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Power Transformer Health Prediction using Machine Learning

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ABSTRACT

Ensuring good conditions and functionalities of these power transformers, these units are constantly monitored and maintained through the implementation of various condition-based maintenance activities. However, despite all of these preventive maintenance practices in place, some transformer defects are still left undetected, especially at an early stage. There is a lack of a holistic risk evaluation system in the power utility company to support and guide the scheduling and prioritization of condition-based maintenance activities. It is reported that there was a total of 20 power transformer failure cases during the years 2005-2019. These failures led to higher operating expenses, arising from the cost of repair and loss of revenues due to outages and downtime. As such, the outcome of this research aims to fill in this gap in the preventive maintenance system currently in practice in the power utility company by developing a transformer failure prediction system to complement the existing maintenance testing activities that are performed routinely as a part of condition-based maintenance in Malaysia. A Tier 1 to Tier 2 prediction algorithm is developed in this project with the help of artificial intelligence to accelerate the availability of Tier 2 electrical test results. This allows early assessment of the transformer's electrical parameters. Thereafter, the predicted Tier 2 test results can be used in conjunction with transformer age, loading, visual inspection as well as Tier 1 oil test results to predict failure probability and fault type through the development of a lookup table. Overall, this algorithm aims to speed up and improve the transformer health assessment to act as an early warning system for future tripping and failure events. This allows condition-based maintenance activities that are currently in practice to prioritize transformers that are undergoing more severe deterioration before permanent irreversible damage occurs.

Keywords: Condition-Based Maintenance, Distribution Network, Failure, Machine Learning, Prediction, Transformer

1. INTRODUCTION

Normal Power transformers play a crucial role in ensuring the proper functioning of the national power delivery system [1, 2]. Maintaining their reliability remains an important yet tricky task. Without proper care, power transformers' failures can result in catastrophic events involving widespread supply disruptions, destruction of infrastructure, and even the loss of lives [3-5]. In the aftermath, the replacement of power transformers and other damaged equipment comes at a huge economic cost to the utility companies [4, 6-9].
Logically, the prevention of power transformer failures has been the main interest of utility operators [10-12]. This has also become the focal point of many research studies which have

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investigated the various causes of power transformer failures as well as ways to predict them before they happen [13-16].

The activities and tasks performed under power transformer maintenance testing can be categorized into 3 main stages/tiers, which are briefly described as follows [17]:

- Tier 1 ➔ Routine condition assessment that is performed online annually for all transformers in service, comprises non-intrusive testing activities such as physical inspection, load monitoring, infrared thermography, ultrasonic scanning, oil quality analysis (OQA), dissolved gas analysis (DGA), and furfural/furan analysis (FFA)
- Tier 2 ➔ Routine condition assessment that is performed offline once every 4 years or when Tier 1 activities indicate abnormal conditions, comprises intrusive testing activities that measure electrical parameters including turns ratio (TR), winding resistance (WR), insulation resistance (IR), dielectric dissipation factor (DDF) and excitation current (EC).
- Tier 3 ➔ Advanced condition assessment that is performed when Tier 1 or Tier 2 activities indicate concerning conditions suggesting problems with a considerable level of severity.

However, despite all of these preventive maintenance practices in place, some transformer defects are still left undetected, especially at an early stage. There is a lack of a holistic risk evaluation system in the power utility company to support and guide the scheduling and prioritization of condition-based maintenance activities in Malaysia. The current power utility company's distribution network asset performance management system (APMS) does not include a transformer predictive failure system. It is reported that there was a total of 20 power transformer failure cases during the years 2005-2019 in the power utility company in Malaysia. These failures led to higher operating expenses (OPEX) to the power utility company, arising from the cost of repair and loss of revenues due to outages and downtime. As such, this paper aims to fill in this gap in the preventive maintenance system currently in practice by developing a transformer failure prediction system to complement the existing maintenance testing activities that are performed routinely as a part of condition-based maintenance.

