN method was introduced by Aravena & Chowdhury (1996) in power system fault detection in 1996. Reference Orille-Fernandez et al. (2006) used ANN to predict the lightning surge and it was found that ANN can be used directly to assess the failure risk of a certain network or indirectly to determine the type of lightning arrester. In the studies conducted by Trappey et al. (2015), Mirowski & LeCun (2012), Morais et al. (2009), ANN has been widely used to classify the fault condition of the transformer based on historical data for dissolved gas analysis.

An association rule A→B extracted from a database, represents a link established between two sets of properties A and B of this database Cuxac et al. (2005), a link whose quality is evaluated according to the number of objects in the database verifying them. To measure the quality of this rule, many indices are based on these numbers, the most common of which are the support, which is the number of objects verifying the properties of A and B, and the confidence, which is the quotient of this support and the number of objects verifying the properties of A. Based on the IEC report on the dissolved gas analysis, Shrivastava & Choubey (2012), Yang et al. (2009) uses association rules for power transformer fault diagnosis. In the studies conducted by Jinshuang et al. (2021), association rules are used to analyze the faults of a device based on its power dictionary. The article Qi et al. (2020) uses association rules to accurately alert the state of a transformer and three identified transformer properties, namely, voltage class, operating age, and oil type.

Support vector machines (SVM) are an algorithm whose purpose is to solve two-class discrimination problems Francoeur (2010). Reference Ray & Mishra (2016) used SVM for fault type and distance estimation in a long transmission line of electrical systems. Although SVM gives good accuracy, the time consumed for learning, however, makes the task complex and sluggish. Reference Schittkowski (2005) mentions that the selection of appropriate SVM parameters is essential for good generalization performance and high accuracy in fault location and transmission line classification.

One of the exploratory data analysis techniques is Principal Component Analysis (PCA). PCA consists of synthesizing the number of variables observed, in other words, it attempts to summarize the information contained in the data table into a reduced set Samuel et al. (2016), Eke (2018) of linear combinations of the initial variables, taking care to minimize the loss of information due to this reduction. These new synthetic variables, called principal components or factors, have the following properties:

The principal components, noted ($C^1, C^2, \ldots, C^q$), are linear combinations of the initial variables ($X_1, X_2, \ldots, X_p$): $C_j = a_1X_1 + a_2X_2 + \ldots + a_pX_p$ *for all* $j = 1, q$ *with* $q \leq p$.

These factors are uncorrelated (the linear correlation coefficients of the components taken two by two are zero), which avoids the redundancy of the information already summarized. The first component summarizes more information than the second, which carries more information than the third, and so on, so that by limiting ourselves to the first 2 or 3 components, a good summary of the information contained in the data is retained Abdesselam (2014). The mathematical tools used are those of linear algebra and matrix calculation, whose principle is as follows:

$$\text{Correlation matrix} \xrightarrow{\text{diagonalization}} \text{eigenvalue matrix}$$

$$\begin{array}{c|cccc|} & X^1 & X^2 & \dots & X^p \\ X^1 & 1 & r_{12} & \dots & 1 \\ X^2 & r_{21} & 1 & \dots & r_{21} \\ \dots & \dots & \dots & \dots & \dots \\ X^p & r_{p1} & r_{p2} & \dots & 1 \end{array} \qquad \begin{array}{c|cccc|} & C^1 & C^2 & \dots & C^p \\ C^1 & \lambda_1 & 0 & 0 & 0 \\ C^2 & 0 & \lambda_2 & 0 & 0 \\ \dots & 0 & 0 & \dots & 0 \\ C^p & 0 & 0 & 0 & \lambda_p \end{array}$$

($r_{12} = r\,(X_1, X_2)$ linear correlation coefficient between the variables X_1 and X_2)

The diagonalization of the correlation matrix whose eigenvectors define the new variables we are looking for: the principal components. The associated eigenvalues are the variances of the principal components; the factorial axes are the lines generated by the eigenvectors.

