Strategic Asset Management Health Index for Predicting Power Transformer Health Conditions

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Abstract: Asset Management assists in operating electrical utilities at high performance and low cost. The Power Transformer Health Index (PTHI) is considered a good health condition evaluation and decision-making tool. PTHI is used to prioritize maintenance decisions, drive maintenance strategy, manage failure impact before it occurs, asset lifecycle planning, deferral big capitals, manage spare parts plan, and extend power transformer life. This paper presents the PTHI models' investigation which was conducted on 4324 transformer records using various Artificial Intelligent Machine Learning (ML) algorithms: Artificial Neural Network (ANN), Support Vector Machine (SVM), Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF) and k-Nearest Neighbours (KNN) in R programming language. Several evaluation metrics present comparable analyses using accuracy, sensitivity, specificity, and F1 score. According to the results, the SVM model was found applicable to local electrical utility transformers' health condition assessment. The paper addressed integrating international best practices and AM into the HI model.

Keywords: Power Transformer; Asset Management; Health Index; Electrical Utility; Decision Making; Strategic Investment Planning; R Programming Language; Python Programming Language, Machine Learning.

1 Introduction

Asset management is described in (ISO55001, 2014) as "systematic and coordinated activities that linked together to achieve the common business strategy, vision, and mission". Power transformers are considered as one of the important, reliable, and expensive assets in electricity networks, this asset is assumed to remain in service for at least 30-40 years (Hillary et al., 2017).

Over the past decade, the Power Transformer Health Index (PTHI) has been considered a reliable health condition assessment tool to classify the power transformer health condition based on the Health Index (HI) model results. PTHI is considered a building block in the overall AM process (Deloitte, 2014). The best performer among the electrical utilities is the ones that operate their power system network on high service and low cost (ITOMS, 2019; ISO55001, 2014). PTHI objectives must be defined in the asset maintenance strategy (Jardine and Tsang, 2021). In this paper the power transformer health condition categorised into the following five classes: very good, good, moderate, bad, and very bad.

Artificial Intelligence (AI) is becoming an innovative solution to improve actual data accuracy for PTHI calculations. Over the last few years, AI has become the best tool for designing PTHI due to rapid development in computer science, and data processing technology has gained rapid development too. One of the important research area and applications for AI using machine learning is investigating the health condition of the electrical transformers. A need to enable a predictive maintenance plan that forecasts the probability of power transformer breakdown and warrants performing the required quality of service since AM is all about a good quality of service ISO55001 (2014). Also, to enable preventing advance repair and earlier breakdown as some transformer downtime is very costly for electrical utilities due to its critical importance and strategic location of this unit within the electrical power supply network. Therefore, using AI is important to automate the decision-making for the required action.

The paper aims to promote the integration of the computational science of artificial intelligence and the engineering process of PTHI into an overall asset management framework as a strategic solution for the electrical utility. The contribution of improving business knowledge and introducing AM culture is challenging to support effective decision-making, especially within noisy data and diverse decision-making situations for the categorised assets based on a good understanding of AM Standard ISO55001 framework as strategic solutions. The AM technical and strategic solutions must be considered in practice to enable good maintenance decisions and lifecycle planning for the power transformers through a good PTHI condition assessment.

While research on the theoretical aspects of health index-based maintenance planning for transformers does exist, however, there is limited research in terms of real-world case studies and practical implementation practices on big datasets as practical studies are particularly important to deliver valuable insights and benefits of implementing AM practice within electrical utilities.

2 Literature Review

2.1 Health Index Identifying Transformers Condition

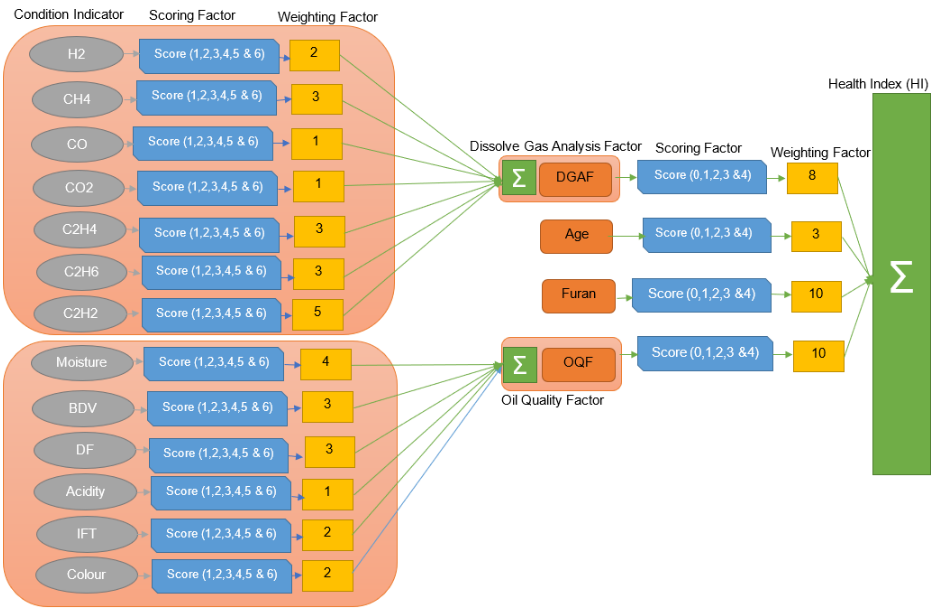
HI is a tool that merges all maintenance strategy condition monitoring information into a single value (Jahromi, 2009). To ensure HI represents the overall power transformer health condition, it requires incorporating field inspections and laboratory testing, historical maintenance, and load profile records which are clearly defined within the maintenance strategy (Taengko and Damrongkulkamjorn, 2013). Hence, each maintenance strategy is supported by the justified purposes of the HI assessment tool (CIGRE 761, 2019).

HI works by aggregating and processing available real data from the electrical utility which is collected from various locations and different work orders into an overall condition evaluation system that serves the implementation of the maintenance strategy (PAS55-1, 2008).

A conventional weighted sum is the most used method to calculate the HI of the power transformers (Nadrian et al.,2008; Jahromi et al.,2009; Kadim et al., 2018; Singh and Swanson, 2018). The approach starts by comparing each feature to a scoring table and then weighting each feature based on its importance. The individual scores are combined into a single index that reveals the overall health condition of the transformers.

Figure 1 indicates the main condition factors which are utilized in this analysis collectively including the related scoring and weighting factors for PTHI assessment.

Figure1 Health Index scoring calculation approach for power transformer.



Several transformer asset management strategies have been suggested in (Naderian et al., 2008). Standardization of maintenance strategy and HI for a certain country, utility or region is essential to ensure capturing the whole required data and process based on one agreed practice and standard even if it is for different assets and networks (ITOMS, 2019; Annex NGET A14.04, 2019). Mastering these data to one master dataset (asset register) will serve the whole electrical networks within the related region or country, which includes generation, transmission, and distribution networks. The maintenance strategy works based on regular updates based on the results of the HI as well the changes that can occur on HI design for power transformer health condition.

ML models have been used widely in the literature in recent years and have shown good and acceptable results in assessing power transformer health conditions. The HI model has been studied in (Arshad & Islam, 2014) to support optimum and reliable transformer strategic asset management decision-making that includes replacement, refurbishment, and relocation. Benhmed at al. (2018) investigated an approach based on feature selection and classification techniques to reduce assessment complexities of power transformer assessment. The investigation asserted the importance of the feature selection process in producing effective health index diagnoses of power transformers. It was found that water content, acidity, Breakdown Voltage (BDV) and Furfuraldehyde (FFA) to be the most important features to estimate the transformer HI. The accuracy achieved was 91.81% using RF and 91.81% with KNN with the K value equal to three.

Alqudsi & El-Hag (2019) also demonstrated the usefulness of using ML for HI problems using varies ML algorithms. The ML models in the experiments achieved high accuracy scores on both all features and reduced features experiments with three training/testing scenarios, NB (94.4%), ANN (95.1%), SVM (92.1%), KNN (95.6%), and RF (96.6%).