2. METHODOLOGY

The methodology section details the inner workings of the proposed transformer failure prediction algorithm. The methodology is also finalized with the inputs from members of the substation unit as well as technical experts/specialists.

Transformer failures are evaluated based on two output parameters:

1) Probability of Failure (P_{fail})

   P_{fail} gives an indication of how likely a transformer is going to fail in a specific timeframe. In the context of this project, it is treated as a parameter that is linearly and inversely proportional to the transformer total condition health index (TCHI), with a value range of 0 – 1. Higher P_{fail} values indicate that the transformer is more likely to fail during the timeframe it is evaluated.

2) Possible fault types

   There are many ways in which a transformer could fail. Conceptually, a transformer would fail when any of its components becomes faulty to an extent where it forces the transformer to be inoperable. Fault types identify what symptoms are observed in these transformer components which is causing them to have a higher likelihood of succumbing to failure. Some examples of fault types include partial discharge, sludge formation as well as oil and insulation degradation.

This prediction is achieved by referring to the values of various transformer parameters which present a correlation with the transformer health. A hybrid artificial intelligence (AI) model + rule-based logical inferencing and scoring algorithm are used to enable a fool-proof and comprehensive analysis of potential transformer failures that is backed by the technical principles stated in the relevant Institute of Electrical and Electronics Engineers (IEEE) standards. The overall methodology can be divided into two main sections i.e. the Tier 1 to Tier 2 prediction section and the failure probability and fault type prediction section. The overall workflow is summarized in Figure 1.

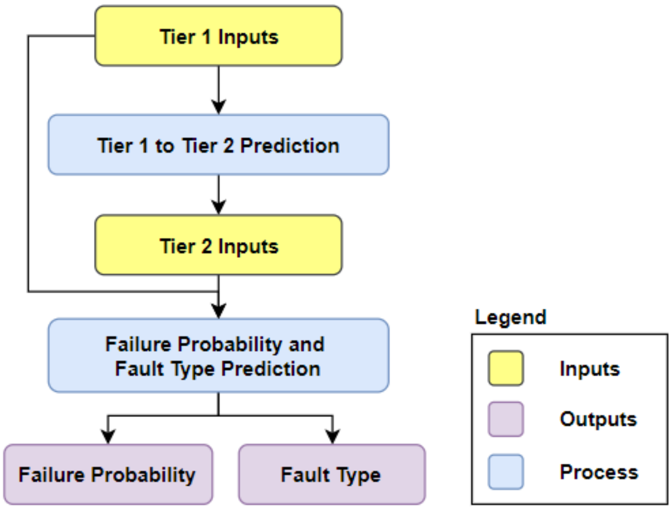

Figure 1. The Overall Workflow of the Transformer Failure Prediction.

Tier 1 inputs are acquired by conducting annual maintenance testing on the transformers. These inputs are fed into the Tier 1 to Tier 2 prediction AI model to generate the expected Tier 2 test results based on the Tier 1 values. Then, the obtained Tier 1 and predicted Tier 2 values are applied to the failure probability and fault type prediction model to perform an evaluation of the transformer's health condition.

The overall workflow begins with the development of the AI model that is responsible for performing Tier 1 to Tier 2 predictions. This is performed prior to the deployment of the algorithm in order to yield the AI model which will be used to predict the Tier 2 test conditions in the failure probability and fault type prediction algorithm. This part is only performed once to generate the AI model, after which the same AI model can be reused in the failure probability and fault type prediction algorithm until the next time the AI model is updated with a new AI model that is trained with the latest data. In the development phase, a training database containing records of various Tier 1 oil test results, transformer age, and their corresponding Tier 2 electrical test results are developed. This database is built from the transformer maintenance records acquired from various departments. Then the data undergoes a series of data pre-processing steps before it is used in the actual AI model training. The output of this section is a trained AI model that is capable of giving Tier 2 predictions based on the Tier 1 inputs with a high level of accuracy.