The principal components thus defined, verify the desired properties: uncorrelated, decreasing variance, and linear combinations of the initial variables. This last property allows us to construct graphs representing individuals and variables in the space defined by the components Abdesselam (2014). In the paper Trappey et al. (2015) PCA is used to improve the preprocessing of the data. According to the study Zhu et al. (2005), GRI correlation, and Bayesian network were used to evaluate the state of the transformers, and factor analysis based on analysis of variance (ANOVA) was used to evaluate their aging.

The Bayesian classifier is a supervised learning technique that predicts the probabilities of class membership. The article Shah & Jivani (2015) uses it to detect cancer and shows that NB classifiers show high accuracy and speed than the Random Forest classifier. Reference Yong-Li et al. (2006) used the NB+SVM classifier for transformer fault diagnosis. The different test scenarios showed that the constructed NB diagnostic model has good performance given the complete test data. In a study by Jiang et al. (2008), a few algorithms were used to predict faults, namely Naïve Bayes, Random Forest, J48, Bagging, IBk (KNN in WEKA tool), and Logistic Regression. It was found that for the PC1 project, the IBk (KNN in the WEKA tool) algorithm with an acceptability threshold of 0.40 performs better. In reference Benmahamed et al. (2018), it is stated that, for diagnosing the insulating oil used in power transformers, the Naïve Bayes and KNN classifiers were used. Based on the evaluation of the Duval triangle ratio, it was found that the KNN algorithm provides a higher accuracy rate than the Naïve Bayes algorithm.

3. METHODS

The method used presents the architecture of the work and a set of works for applying knowledge extraction techniques to power transformer maintenance databases.

3.1. ARCHITECTURE OF THE METHOD

This paper surveyed 80 articles and reference documents on the Google Scholar platform. Searches were made using words derived from the terms: Data Mining on Power Transformer Maintenance Data.

Figure 2

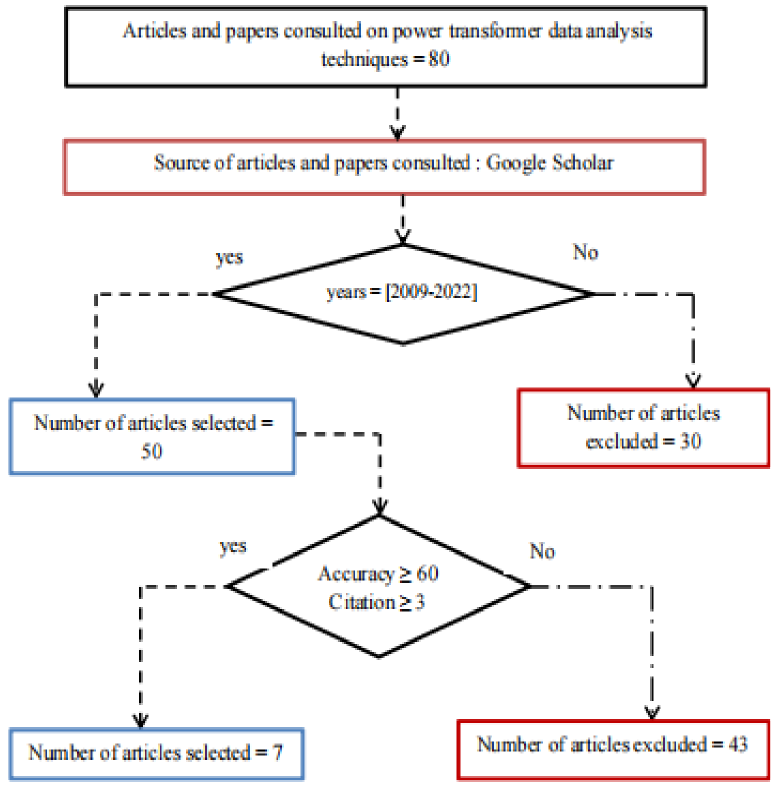

Figure 2 A Working Algorithm for the Literature Review

The first criterion of the choice of the articles was the year. For this purpose, all articles published before 2009 were rejected. The second condition of eligibility of the article is multicriteria and two criteria were defined, namely, the precision higher than 60 and citations higher than 3. All articles in the field that did not give the precision of their algorithm were simply excluded. This method of work made it possible to retain at the end of the chain 7 articles.