Ahmad et al. (2022) also studied the performance of the DT classifier and RF classifier, as the models were trained on a total of 213 data samples power transformers using the Python ML scikit-learn library. DT achieved an accuracy of 96.3%, whereas RF achieved an accuracy of 94.4%.

Rediansyah et al. (2021) also investigated multiple AI-based HI models. The result obtained in this study shows the RF classifier as the best condition classifier with an accuracy percentage of (97.3%). while other classifiers are DT (96.0%), ANN (91.3%), SVM (89.3%), NB (70.7%), and KNN (70.0%).

2.2 Asset Management Practice Supporting HI Aim

AM process is constrained by the principles of capabilities, level assurance, output focus, and learning organization. This section describes the importance of AM as a practice, AM standard as a framework, and the benefits of implementing AM roadmap. HI is considered as a building block for the holistic big picture of the AM process (Deloitte, 2014), and it covers all asset types (Tang & Wu, 2011).

AM standard covers strategic and technical practices that consider every asset as a valuable asset including human, physical assets, intangible assets, money, and information (Asset Management Anatomy, 2015). Efforts are required from electrical utilities to be aware of the value of practicing good AM best practices and sustain with the required continuous improvement level which is difficult and costly to manage over their long service that drives the electrical utility network at a high service and low cost.

AM has its standards which were introduced in 2014 (ISO 55000 series, 2014). AM also has its philosophy, journey, and culture that not every electrical utility is considered as AM utility based on the best performer (ITOMS, 2019). AM was not known until the

1980s when the term AM started to be used in the private and public sectors concerning physical assets in various parts of the world (ISO 55000 series, 2014).

AM strategic standard role is important with it is technical field experience role which is the latest considered as a well-known practice by each utility. Integrating the two roles is the key improvement process because it will provide useful information from a large amount of redundant dirty data, and improve, and speed up decision-making based on the quality of provided information to/by the HI.

Technically, it is a challenge for AM electrical utility to develop a dependable HI process using AI and machine learning algorithms as a strong reliable condition monitoring control system against bad data management practices because a good AM means it is all about integrating the whole business to work together from the highest to the bottom hierarchy of the organization in terms of better HI decision making that reflect the required action, time scale and the required budget or hierarchy in terms of asset register level that record all processes and provide useable and useful data portfolio.

In addition to the earlier definition, AM defined as "systematic and coordinated activities and practices through which an organization optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organizational strategic plan" in (Asset Management an anatomy ,2015 & PASS55, 2008).

AM aids electrical utilities to appreciate the value from their assets in the accomplishment of its organizational business objectives though it needs to balance all the financial, environmental, and social costs, risk, quality of service and performance associated with assets (Theiam.org., 2022). The benefits are achieved and grounded on developing a good AM implementation roadmap that incorporates AM standards clauses and subclauses. This is a long-term journey that begins by presenting AM culture before achieving the mature and AM certification level (Theiam.org. ,2022) that improves the quality of the actual dataset for the HI power transformer health condition investigation.

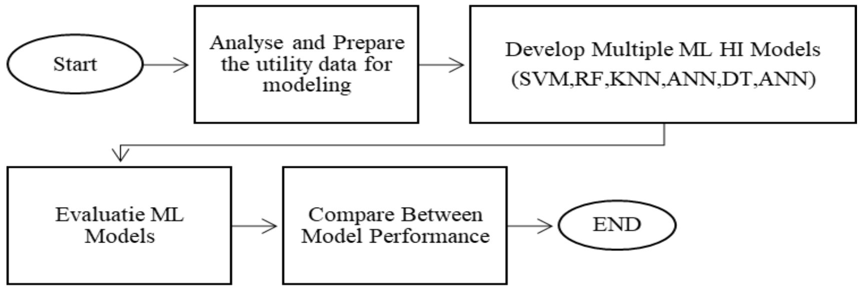
2.3 Health Index Driving Maintenance Strategy.

The maintenance strategy improves the secure operation and maintenance of the power transformer and decreases its operating expenditures. The achievement of these two targets leads to the development and implementation of a good HI as a condition appraisal tool that can be used for an AM power transformer that serves electrical utilities in any investment decision-making. The desirable improvement of HI results will require an action for the estimated power transformer health condition which should be estimated as accurately as possible like giving accurate medication by doctors to patients. If the conditions are incorrectly diagnosed, the cost savings might vanish, additional costs emerge, and time normalisation utilising best labours and resources complications.

3 Research Methodology

This paper focuses on developing power transformer HI based on the recent development of AI ML approaches using various academic literature, a good understanding of AM principles, and utilizing maintenance strategy practice. Figure 2 shows this paper's research workflow. In addition, the AI ML models are developed using real data to reflect it is important and overcome the HI issues in terms of high dependency on expert judgment and missing data challenges (Kadim, 2018).

Figure 2 Research Workflow



To predict the health condition of the power transformer, the following steps were carried out in this study:

Step-1: Data preparation and preprocessing by adding an extra two columns for the HI output feature which shows the PT health condition and the recommended maintenance action, in order the problem to be solved as multi-class classification problem.

Step-2: Stimulating Data for minority classes after finding out about the data imbalance problem.

Step-3: Inject the records into the HI conventional model to confirm the output.

Step-4: Conducting descriptive statistical analysis of the created PTHI dataset.

Step-5: Ensuring PTHI dataset quality and readiness for ML modeling by following various processes including dropping nulls, removing duplicates and outliners, and standardizing the dataset before building machine learning models.

Step-6: Building SVM, ANN, KNN, RF, DT, and NB ML models to predict the classes of the health conditions for the power transformer.

Step-7: Assessing ML model performance and carrying out comparative analysis among various ML model experiment results in this study and with others available in the literature.

Step-8: Recommend the best ML model for the electrical utility real dataset as well recommend the neccasry decisions based on the PTHI results.

3.1 Python Programming Language for Carrying Descriptive Statistical Analysis

Python programming language is a widespread open-source programming language used for various purposes including statistical analysis and machine learning development. This language allows to build machine learning models and statistical analysis straightforwardly using many packages including Pandas for data handling and manipulation and seaborn Library for statistical visualization in order to explore the dataset (*Pandas User guide*, 2024; Waskom, 2024).

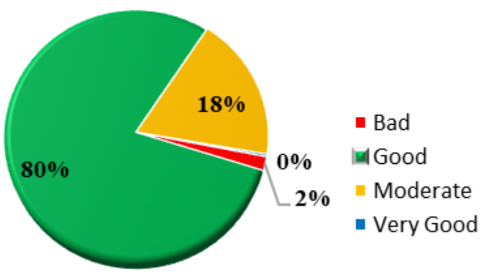
3.2 R Programming Language for Developing HI Machine Learning Models

R programming language is a popular free and purpose-specific language constructed to accelerate statistical analysis and machine learning. This language enables to perform machine learning models and statistical analysis easily using tons of packages (Nwanganga and Chapple, 2020).

4 Case Study Using Artificial Intelligence Health Index's

In this case study, a real dataset initially 969 power transformers under 69kV voltage was planned to be used to build multiple AI ML models to predict power transformer health conditions as a multi-class classification problem in R programming language. However, during data analysis, a data imbalance problem is very clear as shown in the PTHI condition data distribution shown in Figure 3.

Figure 3 PTHI Condition data distribution.