On the other hand, the failure probability and fault type prediction section performs the necessary calculations based on inputs from the user and the previously developed AI model to evaluate the probability of failure and possible fault types of the transformer. It is the main engine of the system that gives real-time transformer failure predictions during deployment. The user inputs to the failure probability and fault type prediction algorithm consist of various parameters which serve as indicators of the transformer health condition. These include transformer age, loading, visual inspection as well as Tier 1 oil test results from the dissolved gas analysis (DGA) [18], oil quality analysis (OQA), and furan analysis. The Tier 1 oil test results and the transformer age are also used in the AI model to predict the values of Tier 2 electrical test conditions for the specific transformer. The predicted Tier 2 values then work together with all the other inputs to undergo a series of scoring calculations to determine the condition of the individual components. The inclusion of both Tier 1 and Tier 2 test results, as well as other parameters in the evaluation, allows the algorithm to present a complete picture of the overall transformer condition.

The results from the scoring of each individual component are then used to evaluate its probability of failure and possible fault types. The probability of failure is calculated using a weighted sum of the individual components whereas the possible fault types are determined with a lookup table which is based on the condition of individual components to predict the likelihood of a transformer failure in the upcoming time cycle.
Once the AI model is developed to incorporate all the best machine learning (ML) models selected for the prediction of each Tier 2 test, the failure probability, and fault type prediction algorithm is ready to predict Tier 2 values from Tier 1 inputs to perform an evaluation on transformer failures. The algorithm utilizes a rule-based approach to assign different scores to each input (e.g. Tier 1, Tier 2, age, and other input parameters) based on the condition of the respective inputs. Thus, the scoring model is devised as a result of the collective knowledge of many years of real practical experience from technical experts. This ensures that the outputs from the algorithm's predictions are always reliable and in line with the fundamental principles of power transformers.
The overall workflow of the failure probability and fault type prediction algorithm is summarized in Figure 2.