3.2. SOME APPLICATIONS OF EXTRACTION TECHNIQUES

The management of power transformer maintenance assets is undergoing a major change and long before 2002, the methods used were traditional, i.e., did not integrate intelligent diagnostic and predictive tools. The work [6] gives a thorough and rigorous presentation. Predictive techniques for intelligent management of transformer maintenance assets are becoming a necessity to avoid unexpected failures. Arshad et al proposed condition-based maintenance to improve transformer performance, reliability, and lifetime early on. They believe that better management of transformers can be achieved through online monitoring, routine diagnostics, and condition-based maintenance Arshad et al. (2004). Dominelli 2004 also developed a transformer diagnostic program using routine transformer inspection data and equipment information (nameplates) such as operating history and age Dominelli (2004). The program calculated condition indices for the transformer components and then combined them into an equipment health assessment. The program also provides diagnostics and assesses the health of the transformers. Jahromi et al presented a health index as an indicator of the health status of power transformers. The health index takes into account power transformer inspection and usage data (e.g., DGA, oil quality, furfural and power factors, tap changer, load history, and maintenance data), and calculates weighting factors, condition ratings, and scores assigned to any parameter. The calculation of these factors is based on the recommendations of the IEC, IEEE, and CIGRE Jahromi et al. (2009). With the comparison and evaluation table presented in this study, users can quickly see the condition of the transformers, their expected life span, and the actions required to maintain, repair, or replace them.

In the overview of asset management activities for processors, the works Abu-Elanien & Salama (2010), Abu-Elanien & Salama (2012) present a comprehensive illustration of them based on health index estimation using in a first step a feedforward artificial neural network composed of four layers and parametric data (water content, acidity, breakdown voltage, H2, CH4, C2H2, C2H4, C2H6, furans, etc). In a second step, the neural network is combined with a logic technique to solve the weight assignment problem. The latter depends on the expertise and experience of the processor experts, which differ from one expert to another, and on the numerical thresholds distinguishing normal from abnormal in the diagnostic tests, which are difficult to determine precisely. Six membership functions (for moisture content, acidity, BDV, DF, DCG, and 2-Furfuraldehyde) are defined to input the parameter values into the fuzzy logic model of the health index.

In addition, thirty-three heuristic rules are used to derive the transformer health assessment. In 2006, Arshad and Islam To have a flexible asset management decision, fuzzy modeling is performed based on the aging rate of transformers and mapping the remaining life Arshad & Islam (2006). In 2015, Trappey et al developed an intelligent engineering asset management system for power transformer maintenance issue of fault prevention to detect the potential failure of transformers under various operating conditions. For this purpose, they use principal component analysis on transformer dissolved gas data (PCA) and an artificial neural network Trappey et al. (2015). Yang et al. (2009), made a Dissolved Gas Analysis based on association rule extraction for power transformer fault diagnosis. The DGA-ARM (Rule Mining Association) method based on the Apriori algorithm was used. The registration tests were planned for 1019 data, but only 177 were tested, which implies that the method would have been more reliable if the test had been on several data Yang et al. (2009), and the test was not done to evaluate the level of accuracy of the algorithm based on the association rules. In 2012, Shrivastava and Choubey A new association rule extraction with dissolved gas analysis based on IEC ratio for power transformer fault diagnosis. IEC Ratio + Association (ARM) to extract knowledge. This approach presents higher accuracy in fault diagnosis Shrivastava & Choubey (2012). In 2018, the factor analysis based on ANOVA is exploited to evaluate the aging of transformers in service Wang et al. (2018). Reference Ardi et al. (2019) for diagnosing incipient faults in power transformers, uses analytical incremental learning (AIL) based on dissolved gas analysis. Here, all weights of the neural network are computed analytically without any randomization. The hidden nodes of the AIL are generated incrementally according to the residual error using the least-squares (LS) method. A comparative analysis between the SVM, NB, Random Forest, and AIL classifiers shows that the AIL has a higher accuracy of