4.1 PTHI Dataset Preparation and Statistical Analysis

Simulating records for the minority classes was considered as a solution to the data imbalance problem as shown in Table 1. Based on the ranking rule of IEEE for DGA and oil grading method of transformers and fuzzy rules adopted from (Abu-Elanien et al., 2012), a simulation was conducted to obtain transformer data for the missing class of very bad. Also, more data was stimulated for the classes bad, very good, and moderate to ensure the data were balanced as shown in Table 2. Figure 4 shows the percentage of each class distribution after balancing the PTHI dataset classes. To ensure the balanced data at the required quality, the simulated data/records were injected into the PTHI conventional mathematical model which is built upon (IEC 60599, 2022; IEC 60505, 2011; IEEE C57.104, 2019; IEEE C57.106, 2015) standards to confirm the HI results and the power transformer health condition are correct and since the ML model needs inputs and outputs data. The idea of using the HI mathematical model is to confirm the simulated data are similar to normal real data. Therefore, this action balanced the dataset recs and obtained a new dataset that is acceptable for all the HI scenarios and beneficial for building ML models. The minority classes were oversampled using the stimulation of more data techniques. To ensure that the predictive model is capable and correctly predicting the cases of the minority group. The datasets for under 69kV transformers include both 66 kV and 33 kV transformer records since both follow the same ranges of the IEC and IEEE standards (Nadrian et al.,2008; Abu-Elanien et al., 2012).

Table 1 Data Before Simulation

Condition	Bad	Good	Moderate	Very Bad	Very Good
No of Records	17	769	178	0	5

Table 2 Data After Simulation

Condition	Bad	Good	Moderate	Very Bad	Very Good
No of Records	886	858	1022	768	790

Figure 4 Dataset PT condition distribution used for modelling.

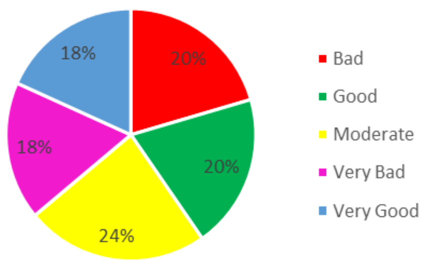


Figure 5 Dataset correlation matrix.

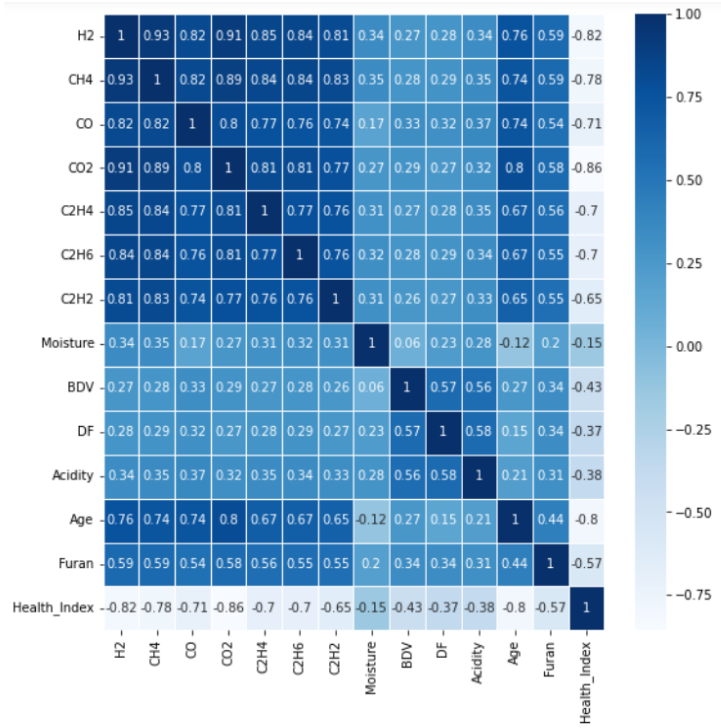


Figure 5 shows a correlation matrix of the dataset used for building the PTHI ML models to understand how the changes in the different features affect the HI values. CO_2, H_2, and Age have the highest negative correlation values with HI which are (-0.86-0.82, -0.8) respectively. Also, a high negative correlation is observed from the following features with HI which are: CH_4 (-0.78), CO (-0.71), C_2H_4 (-0.7), C_2H_6 (-0.7), C_2H_2 (-0.65). Whereas BDV, DF, Acidity, and Furan show less association with HI values of (-0.15, -0.43, -0.37, -0.38, -0.57) respectively.

A part of data preparation and preprocessing was utilizing the domain knowledge from the literature (IEC 60599, 2022; IEC 60505, 2011; IEEE C57.104, 2019; IEEE C57.106,2015). This is by adding an extra two columns for the HI output feature which shows the PT health condition and the recommended maintenance action according to the PTHI values (Jahromi et al.,2009). Table 3 is considered for the ML Modelling dataset preparation which is also used in spreadsheets and utilises the vlookup function.

Table 3: Interpretation of HI numerical scoring value (Jahromi et al.,2009).

Health Index Range	Condition	Maintenance Action
0-29	Very Bad	Replacement
30-49	Bad	Replacement
50-69	Moderate	Repair & Refurbishment
70-84	Good	Inspection
85-100	Very Good	Inspection

In this study, the problem was treated as a multi-class classification problem, therefore the choice of using SVM, ANN, KNN, RF, DT, and NB ML models is considered based on the fact that the chosen ML models are widely known to solve classification problems and have been widely used in many literatures by (Benhmed at al.,2018; Alqudsi & El-Hag,2019; Ahmad et al.,2022). Hence, it has demonstrated a reliable and viable solution.

According to (Pham, 2019); PTHI dataset features contrast, in terms of their quality and their type as some are continuous while others are nominal. Table 5 below shows a statistical analysis summary of the dataset features.

Table 5 Shows a descriptive statistical analysis of PTHI dataset features.

Features	**Descriptive Statistical Analysis for PTHI Dataset**							
	mean	**median**	**std**	**min**	**25%**	**50%**	**75%**	**max**
H2	223.88	60.12	295.04	0	18.69	60.13	276.55	999.99
CH4	190.83	45.17	281.88	0.04	10.595	45.17	181.06	998.74
CO	1314.20	237.50	2374.41	0	70	237.5	852	9991
CO2	2760.53	1628.50	2715.80	0	693	1628.5	3788.25	12210
C2H4	146.70	32.63	245.50	0.01	14.415	32.63	96.36	995.9
C2H6	146.40	35.06	245.67	0	8.1475	35.065	96.23	999.95
C2H2	120.33	2.46	253.97	0.01	0.65	2.455	27.81	994.92
Moisture	59.13	58.00	33.33	0	48	58	72	296
BDV	73.35	61.00	56.67	0	32	61	110	610
DF	23.42	0.21	31.84	0	0.047	0.211	46.61	99.975
Acidity	22.47	0.75	31.17	0	0.05	0.75	43.91	100
Age	35.28	19.00	33.24	0	7	19	55	120
Furan	0.29	0.08	0.38	0	0.04	0.08	0.62	6.2
Health Index	59.29	67.74	28.85	15.32	38.71	67.74	79.03	100

Table 6: PTHI dataset feature description.

Feature	**Type**	**Description**	**Remarks**
H_2	Numerical (Float)	Hydrogen	Dissolved Gas Analysis (in ppm) value
CH_4	Numerical (Float)	Methane	
CO	Numerical (Float)	Carbon monoxide	
CO_2	Numerical (Float)	Carbon dioxide	
C_2H_4	Numerical (Float)	Ethylene	
C_2H_6	Numerical (Float)	Ethane	
C_2H_2	Numerical (Float)	Acetylene	

Feature	**Type**	**Description**	**Remarks**
Moisture	Numerical (Integer)	Moisture level in ppm	Oil Quality Analysis
BDV	Numerical (Integer)	Break Down Voltage in kV	
DF	Numerical (Float)	Dissipation Factor	
Acidity	Numerical (Float)	Acidity level in ppm	
Age	Numerical (Integer)	Transformer age, actual age from years of installation as 2022 (reference years)	
Furan	Numerical (Float)		
Health Index	Numerical (Float)	Health values ranges from 0 to 100	
Condition	Categorical (String),5 classes: Very Good, Good, Moderate, Bad, very bad	The transformer health is classified into 5 condition according to Table 3 above	
Recommendation	Categorical (String), 3 classes: Inspection, Repair & Refurbishment, Replacement	The recommended maintenance decision based on the health condition according to Table 3 above	

In addition to the earlier descriptive summary statical analysis conducted in Python and the description of PTHI dataset features, the distribution of PTHI dataset features is also studied using density plots. Figure 6 shows a group of density plots for PTHI Dataset 12 input features, and it is very clear that the dataset features follow asymmetrical distribution, and it is right skewed. Decision tree-based models similar to DT and RF are a better choice for modelling skewed data as they utilize feature limits to divide the trees which influences them to be less delicate to skewed data distribution, according to (Mishra & Ghorpade, 2018; Ahmad et al.,2022) Random Forest performed the best with skewed datasets.

