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Original Article

Evaluation of Machine Learning Algorithms for Predicting the Health Index of Power Transformers

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Abstract: The health index of a power transformer is a key indicator used in condition monitoring to prevent failures and extend equipment life. Traditional condition monitoring techniques are costly, time-consuming, and susceptible to human error. Machine learning offers an alternative by learning from historical condition-monitoring data, handling large and complex datasets, and delivering higher predictive accuracy than conventional approaches. This study evaluates and compares the performance of several machine learning algorithms—including logistic regression, random forest, gradient boosting, and XGBoost—for predicting transformer health index. A dataset of 470 samples sourced from Kaggle was used, and experiments were conducted in Python using Google Colab. Results show that RF outperformed the other models, achieving the lowest MAE, RMSE, and MAPE values of 6.3348, 9.3721, and 26.0794, respectively, and the highest R^2 of 0.7435, indicating superior predictive accuracy. Future work will focus on data augmentation and hyperparameter tuning to further improve model performance.

Keywords: Boosting Algorithms, Health Index, Machine Learning, Power Transformer, Prediction

1. Introduction

In power systems, power transformers are significant parts that enable the smooth distribution and transmission of electricity. Power transformers are known for their potential lifespan of about 60 years and their reliability [1]. For maintaining the functionality and stability of entire power networks, the smooth and reliable operation of power transformers is necessary. Apart from these, transformers can degrade over time, subject to aging, and can encounter unexpected failures. These can lead to significant financial and operational losses for both consumers and utilities. Fixing the transformers requires lengthy repairs and a long duration for replacement. To avoid such problems, there is a need to assess the accurate health condition of power transformers to predict their remaining lifespan. This is essential for better replacement techniques and proactive maintenance [2].

In previous studies, the four main approaches were designed to evaluate the health index (HI) state of the power transformer. These approaches are named as the scoring & ranking method, combination of scoring and ranking, tier method, and the multi-features factor assessment model [3]. The first scoring & ranking method is most effective for evaluating the HI state of power transformers. In this method, the most general parameters for assessing the power transformer's HI state are OQ, DGA, and DP tests. In the first step, the HI code or factor (HIC) is determined for each test. Then, the HIC for OQ, DGA, and DP are standardized by using the weighing and scoring values (4, 3, 2, 1, and 0). At last, the HIC is used for estimating the final value for the HI state of a power transformer using a weighting factor Kj that remains constant. The major limitation of such approaches is that these needed large number of features, from 24 to 27. As a result, these require high effort, high cost, and high-test times [4].

In recent years, to address these issues, researchers have shifted to using ML and DL based classification models that learn patterns from past transformer data instead of programming specific rules. These data-driven models showed enhanced performance as compared to statistical learning. These models are also able to discover nonlinear feature interactions to improve model's scalability and robustness [5].Therefore, the main aim of this study is to develop a health index prediction method for power transformer based on machine learning algorithms and evaluate their performance based on different performance indices. The main contribution of this study is summarized below.

- Evaluation of LR, RF, GB, and XGBoost algorithms for predicting the health index of the power transformer.
- The proposed method is evaluated for the standard dataset, and the result indicates that XGBoost provides superior performance over others.

The rest of the paper is organized as follows. Section 2 presents the related work on health index prediction for power transformers. Sections 3-4 define an overview of the ML algorithms and explain the proposed method. Section 5 shows the simulation evaluation. Finally, Section 6 presents the conclusion and future scope.

2. Related Work

Mogos et al. [6] used the LightGBM algorithm as a regression method to predict the HI of the transformer. In their work, the pre-processing of the dataset was done using the robust expectation-maximization (EM) algorithm to handle the missing data. The deployment of the EM method improves the results by 71%. In a similar study, Soliman et al. [7] used the LightGBM algorithm and performed the data balancing, feature engineering, and parameter tuning to enhance the performance of their model. Kumar et al. [8] developed an RF-XGBoost framework for predicting the health index of the power transformer. The data augmentation and hyperparameter tuning using the Optuna optimizer were performed to enhance the robustness and generalization of the developed models. Arsya et al. [9] evaluate the performance of the ML GB algorithm with respect to the traditional scoring and weighting methods for the oil-immersed power transformer. The GB outperforms in terms of different performance indices. Chandramohan et al. [10] combine the predictions of four ML algorithms, including RF, CatBoost, LightGBM, and XGBoost, using the ensemble learning approach. The evaluation on the Kaggle dataset shows that the designed approach outperforms the individual ML algorithms.