91.82%. To predict defects in transformers Fauzi et al. (2020), its oil is characterized by optical spectroscopy from 200 nm to 3300 nm and the accuracy is about 98.1%.

Regarding the development of transformer maintenance data management systems, works Bangemann et al. (2006), Wagle et al. (2008) used an integrated platform and website to perform remote maintenance, asset management, and decision support.

4. RESULTS AND DISCUSSION

The work method proposed here has found that among the descriptive and predictive analysis techniques, predictive analyses are more used in the analysis of power transformer maintenance data. The commonly used classification algorithms are support vector machine (SVM), k-nearest neighbor (k-NN), artificial neural network (ANN), exploratory association rules (ARM), and Naïve Bayes (NB). In view of the above work, the data analyzed to diagnose the condition of power transformers are dissolved gases Mirowski & LeCun (2012), Yang et al. (2009), Ardi et al. (2019). The most used classification algorithms are ANN, kNN, and SVM, which present average accuracy of about 90%. The exploration of other classifiers such as ARM nowadays presents accuracies of 98.21%, largely above 96.97% for ANN and 95.26 % for SVM Qi et al. (2020). Table 3 presents the 7 articles selected, their year of publication, the classifiers used, and their precisions.

Table 3

Table 3 Algorithm and Data Mining Techniques

Authors	Algorithm	Accuracy (%)	years	Citation*
Trappey et al	ACP+BPANN	96	2015	75
Mirowski et LeCun	kNN	93	2012	102
	SVM	89		
Morais et al	ANN	69		
	NB	63	2009	34
	kNN	86		
Yang et al	ARM	91.53		
	SVM	82.1		
	ANN	62.43	2009	148
	kNN	65.85		
Qi et al	ARM	98.21		
	ANN	96.97		
	SVM	95.26	2020	13
	Fuzzy	96.21		
Benmahamed et al	NB	84	2018	21
	kNN	92	2018	
Fauzi et al	SVM + optical spectroscopy	98.1	2020	4

The most accurate classification algorithm is based on association rules (ARM) 98.21% Qi et al. (2020), in work Yang et al. (2009) the association rules (ARM). In works Mirowski & LeCun (2012), Morais et al. (2009), Benmahamed et al. (2018), the kNN classifier has the highest accuracy, respectively, 93%, 86%, and 92%. The articles Trappey et al. (2015), Fauzi et al. (2020) have opted for a combination of classifiers, and the accuracy seems to be better than the one of the classifiers used individually.