Figure 6: Dataset features distribution.

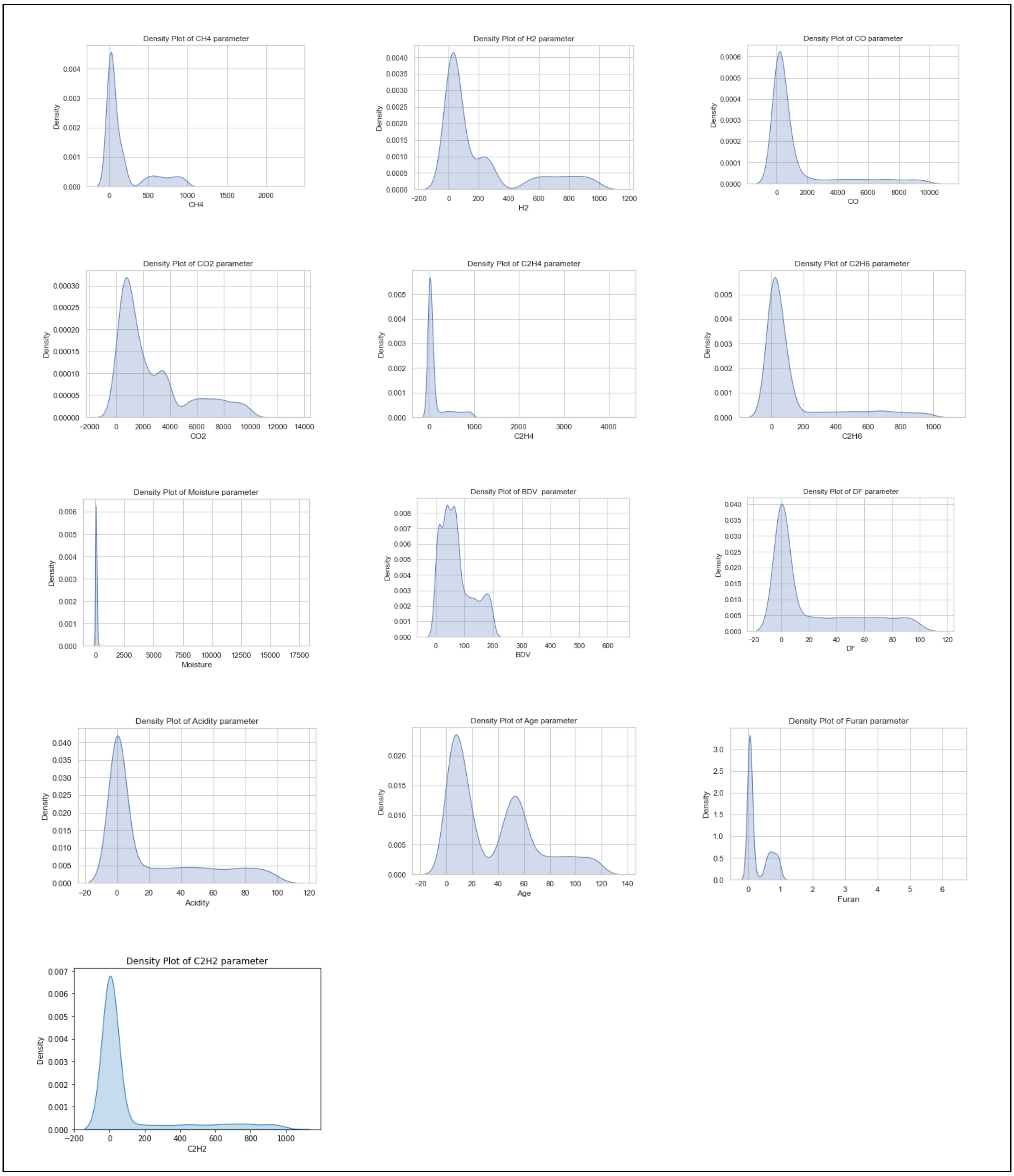
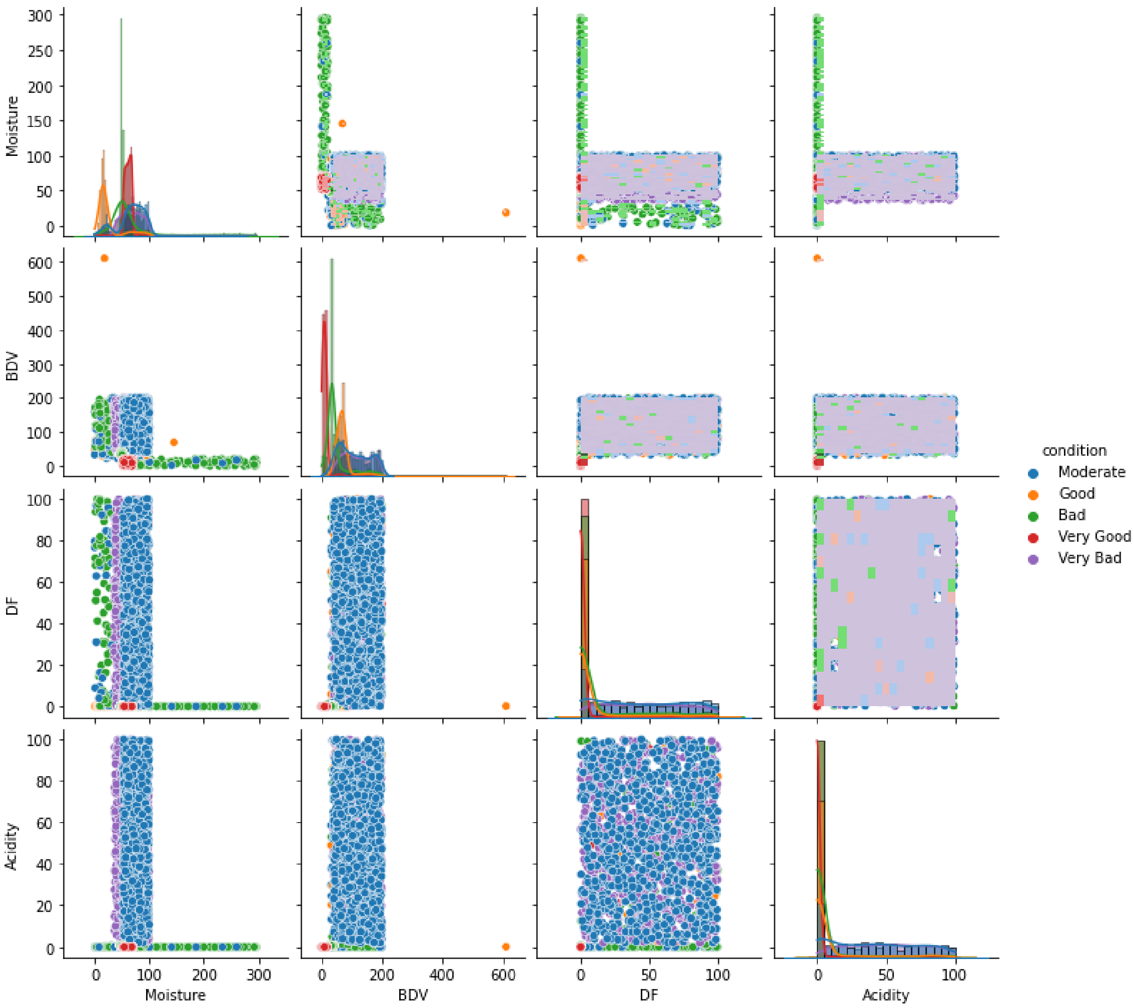


Figure 7 shows a pairplot of some chosen features for clarity as the PTHI dataset had 16 features. The chosen features are Moisture, BDV, DF, and Acidity colored by the condition class features. It demonstrates the relationship or patterns between the features as seen that the data points are overlapped which indicates a nonlinear relationship. Therefore complex models are better suited than simple models according to (Ghosh et al., 2019). In terms of ensuring PTHI dataset quality, various process was followed including dropping nulls, removing duplicates and outliners, and standardizing the dataset before building machine learning models.