3. Overview of ML Algorithms

LR, RF, GB, and XGBoost algorithms were taken to predict the health index of a power transformer. This section gives an overview of these algorithms.

- **Linear Regression (LR)**: It is a supervised ML algorithm that models the linear relationship between a target variable and one or more independent variables. The relation between the variables is defined using a mathematical equation. This method normally results in a high accuracy level as it allows the determination of relationships among variables. The algorithm uses a best-fit line to generate predictions [11].

- **Random Forest (RF)**: This is an ensemble learning algorithm, and it combines multiple DTs to make predictions. RF algorithm is based on the concept of bagging, as it includes every DT on a small subset of the entire dataset. In this, the parameters of the model are determined using the aggregations of every DT's prediction. The most used method for aggregation includes majority voting or averaging [12]. The RF algorithm has several advantages over a single ML algorithm as it combines several ML models, resulting in overall higher accuracy. This is because the combination of several models helps to reduce variance and bias. Moreover, RF algorithm results in reduced overfitting because by voting or averaging the model generalizes the predictions. Furthermore, the DT algorithm is the basis of the RF algorithm.
  In the beginning, several DTs are generated by dividing the dataset into small subsets. Every DT works on a subset of the dataset and performs splitting and random selection of variables for the split. In the end, the final RF model is constructed from the several DTs, and the result of the classification is estimated by aggregating the predictions using a voting method. Overall, the RF algorithm combines the advantages of individual DTs to produce a more reliable and powerful classification model.
- **Gradient Boosting (GB) and Extreme Gradient Boosting (XGBoost):**GB is an ML algorithm that works by combining the predictions from multiple weak models to produce a stronger prediction model [13]. GB algorithm is commonly used for classification and regression problems. XGBoost, on the other hand, is a scalable method of tree boosting. It was developed by Chen and Guestrin. XGBoost uses CART (Classification and Regression Trees) as the base classifiers and combines them with GB. XGBoost algorithm reduces model complexity by adding a regularization term in the loss function. This is also useful for balancing the model's accuracy and complexity. In XGBoost, a new CART is added based on the prediction residuals of the previous CART. The result of the model is estimated as the accumulated predictions of all CARTs. As a result of this, the XGBoost model is a highly efficient, portable, and flexible technique for ML problems.

4. Health Index Prediction Method for Power Transformer

Figure 1 shows the health index prediction method is developed using the ML algorithms for the power transformer. The developed method has five steps and detailed description of these steps is given below.