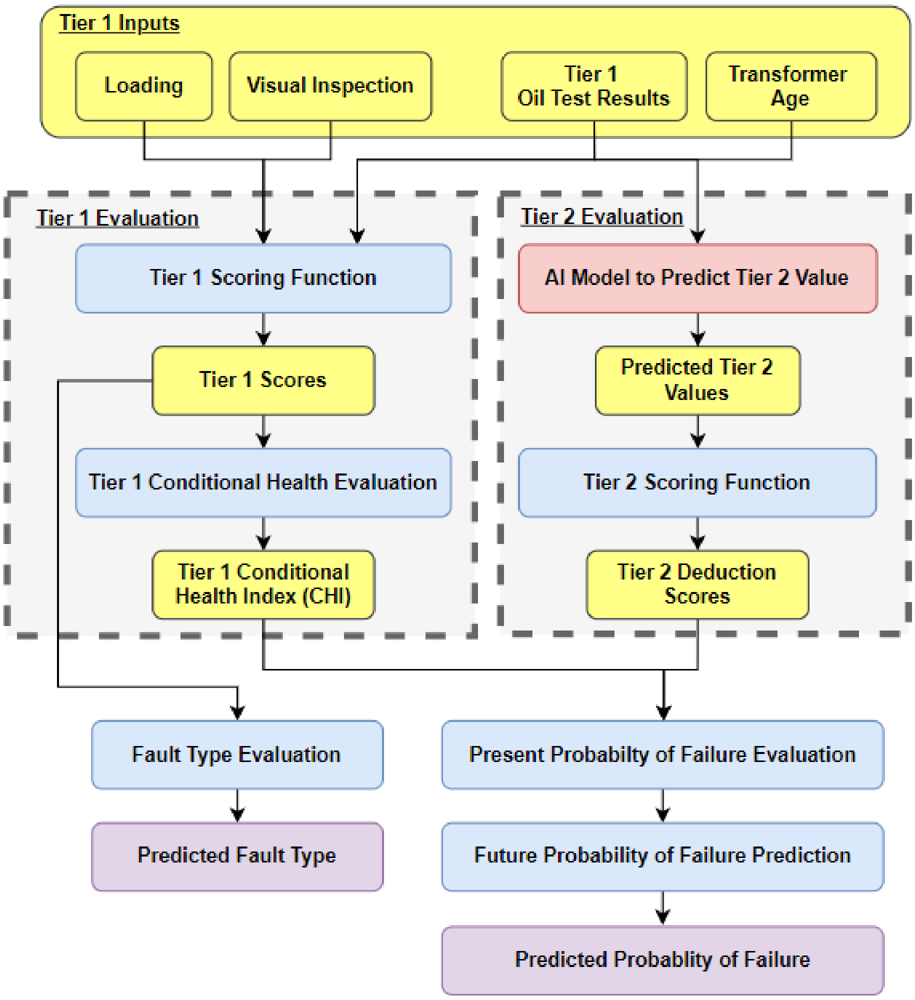

Figure 2. The Overall Workflow of Failure Probability and Fault Type Prediction Algorithm.

In the failure prediction evaluation algorithm, the Tier 2 inputs are used to balance out the scoring results obtained from the Tier 1 inputs. This is achieved by calculating a Tier 2 deduction score to be subtracted from the Tier 1 CHI score. The Tier 2 deduction score serves as a mechanism to perform checks and balances so that the final failure prediction is more accurate by preventing any individual Tier 1 or Tier 2 inputs from exerting too much influence on the final prediction output. The Tier 2 deduction score is a penalty score that increases when the Tier 2 conditions are bad and vice versa. The following equation shows the proposed solution to how the Tier 2 deduction score, $X_{Tier\ 2\ (deduct)}$ is calculated.

$$X_{Tier\ 2\ (deduct)} = \left(15 - X_{Tier\ 2\ (total)}\right) \times \ a_{conv} \tag{1}$$

where a_{conv} is the conversion factor to transpose the Tier 2 deduction score onto a scale that is suitable to allow balanced mathematical operations with the total condition health index (total CHI). For this scope, the Tier 2 deduction score is transposed from a range of 0 – 15 to the range of 0 – 7.5 using the following definition of the conversion factor.

$$a_{conv} = \frac{7.5-0}{15-0} = \frac{1}{2} \tag{2}$$

The range of 0 – 7.5 is deemed as a suitable range of compensation values from the Tier 2 parameters in giving a corrective functionality to the calculation of the overall total CHI of the transformer. As a result, the Tier 2 deduction score equation can be simplified into the following expression.

$$X_{Tier\ 2\ (deduct)} = \frac{(15-X_{Tier\ 2\ (total)}}{2} \tag{3}$$

This Tier 2 deduction score is then subtracted from the Tier 1 CHI value to obtain the total condition health index (total CHI) of the transformer, which is a summarized indicator of the overall transformer health considering all the Tier 1 and Tier 2 inputs that are studied in this algorithm. The evaluation of the total CHI can be expressed as follows.

$$Total\ CHI = Tier\ 1\ CHI - X_{Tier\ 2\ (deduct)} \tag{4}$$

Lastly, the probability of failure for the transformer is deduced from the Total CHI value by inversing the Total CHI and scaling it onto a range of 0 – 1. This is performed based on the fundamental rationale that the health condition of the transformer has a logical inverse relationship with the likelihood that the particular transformer is moving towards failure. Thus, the probability of failure, P_{fail} is calculated as follows.

$$P_{fail} = \frac{10-Total\ CHI}{10} = 1 - \frac{Total\ CHI}{10} \tag{5}$$

To clip the range of P_{fail} to be only from 0 to 1, the full expression for the calculation of P_{fail} becomes a piece-wise function as shown below.

$$P_{fail} = \begin{cases} 1 - \frac{Total\ CHI}{10} & if\ Total\ CHI > 0 \\ 0 & if\ Total\ CHI < 0 \end{cases} \tag{6}$$

The prediction of fault type is based on the condition indicators of individual parameters from both Tier 1 and Tier 2. This is based on the rationale that different Tier 1 and Tier 2 parameters monitor and represent the health and condition of different components of the transformer. Thus, having a bad result for a particular test parameter gives an indication on which components are actually expected to fail as well as the method upon which they are expected to fail.