Figure 7: Moisture, BDV, DF and Acidity pairplot.

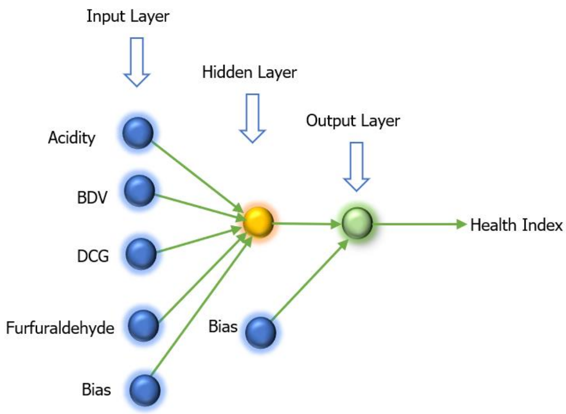


4.2 Machine Learning Models

A description of the AI ML algorithms used is given below:

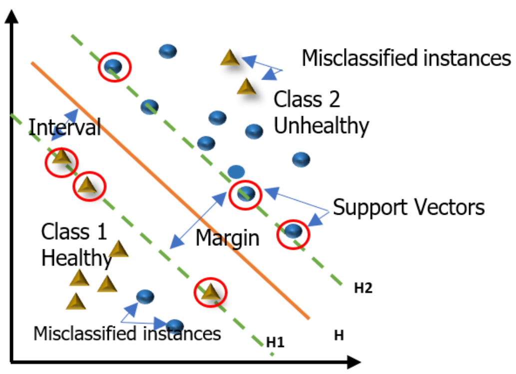
1. Artificial Neural Network (ANN) Algorithm: it is AI algorithm that can be applied for binary classification modelling based on various literatures as the algorithm performs effective results as shown in the research paper presented by (Islam,2018). An illustration of ANN is presented in Figure 8 below.

Figure 8 Artificial Neural Network model design for the HI to be implemented.



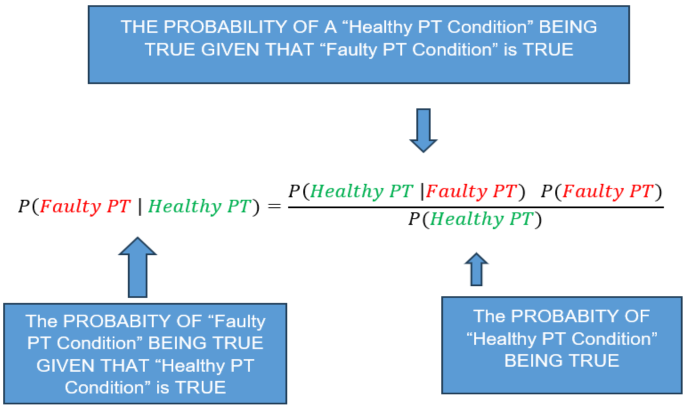
2. Support Vector Machine (SVM): The SVM model positioned a linear boundary between the unlike classes and position input features concerning which the boundary is expanded (Samanta et al., 2003). But SVM algorithm struggles to establish a hyperplane for nonlinear datasets. Hence, the Kernel function is the substitute for resolving this issue (Alqudsi & El-Hag, 2019).). A presentation of SVM is presented in Figure 9 below

Figure 9 Drawing of the Support Vector Machines (SVM) method.



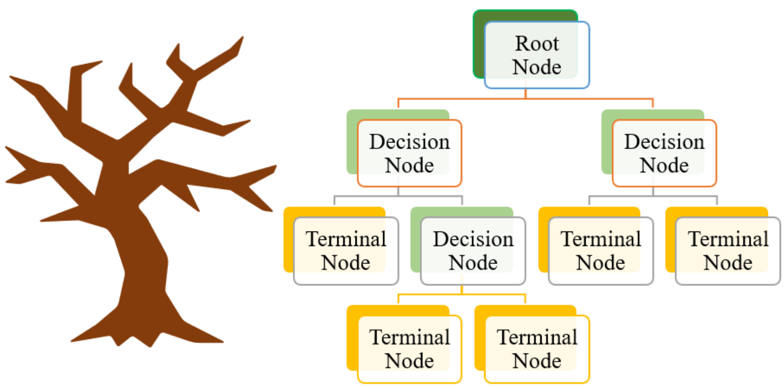
3. Naïve Bayes (NB): NB is also called as a probabilistic classifier reliant on Bayes theorem (Mitchell,2015). It is simpler to understand NB algorithm through describing the ABCs of Bayesian statistics. NB algorithm is reliant on hypothesis which the predictor variable is tentatively independent assumed the category of the statistics model in doubt which means the posterior probability of experiment for specific class granted the predictor variables is calculated applying Bayes theorem (Mitchell,2015). Application of Bayesian theorem to power transformer health condition classification is demonstrated in the below Figure 10.

Figure 10 Illustration using Bayesian theorem which is the base of NB algorithm.



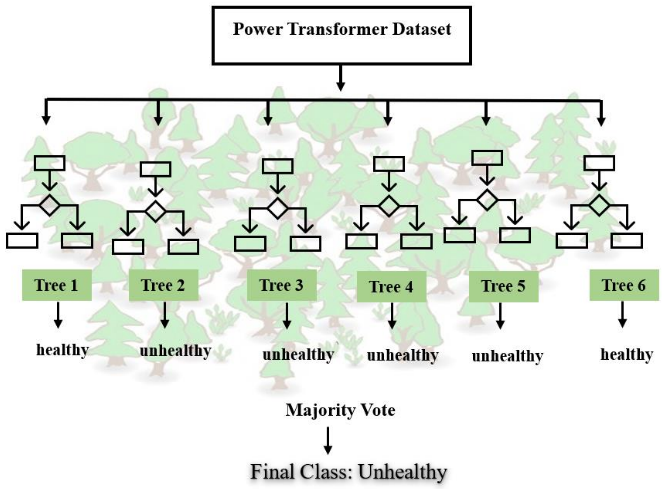
4. Decision Tree (DT): DT algorithm works by calculating the information obtained from the attributes and the maximum normalized information is then employed to split the instances into subsets of the same class label as shown in Figure 11. The same process is repeated with all split subsets as children of a node. Lastly, the tree is trimmed by eliminating the branches that do not assist in classification (Alqudsi and El-Hag, 2019).

Figure 11 Illustration of the Decision Tree (DT) method.



5. Random Forest (RF): Is considered an ensemble algorithm as it consists of multiple decision trees. The result of the algorithm is the vote agreed by most of the decision trees (Alqudsi and El-Hag, 2019) as illustrated in Figure 12. It is stated that RF does not overfit as more trees are added which causes limiting value for the generalization error. With RF, it is easy to measure the relative importance of the input features to the target variables (prasojo et al.,2021).

Figure 12 Illustration of the Random Forest (RF) method.



6. k-Nearest Neigbours (k-NN): In the featured space, consider three neighbours according to Euclidean distance. The new instance will be allocated to the class with the most neighbours. (Kherif et al., 2021). For example, the new instance in Figure 13 below has three neighbours in the circle drawn and will be allocated to the unhealthy transformer class as shown it has two neighbours of class unhealthy transformer and 1 of class healthy.

Figure 13 Illustration of the K-Nearest Neigbours (KNN) method.