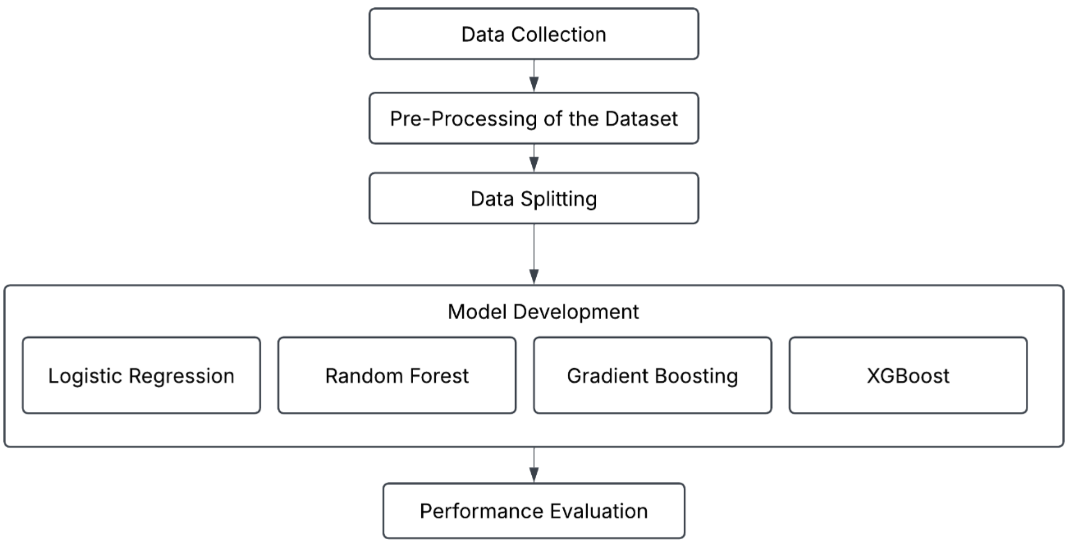

Figure 1. Health Index Prediction Method for Power Transformer

- Data Collection: The dataset was taken from the previous studies that collected the dataset from the open-source Kaggle repository. The dataset contains 470 samples and each sample contains the 16 features that represents the transformer parameter characteristics. Figure 2 shows the frequency distribution of the data samples.