Figure 3

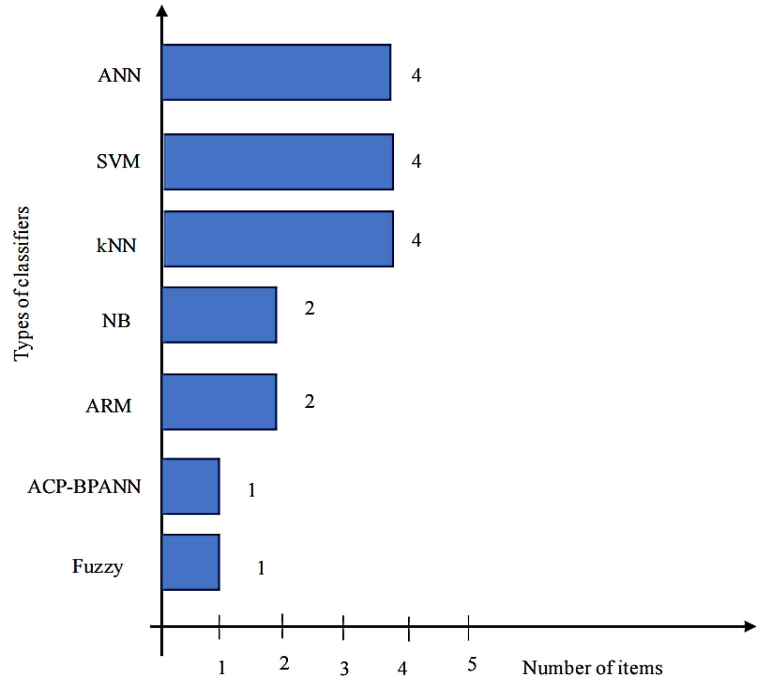

Figure 3 Classifier Based on Number of Items

Of the 7 papers selected, 4 used artificial neural network classifiers (ANN), support vector machine (SVM), and k-nearest neighbor (kNN). 2 used association rule mining (ARM) and Bayesian naive (NB).

Figure 4

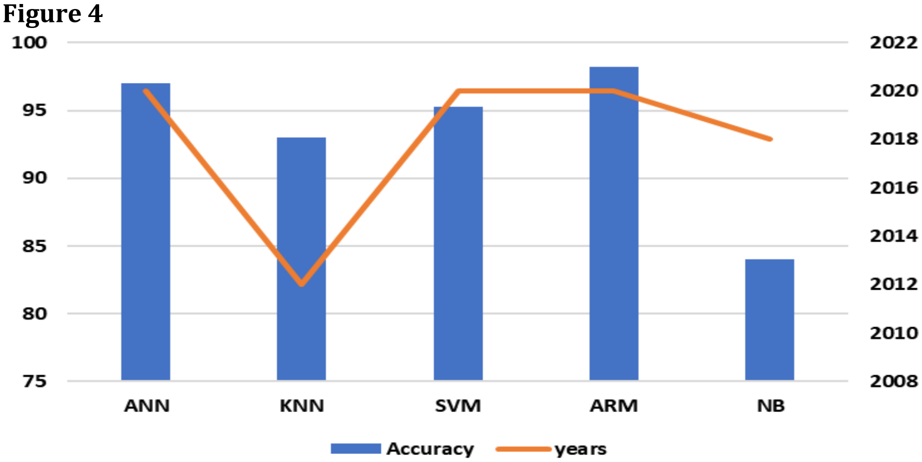

Figure 4 Accuracy by Years

Figure 4 shows the accuracy level of commonly used classifiers taking into account the year. The most accurate classifier is ARM in 2020 with an accuracy of 98.21%, ANN is the second with 96.97% accuracy in 2020, and SVM is the third with an accuracy of 95.26% in 2020.

5. CONCLUSION

The work done in this article is based on the review of methods and data mining algorithms used for the development of models for the description and prediction of fault potentials of power transformers. 80 articles have been listed on Google Scholar. Taking as criteria of relevance the year of publication of the article, the precision greater than or equal to 60, and many citations greater than or equal to 3, 73 articles were excluded and only 7 met these criteria and the theme was retained. From this work, it appears that the most used data mining methods are predictive and that one of the most developed algorithms adapted to dissolved gas defects is the ANN, whose highest accuracy is 96.97% Qi et al. (2020). The ARM algorithm is also used for dissolved gas fault analysis and many other types of faults because it has good accuracy than ANN, SVM, and KNN classifiers. Well before 2020 and precisely in 2015, work Trappey et al. (2015) showed that an ANN classifier preceded by PCA (predictive method) can have its accuracy significantly improved. To make predictions more reliable, it would be appropriate to take into account other failures by using joint or hybrid (descriptive + predictive) classification algorithms.

CONFLICT OF INTERESTS

None.

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