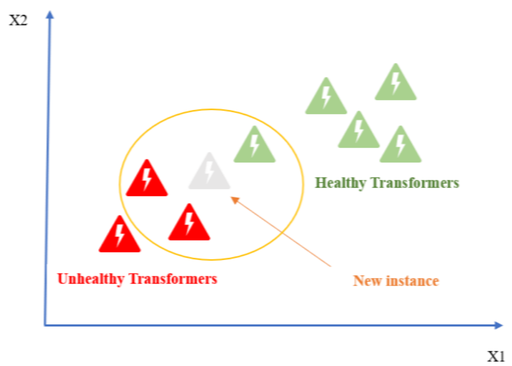


Table 7 Performance metric for PTHI condition classification (Caret: Classification and regression training - the comprehensive R, 2023).

Performance metric	Formula	Metric Description
Sensitivity	True Positive / (True Positive + False Negative)	Measure the percentage of positive instances that are correctly classified.
Specificity	True Negative / (True Negative + False Positive)	Measure the percentage of negative instances that are correctly classified.
Prevalence	(True Positive + False Negative)/ (True Positive + False Negative + False Positive + True Negative)	Measure the percentage of records in the dataset that present a specific class label.
Pos Pred Value	(sensitivity*Prevalence))/ ((sensitivity*Prevalence)+((1-specifity)*(1- Prevalence)))	Measure of model precision which represents correctly predicted positive class.
Neg Pred Value	(specificity*(1-Prevalence))/ (((1-sensitivity)*Prevalence)+ ((specifity)*(1- Prevalence)))	Measure of model precision which represents correctly predicted negative class.
Balanced Accuracy	(sensitivity + specificity)/2	Measure the model's accuracy by taking the average of both sensitivity and specificity which is best suited for an imbalanced dataset.
F1 Score	(1+beta2) * precision * recall/((beta2 * precision) +recall)	Measure the model predictive ability by combining both the precision and recall.

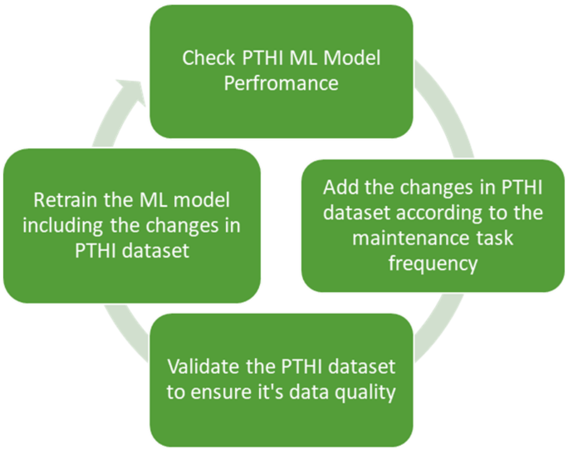
4.3 Power Transformer Health Index Machine Learning Model in Production and Asset Management Continuous Improvement Principle

PTHI ML model in the production stage needs to follow agile methodology which contributes to applying a continuous retraining strategy (Baumann et al., 2022). This is to continuously monitor the ML performance and continuously retrain ML model without compromising on the importance of data validation process to ensure that the PTHI ML model keeps updated with the changes in PTHI according to the maintenance task frequency. This will enable the PTHI to capture the changes of maintenance task's nature and frequency.

In practice, this should be performed by applying automation data pipeline process as the Maintenance Asset Register should be an online system that is updated regularly to keep track of PT technical details and history information (Hastings, 2021), and the ML model should be retrained automatically (Kavikondala et al.,2019) on the real data which includes the changes in PTHI according to the maintenance task frequency through automated data pipeline to ensure that the quality of the model is up to date.

Figure 14 show how the PTHL ML model keeps performing well in the production cycle after deployment even with the changes in real data. This is to ensure the confidence of data quality is high as it should follow a continuous improvement and learning approach according to Asset Management principles.

Figure 14: Applying continuous AM improvement learning cycle for PTML model in the production stage.



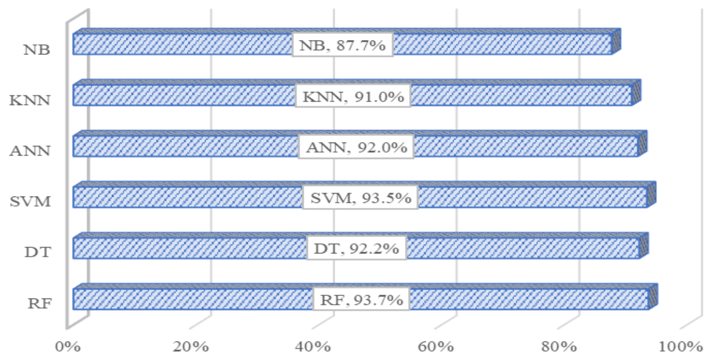
Consequently, Asset Management maintenance needs to ensure asset maintenance is driving the annual maintenance plan and maintenance strategy through good daily operation and maintenance switching schedule which implies based on the annual maintenance plan and maintenance strategy which has been updated based on PTHI condition findings. Nevertheless, AI supports the accuracy of required new maintenance decisions by utilising the importance of actual data that leads to optimising maintenance strategy.

Electrical utilities must develop good Asset Management practices that reflect on improving the quality of power system services. Good Asset Management means good quality of services that suit a good maintenance annual plan and maintenance strategy. On the other hand, if ML PTHI identifies power transformer health conditions based on investigating failure modes and mechanisms before degradation increases and failure occurs, then the number of maintenances switching schedules frequency will increase or decrease based on good optimal cost justification that developed for implementing good maintenance strategy that improves the secured in-service power transformers and decreases unnecessary operation and maintenance expenditures. This works by optimizing the required maintenance for improving the power system security performance which concludes the importance of Asset Management in managing a continuous power transformer lifecycle, operating the in-service transformers at high performance, less cost, and managing unexpected risks before occurring.

5 Results

AI machine learning models' output are examined, and a comparative analysis of the result is performed using the utility dataset available, and the various ML algorithms namely DT, ANN, RF, SVM, and NB models in R programming language. Utilizing performance evaluation metric formula as shown in table 1 above. The classification was done on 13 input features: H_2, CH_4, CO, CO_2, C_2H_4, C_2H_6, C_2H_2, Moisture, BDV, DF, Acidity, Age, Furan and the results were represented as a range for each predicted condition classification. Expressions of the condition classification can oscillate between five conditions, very good, good, moderate, bad, and very bad. Very good and good is an expression that belongs to the positive concept, if it transmits the user's satisfaction or gratitude. Bad and very bad are an expression that belongs to the negative concept if it shows dissatisfaction and actions immediately required. The RF and SVM models performed the best with an accuracy of around 93%. While NB performed the least with 87% accuracy as shown in Figure 15.

Figure 15 ML Model's Accuracy.

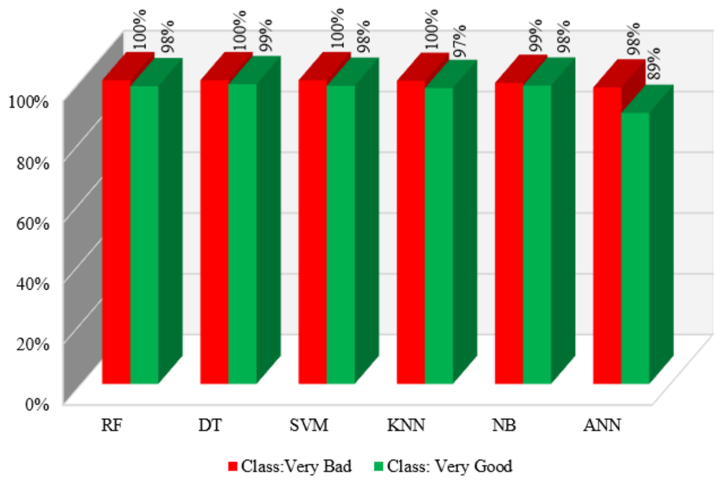


Secondly, utilizing F1 score which is an accuracy metric that is used to show the percentage of the correct prediction for each class. It is identified as a harmonic means of precision and recall. It was considered for class very bad and very good because if a transformer is bad and the model predicts it wrongly as good, the effect will be catastrophic if it is neglected, and the necessary action is not taken within the time frame which can lead to not including the required budget for the related action in a real practical case. Figure 16 shows:

• For class: Very Bad, SVM, RF, and DT have F1 score of 100% which mean that the model has made no errors in predicting the very bad class.