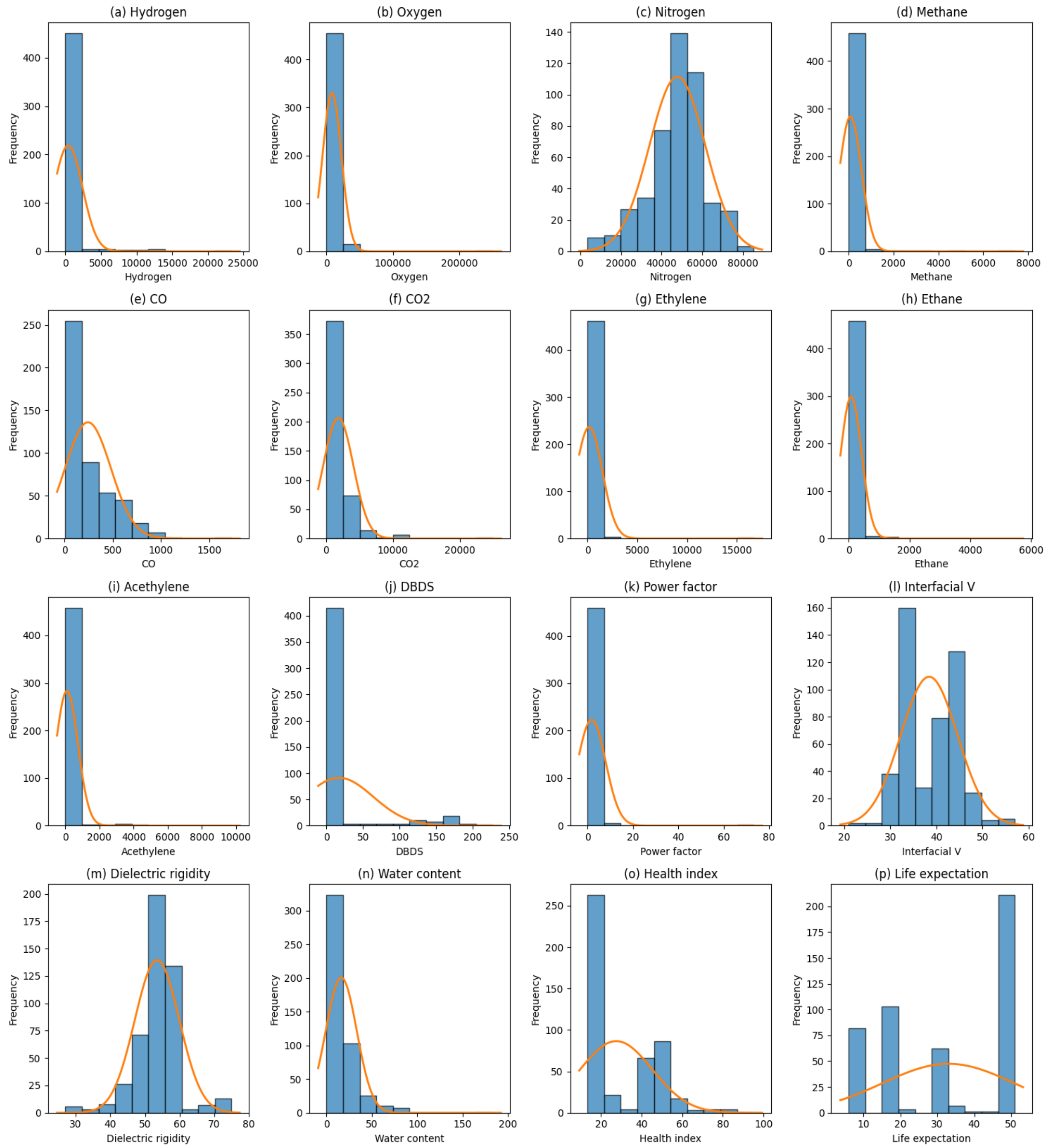

Figure 2. Frequency Distribution of the Samples

- Pre-Processing of the Dataset: In this step, preprocessing was done to handle the missing/null values. Following that, the feature engineering was done to extract, transform, and select the features of the data samples for the model development.
- Data Splitting: The data split is performed to divide the dataset into training and testing ratios. 80:20, 70:30, and 60:40 are the standard splitting ratios utilized in the ML models. In this study, we have split the dataset into an 80:20 ratio. This ratio indicates that 80% random data is selected to train the ML algorithms and 20% random for testing purposes.
- Model Development: In this study, four ML algorithms, including LR, RF, GB, and XGBoost, were employed to predict the health index of the power transformer. The parameters of these algorithms were initialized. After that, these algorithms were trained using the training ratio to learn the features of the dataset, and the testing ratio was used to evaluate the performance of it.

- Performance Evaluation: MAE, RMSE, R^2, and MAPE performance indices were used to evaluate the ML algorithms used for health index prediction of power transformer [14-15].

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

$$MAPE(\%) = \frac{100}{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad (5)$$

In the above equations, n denotes the total number of samples, and y_i and $\hat{y}_i$ represent the actual and predicted values. A lower value of error metrics (MAE, RMSE, and MAPE) and a higher value of determination of coefficient (R^2) show that the ML algorithms efficiently predict the health index with respect to its actual values.

5. Simulation Evaluation

The simulation evaluation of the proposed method was performed in the Python-based environment using Google Colab. A Windows 10 operating system-based local computer was used for evaluation purposes, and its system configuration was an IntelI Core I i7-7500 CPU @ 2.70 GHz, 16 GB of RAM, and a 1 TB hard disk drive. Besides that, the inbuilt libraries and functions of Python were employed to design the proposed method.

5.1 Evaluation Criteria

Initially, the Python libraries and functions were called to read the dataset and the libraries of ML algorithms. The dataset contains 470 samples and 16 features. These features were split into input and target attributes. Thereafter, the samples were split into an 80:20 ratio for training and testing purposes. Table 1 presents the parameter configuration of the ML algorithms selected for evaluation.

Table 1. Parameter Configuration of the ML Algorithms

ML Algorithm	Parameter	Value
RF, GB, XGBoost	N-Estimators	200
RF, GB, XGBoost	Random State	42
RF	Maximum Depth	10
XGBoost, GB	Learning Rate	0.05
	Maximum Depth	4

5.2 Simulation Results

Table 2 shows the performance evaluation of the ML algorithms that were considered in this study to predict the health index of the power transformer. RF achieved the lowest MAE (6.3348) along with the highest R^2 (0.7435), indicating superior predictive accuracy compared to the other algorithms. On the other side, the LR algorithm achieves the lowest performance due to its inability to handle the non-linear relationship among the attributes of the dataset, as shown in Figure 3-6.