For the proposed failure prediction system, this is done by looking at the scores given to each of Tier 1 and Tier 2 parameters during the respective evaluation processes. Tables 1 and 2 are referred to 5 in order to determine the expected fault type for the transformer based on different conditions of Tier 1 and Tier 2 test parameters.

Table 1 The Fault Type Mapping for Tier 1 Parameters

Group	Parameter	Score	Condition	Severity	Fault Type
DGA	H2	0	Bad	Severe	Partial Discharge
		1	Poor	Indicate	
		2	Fair	Possible	
DGA	C2H2	0	Bad	Severe	Arcing in Oil
		1	Poor	Indicate	
		2	Fair	Possible	
DGA	CO	0	Bad	Severe	Paper Degradation
		1	Poor	Indicate	
		2	Fair	Possible	
DGA	C2H4	0	Bad	Severe	Contact Burning
		1	Poor	Indicate	
		2	Fair	Possible	
DGA	CH4	0	Bad	Severe	Overheated Oil
		1	Poor	Indicate	
		2	Fair	Possible	
DGA	C2H6	0	Bad	Severe	Overheated Oil
		1	Poor	Indicate	
		2	Fair	Possible	
Furan	2FAL	0	Bad	Severe	Paper Degradation
		1	Poor	Indicate	
		2	Fair	Possible	
OQA	Moisture	0	Bad	Severe	Oil Degradation
		1	Poor	Indicate	
OQA	BDV	0	Bad	Severe	Oil Degradation
		1	Poor	Indicate	
OQA	Acidity	0	Bad	Severe	Sludge Formation
		1	Poor	Indicate	
OQA	IFT	0	Bad	Severe	Sludge Formation
		1	Poor	Indicate	

Table 2 Fault Type Mapping for Tier 2 Parameters

Group	Parameter	Score	Condition	Severity	Fault Type
Tier 2	Turns Ratio	0	Bad	Severe	Turn to Turn Short Circuit

		1	Poor	Indicate	
Tier 2	Dielectric Dissipation Factor	0	Bad	Severe	Insulation (Oil + Paper) Degradation
		1	Poor	Indicate	
Tier 2	Winding Resistance	0	Bad	Severe	Contact Degradation
		1	Poor	Indicate	
Tier 2	Insulation Resistance	0	Bad	Severe	Insulation (Oil + Paper) Degradation
		1	Poor	Indicate	
Tier 2	Excitation Current	0	Bad	Severe	Magnetized Core / Damaged Lamination
		1	Poor	Indicate	

From the fault type mapping above, it can be observed that the fault types are predicted when the corresponding input parameter (from Tier 1 or Tier 2) is in a sufficiently bad condition. For some of the parameters, the fault type is indicated only when the condition of the corresponding parameter's test result has gone into the "Poor" and "Bad" band, based on the scores given during the evaluation of each individual parameter in their respective scoring functions. On the other hand, for some parameters, the fault type is already flagged even when the parameter's score is only in the "Fair" range to show that there is a considerable possibility that the fault type is happening in the transformer based on the test results of the particular parameter.
This method of mapping for the fault type prediction guarantees that each fault type is predicted based on its corresponding test parameters to give a more reliable, stable, and logical prediction result

3. RESULTS AND DISCUSSION

The accuracy definition that is developed in the Methodology section is used as the key performance indicator for the evaluation of the ML models. The five ML that were evaluated were logistic regression (log), decision tree (dtree), random forest (forest), adaptive boosting (ada), and extreme gradient boosting (xgb). To decide on the best ML model, the ML models are evaluated based on the accuracy of each testing dataset. This is because the ML models are developed using the training dataset whereas the models have never seen the testing dataset before during the training process. Thus, evaluating the model accuracy on the training dataset gives an indication of how well the individual ML model has learned the patterns information from the training dataset whereas evaluating the model accuracy on the testing dataset gives an unbiased indication of the actual performance of the ML model that is to be expected from data inputs that are never seen before by the ML models.