• For class: Very Good, DT performed the best with a score of (99%), followed by SVM, NB, and RF with an F1 score of 98% and KNN performed 97%. Whereas NN performed the least with a score of 89%.

Figure 16 F1- Score Comparison.



In addition, the KPIs of sensitivity, specificity, pos pred value, neg pred value, precision, recall, and F1 score for RF and SVM as shown in Figures 17 and 18.

Figure 17 RF performance Comparison.

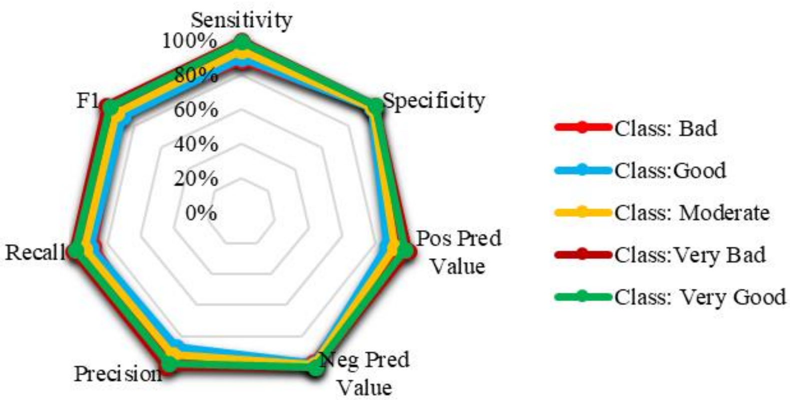
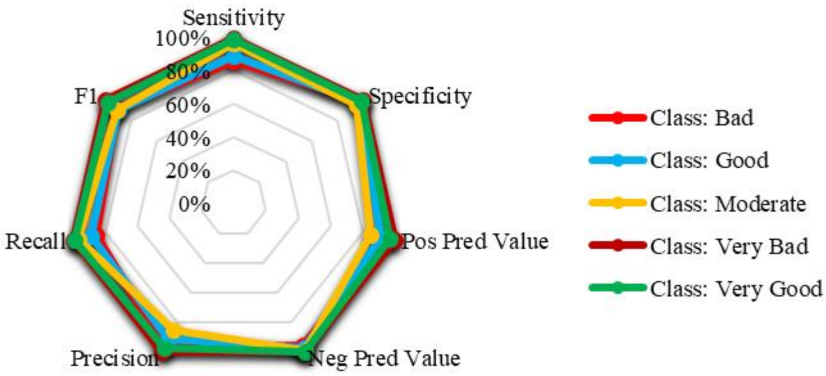
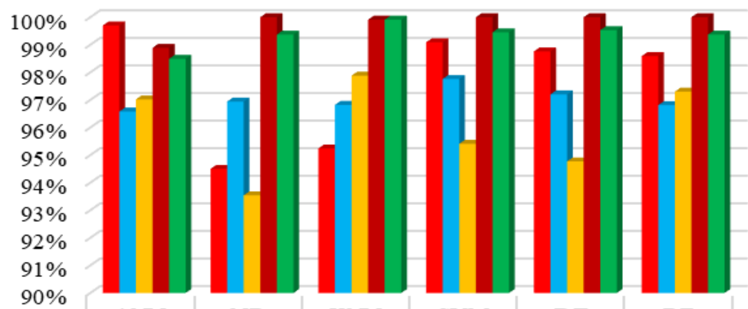


Figure 18 SVM performance Comparison.



The specificity measures for class very bad are the highest in all developed models with the values of above 98%, followed by class very good. Where ANN has the highest specificity for class bad, SVM has a good performance as the SVM for classes: bad, good, very bad and very good are above 97.7% as shown in Figure 19. Furthermore, sensitivity measures for SVM are equally good for class moderate, very bad and very good which are above 96% as shown in Figure 20.

Figure 19 Specificity measure for ANN, NB, KNN, SVM, DT, RF per condition class.



	ANN	NB	KNN	SVM	DT	RF
Class: Bad	100%	95%	95%	99%	99%	99%
Class:Good	97%	97%	97%	98%	97%	97%
Class: Moderate	97%	94%	98%	95%	95%	97%
Class:Very Bad	99%	100%	100%	100%	100%	100%
Class: Very Good	98%	99%	100%	99%	100%	99%

Figure 20 Sensitivity measure for ANN, NB, KNN, SVM, DT, RF per condition class.

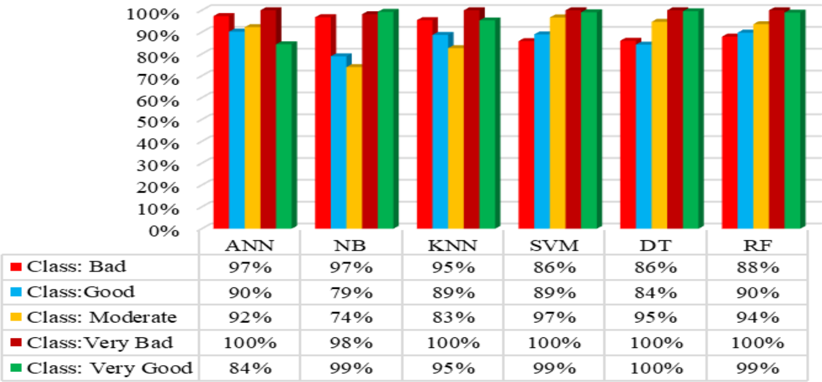


Table 8 Machine Learning models performance comparison for identifying transformer in very bad condition that needs urgent asset management interventions.

Performance Comparison				
	Accuracy	F1 Score	Specificity	Sensitivity
SVM	93.50%	100%	99%	99%
RF	93.70%	100%	99%	99%
DT	92.20%	100%	100%	100%
KNN	91%	100%	100%	95%
ANN	92%	97.60%	98%	84%
NB	87.70%	99%	99%	99%

Figure 21 Decision Tree model plot.

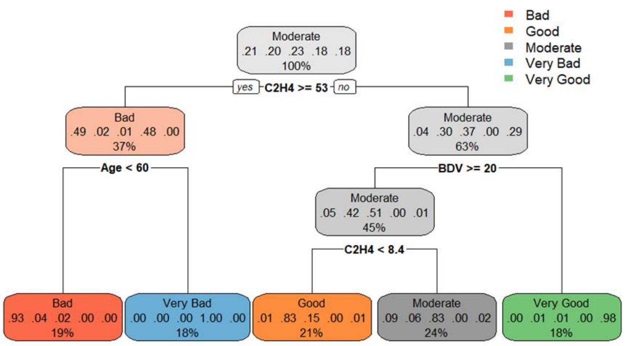


Figure 21 shows the results obtained from the DT model that represents the attributes that affect the decision model as Ethylene (C_2H_4) gas, Breakdown voltage (BDV), and age. The age was found to be one of the most significant features to assess the transformer health condition based on the used dataset. Predicting the real condition of the transformer is found to enable extending the transformer age to an additional 20 years (Foros and Istad, 2020). Hence, deferral of unnecessary costs for transformers it needs sometimes minor actions and avoiding wrong actions for the older transformers aged (+70) years and youngest (-5) years. This also assists in considering the optimum cost value for preventing an increase in operation and maintenance costs which might be higher than the initial project value (Asset Management Anatomy, 2014). Although this will enable new replacements to take place at the required timeframe.