Table 2. Performance Evaluation of the ML Algorithms for Health Index Prediction of Power Transformer

ML Algorithms	MAE	RMSE	MAPE	R^2
LR	9.6272	13.1437	41.4583	0.4956
RF	6.3348	9.3721	26.0794	0.7435
GB	6.4885	9.6497	27.6556	0.7281
XGBoost	6.3793	9.3906	26.1977	0.7425

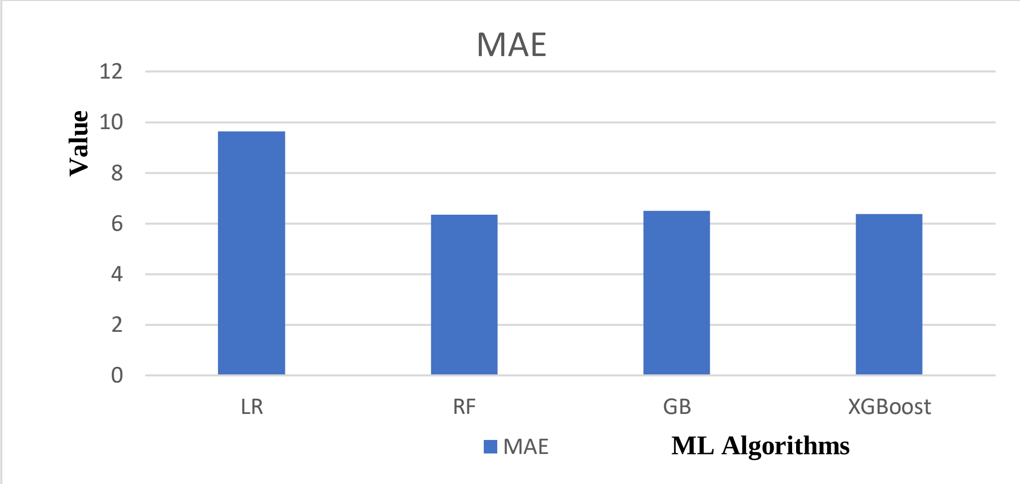

Figure 3. Comparative Analysis based on MAE

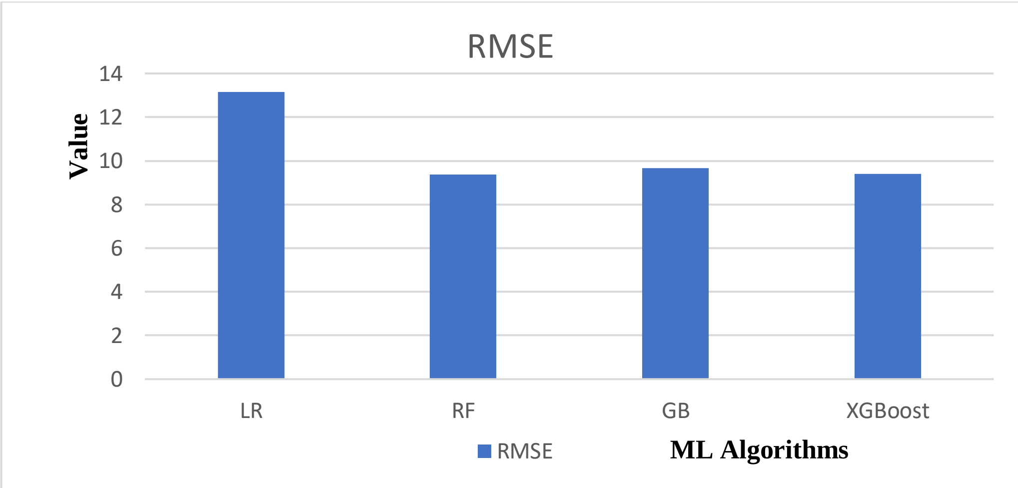

Figure 4. Comparative Analysis based on RMSE

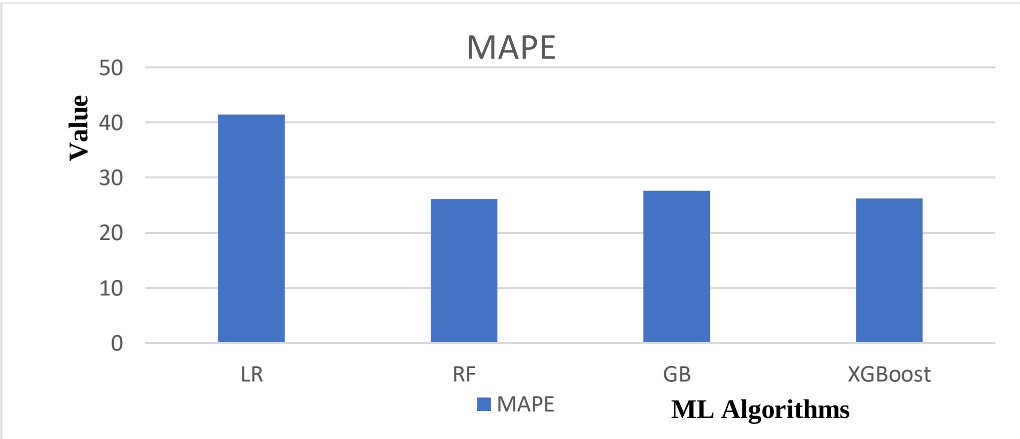

Figure 5. Comparative Analysis based on MAPE

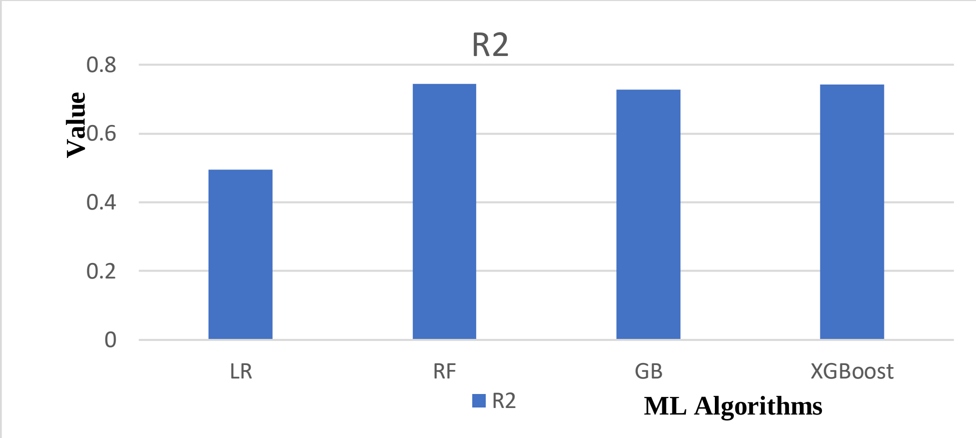

Figure 6. Comparative Analysis based on R^2

6. Conclusion

The health index prediction of the power transformer helps in fault detection and its life cycle. The machine learning algorithms gained popularity over traditional approaches for better accuracy, lower cost, and handling the complex past data of the transformer. In this study, we have successfully evaluated the performance of four ML algorithms, including LR, RF, GB, and XGBoost, for predicting the health index of the power transformer, using the standard dataset from Kaggle. The result indicates that the RF algorithm achieves the superior performance, whereas the lowest is achieved by the LR algorithm due to its limited ability to handle the nonlinear relationship between data attributes. The sample size of the data collected is limited, which impacts the robustness and generalization of the designed method. Future work addresses this limitation by performing the data augmentation in the preprocessing step. Additionally, the hyper-parameter tuning of the ML algorithms using the optimization approaches will be explored to further enhance the performance of the model.