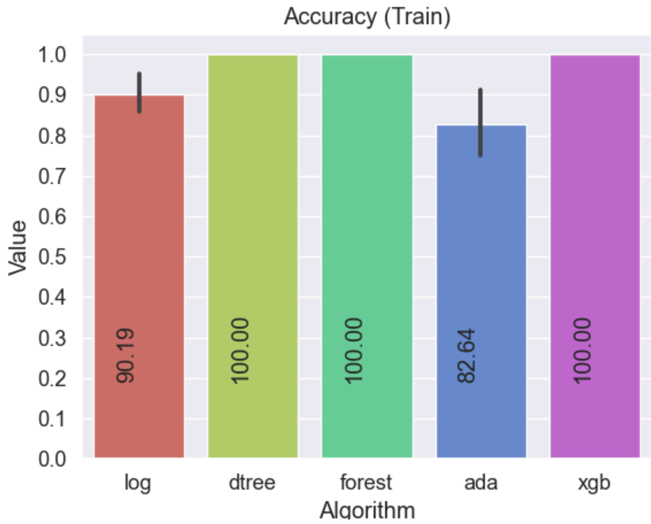

Figure 3. Average Accuracy of ML Algorithm Frameworks (Training Dataset, without Furan).

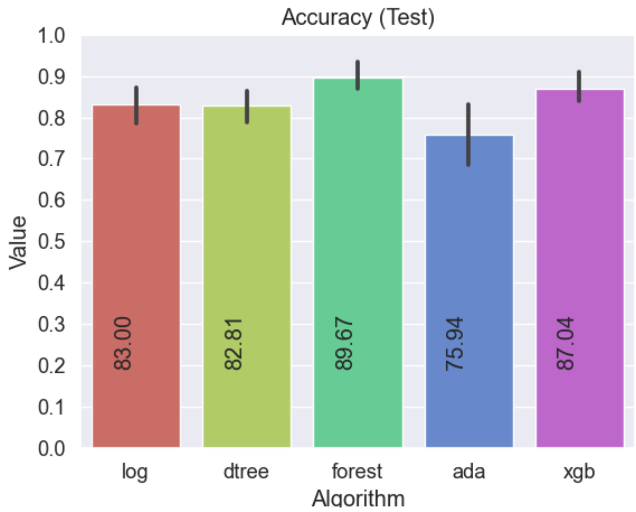

Figure 4. Average Accuracy of ML Algorithm Frameworks (Testing Dataset, without Furan).

Moreover, it is observed that the Furan analysis test is not always performed for newer transformers, following the rationale that the paper insulation degradation of these newly built transformers should be negligible and does not necessitate the monitoring through Furan analysis. Since this situation is observed quite often, a different set of ML models is developed to cater to transformers that do not have information about their Furan test results. Thus, two different AI models are to be implemented in the system – one for when Furan test results are present and one for when it is absent. This allows a whole new ML model to be trained for Furan-absent transformers, enabling better predictions for this subgroup of transformers since the patterns and correlations will be completely relearned from the training dataset without consideration of the Furan test results.

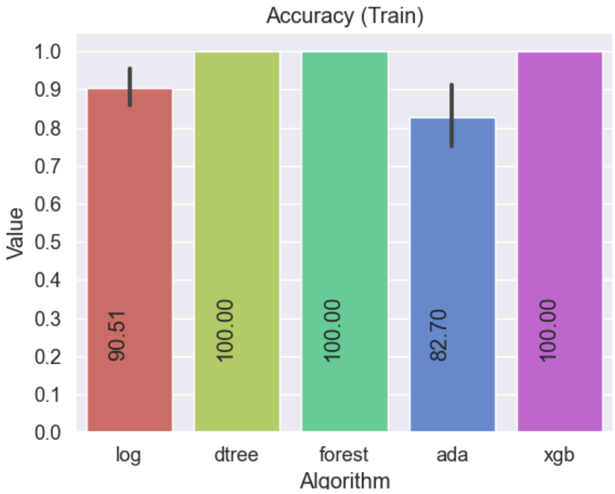

Figure 5. Average Accuracy of ML Algorithm Frameworks (Training Dataset, with Furan).