5 Discussion

AI algorithms offer various solutions to overcome the HI issues in terms of the lack of data or the high dependency on expert judgment (Kadim, 2018 and Tang & Wu, 2011). The previous studies agreed that HI assessment focuses on studying the critical, expensive, and reliable assets including power transformers or overhead lines. AI is considered a solution to overcome the HI method weakness as it is more efficient with applying AI algorithms and machine learning methodology. This is more vital and a further improvement in HI for electrical utilities. AI leads to intelligent HI by developing the required algorithms that work with the required and available dataset. AI is used to solve dataset issues to predict the related numerical missing data and improve data uncertainty. This will improve the HI estimation accuracy, but the dataset will remain as estimated data despite the fact the data is checked using the mathematical conventional model. Nevertheless, it confirms that HI findings are useful for finding faulty transformers in a large fleet of power transformers and considering appropriate actions.

In addition, since the PTHI dataset size is large as it has 4323 records, complex models are more suited to similar large datasets according to Ajiboye et al. (2015). Also, since the PTHI Dataset follows a nonlinear pattern between the different features according to Ghosh et al. (2019) and as the data points are overlapped as shown in Figure 7. Therefore, complex models that are suited to solve nonlinear classification are more suited to this study which is the reason that RF and SVM performed the best compared with NB.

Furthermore, Decision trees-based models like DT and RF are the best choice for modelling skewed datasets as they use the decision threshold to split the trees which causes them to be less delicate to skewed distribution, that is the reason that Random Forest in this study showed a high performance and accuracy of 93.7% similar to (Mishra and Ghorpade, 2018) study where Random Forest performed the best with skewed datasets.

Most asset failures of any power systems including power transformers are seen in electrical active part components, plant control systems (actuators), and sensors, which may cause dangerous situations, high repairable cost, and long downtime (CIGRE. Technical Brochure, 2007).

As a result, there is strong stimulation to improve the operation and maintenance reliability of the HI system by using real-time monitoring, prognosis, and resilient control techniques for the HI tool. This is because there is a large amount of data that shall be expected either recorded via any of the online systems including Supervisory Control and Data Acquisition (SCADA), Enterprise Resources Planning (ERPs) systems, asset register, collected from other data storage and/or obtained through visual site inspection.

This paper considered PTHI ML methodology to capture the changes in the maintenance task's nature and frequency by applying a continuous retraining model strategy according to studies by (Kavikondala et al.,2019; Hastings, 2021; Baumann et al., 2022); which showed the importance of implementing continuous improvement approach that required to be allied with Asset Management principles to optimise and prioritise maintenances work orders that can impact both efficiency and security of required transformer performance.

Even though in this paper the best model's accuracy result achieved was 93.7% for RF and 93.5% for SVM, which is less percentage compared to other literature including (Ahmed et al., 2022; Alqudsi & El-Hag, 2019; Rediansyah et al., 2021). However, this is assumed to be due to the sample dataset size, type, and data distribution used in the AI ML modelling experiments. Ahmed et al. used a small dataset and didn't mention the data distribution of the training dataset. Whereas Alqudsi & El-Hag (2019) used an imbalanced dataset as the ratio of bad to good was 1:22 in total as there were 33 transformers in bad condition and 734 in good condition. Also, Rediansyah et al. (2021) didn't consider the condition distribution issue as the dataset size used was a total of 504 power transformers and the ratio of very bad to very good is equal to 1:17 as in total there are 10 transformers in very bad condition and 174 in very good condition.

Furthermore, the distribution of classes shows data imbalance problems without solving the data imbalance problem which is a must before experimenting/conducting ML modelling. It was found from the literature that a small sample size can result in overfitting of the model, resulting in poor generalization (Pereira et al., 2009). It has been also found that sample size negatively impacts classification accuracy (Arbabshirani et al., 2016; Varoquaux, 2018). Therefore, accuracy is not the right measurement metric for the small, unbalanced dataset, as F1 score metrics are a better choice for such evaluation. The F1 score is a good measure of the ML model's capability of detecting transformers that need urgent actions including transformers in very bad and bad conditions. The F1 score evaluation was not considered in the previously mentioned papers, but it was considered in this paper and achieved high percentages as shown in Figure 16.

Due to limited data and challenges of the actual data, the academia can bring HI researchers to work together with the required team within the electrical utility to develop a better HI tool which can lead to better AM utility implementation since AM is about a good quality of service. The working process and collaboration among several departments within the electrical utility will enable the development of the culture of a healthy AM environment as considers the value and importance of best practices that integrate HI with the big picture of asset management that enables the use of a better quality of real data.

6 Conclusion

Electrical utilities are keen to control future funding for assets aging challenges, specifically for reliable assets including power transformers while introducing best international practices, AM concepts, standards, and culture are important in terms of achieving the electrical utility strategic goals and reshaping for a better real dataset for HI use. Hence, it became essential to implement a good AM as most electrical utilities are monitored by technical regulatory guidance and compliance policy. This AM monitoring philosophy is part of utility master planning, government obligations, and funding price control strategy.

HI provides rich information about the improvement of operation and maintenance systems on daily decision-making for executing maintenance plans. Therefore, how to use the available data for the HI approach is the monitoring capability, which needs prognosis, and even a resilient control algorithm. AI machine learning algorithms are becoming a great interest in academia as well as in practice. This has received a huge considerable attention in fault diagnosis by the maintenance and asset management team. However, it is very complicated to get auditable useful information from a large amount of redundant imbalanced data. It is also very complicated and challenging to develop reliable monitoring tools which are prognosis, and resilient control algorithms against noisy and even bad data.

During the HI investigation it is important to investigate all the relevant data sources using available failure modes, and how those can be grouped into logical HI assessments score for power transformer and its subsystems. Such sets make sense in terms of user experience on HI assessment. Then this will gain a true value from using the HI for better timely decision making. This means improving the short-, medium-, and long-term asset lifecycle and aligning costs for Operating Expenditures (OPEX) that include operation and maintenance costs. Also, HI can play a role in reducing the Capital Expenditures (CAPEX) and mastering the whole investments into one robust Master Plan which can be named Total Expenditures (TOTEX).

Good data analysis improves HI results and helps in good decision-making. The HI scores indicate the critical of unhealthy transformers that need action from the healthy transformers that do not. These actions are varied and reflect the required optimal decision-making process whether it is routine maintenance that needs small repairs within transformer active parts or even a replacement decision for the whole power transformer. This is to ensure cost-effective decisions while considering controlling power supply interruption and preventing major system outage values that can lead to uneconomical power supply interruption.

In recent years, AI has become the main key player that plays for improving the calculation accuracy of designing and developing an effective and efficient HI. It has been introduced as an alternative super approach to estimate the value for the missing data, or data uncertainty, and for detecting power transformer health conditions. Our study concluded that decision tree-based models like RF are a better choice for modelling skewed data as proven in this study's experiments as RF achieved the highest accuracy of 93.7% because it utilizes the features limits to divide the trees causing it to be less impacted by the right-skewed data distribution.

This paper also recommends that during ML studies investigation for PTHI it is best to utilize F1 evaluation metrics which is proven to be the best measure of the ML model's capability of detecting transformers that need urgent actions including transformers in very bad and bad conditions. It is found in this evaluation that for transformers in a very bad condition, SVM, RF, and DT has F1 score of 100% which means that the models have made no errors in predicting the transformers that require immediate action. Detecting and handling faults at early phases is a critical key for extending transformers' life to an additional 20 years. In power grid stations, power transformers are the most expensive component, therefore health index ML-based models are necessary to maximize operating the electrical network economically and efficiently and ensure the accuracy of decisions is higher than operating in-service power transformers only efficiently. To ensure the PTHI ML-based tool is resilient to change in maintenance activities, the PTHI ML based tools in the production stage should follow a continuous

AM improvement principle by applying continues retraining ML model on actual recent available data.

Finally, HI plays a good AM technical role in extending transformer life and managing asset lifecycle by regularly improving the AM maintenance strategies decision-making process towards improving all the electrical utility business objective and establishing preventive maintenance system that reduces unnecessary spending. This will advance the role of AM within the organizations, leading to good optimization of the investment maintenance practices, enhance grid reliability, and customer satisfaction focus, and support business efficiency by improving the quality of services and HI results accuracy.

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