References

[1] S. T. Zahra, S. K. Imdad, S. Khan, S. Khalid, and N. A. Baig, "Power transformer health index and life span assessment: A comprehensive review of conventional and machine learning based approaches," *Engineering Applications of Artificial Intelligence*, vol. 139, p. 109474, Oct. 2024, doi: 10.1016/j.engappai.2024.109474. Available: https://doi.org/10.1016/j.engappai.2024.109474

[2] M. Badawi *et al.*, "Reliable estimation for health index of transformer oil based on novel combined predictive maintenance techniques," *IEEE Access*, vol. 10, pp. 25954–25972, Jan. 2022, doi: 10.1109/access.2022.3156102. Available: https://doi.org/10.1109/access.2022.3156102

[3] I. B. M. Taha, "Power Transformers Health Index Enhancement Based on Convolutional Neural Network after Applying Imbalanced-Data Oversampling," *Electronics*, vol. 12, no. 11, p. 2405, May 2023, doi: 10.3390/electronics12112405. Available: https://doi.org/10.3390/electronics12112405

[4] S. Li, X. Li, Y. Cui, and H. Li, "Review of Transformer Health Index from the Perspective of Survivability and Condition Assessment," *Electronics*, vol. 12, no. 11, p. 2407, May 2023, doi: 10.3390/electronics12112407. Available: https://doi.org/10.3390/electronics12112407

[5] S. T. Zahra, S. K. Imdad, M. F. Qureshi, & N. A. Baig, "Power Transformer Health Index Assessment: An Explainable LightGBM based minority aware learning using SMOTE-ENN hybrid resampling," *Available at SSRN 7162474*.