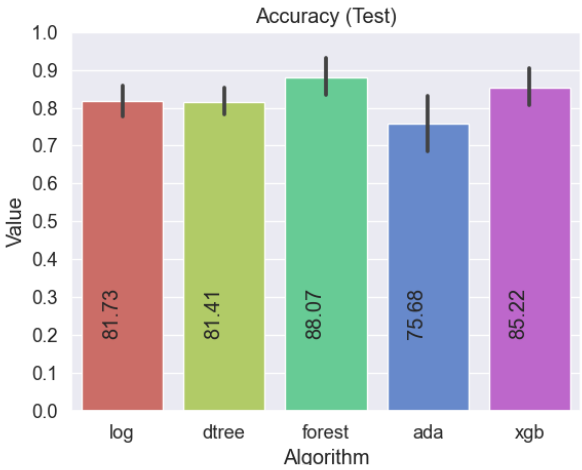

Figure 6. Average Accuracy of ML Algorithm Frameworks (Testing Dataset, with Furan).

From the training dataset accuracies, it is noted that most of the ML models scored considerably high accuracies when performing predictions back onto the training dataset, from which the patterns in the data are learned by the respective ML algorithm frameworks. This indicates that good information retrieval is achieved from the ML training process. There is also quite a number of models that have been able to achieve 100 percent (%) accuracy in the training dataset because they have captured the information offered in the training dataset very well. In general terms, this is desirable.

Meanwhile, from the testing dataset accuracies, it is noted that the random forest (forest) models have scored consistently higher accuracies over all the other models that use different ML algorithm frameworks. The forest model always has the highest testing dataset accuracy among all the 5 Tier 2 tests. Another notable model is the extreme gradient boosting (xgb) model, which is a close competitor to the forest model in terms of testing dataset accuracy. In some cases, both of these models have achieved similar accuracy results. In this situation, to break the tie and select only the best ML model for deployment in the final product, the model with a lower level of complexity is chosen. This is based on the problem-solving principle of Occam's razor which is very applicable in ML design, which states that "entities should not be multiplied beyond necessity" or in laymen's terms. Following this principle, the simpler model is preferred over the more complicated model if both models have similar performance. From a practical point of view, the simpler model also consumes fewer resources and requires less computing power, and is thus more efficient and should be selected. In this case, the forest model is simpler in operating principles compared to the xgb model. Thus, for all of the Tier 2 tests, the forest model is used as the final ML model to perform Tier 2 predictions.

4. CONCLUSION

This paper presented a novel power transformer health prediction by combining the actual tier 1 values from the site and predicted tier 2 values to obtain the failure probability and possible type of fault that will occur. Five ML models were utilized to predict tier 2 values from tier 1 values. To decide on the best ML model, the ML models were evaluated based on the accuracy of each testing dataset. from the testing dataset accuracies, it is noted that the random forest (forest) models have scored consistently higher accuracies over all the other models that use different ML algorithm frameworks. The forest model always has the highest testing dataset accuracy among all the 5 Tier 2 tests. The developed health prediction will be able to complement the existing condition-based maintenance practices to perform better evaluation and detection of possible power transformer defects. The Tier 1 to Tier 2 prediction algorithm improves the availability of Tier 2 test results by making intelligent predictions based on the annually sampled Tier 1 test results. This is achieved with the application of several artificial intelligence techniques. The predicted Tier 2 test results are then used in conjunction with other Tier 1 test parameters and transformer age to perform a holistic evaluation of the overall transformer health condition, effectively allowing the calculation of transformer failure probability and the expected fault types.

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