[6] A. S. Mogos, X. Liang, and C. Y. Chung, "Enhancing Transformer Health Index prediction using dissolved gas analysis data through integration of LightGBM and robust EM algorithms," *IEEE Access*, vol. 12, pp. 108472–108483, Jan. 2024, doi: 10.1109/access.2024.3439248. Available: https://doi.org/10.1109/access.2024.3439248

7] A. Soliman, M. Elhemaly, and S. S. M. Ghoneim, "Integrating machine learning models for enhancing power transformer health Assessment based on the insulating Paper State," *Measurement*, vol. 256, p. 118222, Jun. 2025, doi: 10.1016/j.measurement.2025.118222. Available: https://doi.org/10.1016/j.measurement.2025.118222

[8] P. Kumar, V. Parkash, and N.K. Sharma, "A Hybrid Random Forest–XGBoost Framework for Power Transformer Health Index Prediction," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. *18*, no. 16s, pp.1547-1560, 2026.

[9]N. R. Arsya, Suwarno, R. A. Prasojo, G. A. Sudrajad, and A. Abu-Siada, "A holistic integration of conventional and machine learning techniques to enhance the analysis of Power Transformer Health Index considering data unavailability," *IEEE Access*, vol. 12, pp. 124549–124561, Jan. 2024, doi: 10.1109/access.2024.3450110. Available: https://doi.org/10.1109/access.2024.3450110

[10]J. Chandramohan, K. Karthick, A. S. K, and G. Ponkumar, "A robust explainable machine learning pipeline for transformer health index prediction addressing data pathologies and redundancy," *Electric Power Systems Research*, vol. 259, p. 113275, May 2026, doi: 10.1016/j.epsr.2026.113275. Available: https://doi.org/10.1016/j.epsr.2026.113275

[11]N. Sartika, S. A. Nuramalia, and R. R. Nurmalasari, "Power transformer loading prediction using linear regression as a basis for remaining life estimation," *Infotekmesin*, vol. 17, no. 1, pp. 96–102, Jan. 2026, doi: 10.35970/infotekmesin.v17i1.3087.

[12]Y. Gao *et al.*, "A model for identifying the feeder-transformer relationship in distribution grids using a data-driven machine-learning algorithm," *Frontiers in Energy Research*, vol. 11, Jul. 2023, doi: 10.3389/fenrg.2023.1225407. Available: https://doi.org/10.3389/fenrg.2023.1225407

[13] A.O. Abdulkareem, B. Jimada-Ojuolape, M.O. Balogun, and L.M. Adesina, "Comparative Analysis of XGBoost and Random Forest Algorithms for Transformer Failure Prediction," *Annals of the Faculty of Engineering Hunedoara*, vol. *22*, no. 4, pp.137-146, 2024.

[14] Z. Arslan, M. E. Sahin, and H. Ulutas, "Comparative evaluation of machine learning and Transformer-Based deep learning for solar energy forecasting on a Real-World dataset," *Arabian Journal for Science and Engineering*, vol. 51, no. 5, pp. 6833–6863, Nov. 2025, doi: 10.1007/s13369-025-10769-8. Available: https://doi.org/10.1007/s13369-025-10769-8

[15] M. A. A. Putra, Suwarno, and R. A. Prasojo, "Improving Transformer Health Index Prediction Performance Using Machine Learning Algorithms with a Synthetic Minority Oversampling Technique," *Energies*, vol. 18, no. 9, p. 2364, May 2025, doi: 10.3390/en18092364. Available: https://doi.org/10.3390/en18092364

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