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Design and Simulation of a Predictive Maintenance Model for a Power Transformer: A Case Study of a Transmission Substation in Nigeria

Gerard Nonso Obiora*[1], and Olusegun Julius Adebowale[2]

[1]Department of Electrical/Electronics and Telecommunication Engineering, Bells University of Technology, Ota, Ogun State, P.M.B. 1015, Nigeria.

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ABSTRACT

The most crucial component of a high-voltage transmission system are power transformers, whose unplanned failure can cause major operational interruptions, monetary losses, and widespread power outages. A predictive maintenance framework and simulation for a 300-MVA power transformer at a 330/132 kV transmission substation in Lagos State, Nigeria, is presented in this study. Gradient Boosting Algorithm (GBA) was utilized to analyze the transformer's historical data in order to predict potential transformer faults. Important data were collected and pre-processed, including Dissolved Gas Analysis (DGA), load profile, insulation resistance, top-oil and ambient temperature. The GB model was then trained and tested using the dataset. The obtained results indicates that the most significant indicators of transformer malfunctions were the presence of acetylene and hydrogen compounds. The model achieved 97% accuracy, with average Area Under the Curve (AUC) of 98%, recall and precision of 97% respectively. This suggests that the model has an effective fault prediction capability. Because it helps with problem identification, the study has demonstrated that GB can be utilized to increase the reliability of power transformer operations. Utilities seeking to minimize transformer downtime will find the model useful.

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1. INTRODUCTION

Power transformers are crucial parts of electrical power systems because they make it easier to control voltage and transfer electricity from sources of generation to end-users. These transformers operate under continuous electrical and mechanical stress, which over time leads to degradation, insulation failure, overheating, and mechanical wear [1], [2]. Transformer failure disrupts the end users' power supply, which makes it difficult for them to do their daily tasks or work. Furthermore, transformers have premium market value [1], and any potential malfunction results in heightened costs for power system operators since the heartbeat of any power system substation is the transformer. Therefore, system operators give priority to the maintenance of power transformers in substations to avoid failure in the networks. There are several approaches used in determining the period of maintenance of equipment in power systems.

According to [3], maintenance action of transformers is classified into corrective, preventive, and predictive maintenance (that is, CM, PM and PdM). The action of CM and PM can lead to system equipment failure, causing unscheduled downtime, which serves as a loss to the system operators, and as well as high repair costs. Corrective maintenance approach is commonly used in many power stations in Nigeria, and it has been a major problem to power system operators. In the grid network, this approach has sometimes led to loss of synchronism between generators due to the failure of a power transformer in a substation. This usually leads to partial or total grid collapse, and in turn, affects the country. Furthermore, this method involves identifying root causes and implementing measures to prevent recurrence. This approach often includes policy updates, retraining of personnel, redesign, or long-term changes of maintenance routine. The major difference between the predictive and corrective approach is that the later involves not only fixing a faulty transformer but also analyzing why the

*Corresponding author:
E-mail address: Gerard Nonso Obiora < gnobiora@bellsuniversity.edu.ng >.
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fault occurred and updating protection settings to avoid further occurrences. To mitigate the failure caused by corrective maintenance, a scheduled maintenance plan is outlined for each transformer in the substation. This is to stop a transformer from abruptly failing. We refer to this strategy as PM. On the other hand, PM is executed in accordance with time or operation hours at prearranged intervals, which occasionally leads to unneeded maintenance or breakdowns that go unnoticed because of unanticipated circumstances [4], [5]. In important infrastructures like the transmission substation used as a case study in this work, these traditional maintenance techniques are ineffective and might not successfully prevent transformer failures. Therefore, researchers have developed the predictive maintenance (PdM) technique to prevent needless damage that could result in transformer failure [6].

PdM uses an equipment's past data to decide when maintenance should be performed before something unexpected happens. It uses the transformer's characteristics or operating variables to anticipate possible transformer failure so that appropriate measures can be taken. Research conducted by [6] reveals that the application of predictive maintenance technique for transformers minimizes downtime and boosts dependability of the substation where the transformers are installed. Furthermore, the idea of PdM has become a viable solution for power transformer monitoring thanks to developments in data analytics, Machine Learning (ML), and sensor technologies. To assess transformer health and anticipate possible problems before they arise, PdM relies on real-time condition monitoring and failure prediction algorithms. Utilities may only carry out maintenance when necessary thanks to this technology, which analyzes data like load changes, DGA, insulation resistance, and vibration analysis to identify anomalies and forecast failures. Also, the input formulation data, the prediction model, and the type of data all affect how well a machine learning model predicts the transformer maintenance duration [7]. Thus, when creating a predictive model, the transformer's vital operating data is required.

In Nigeria's context, the Nigerian power grid is important to the nation's economic development, providing electricity for industries, households and so on. However, the country's electricity sector has faced a lot of challenges, many of which are related to the maintenance of important infrastructure, such as power transformers. Power transformers have been a major asset to Nigeria's grid operators, as it is the most important element found in the substations of Nigeria's grid network. Other elements in the substation aids to protect the transformer from failing. Transformers are vital for stepping up and stepping down voltage levels within the power grid, which makes it prone to wear and tear. In Nigeria's power substations, the approach used for maintenance of transformers includes the reactive or corrective, preventive, and random approaches. For instance, the reactive approach is initiated after a transformer has failed. This approach is typically unplanned and it borders around mitigating the effect of the damage by restoring the transformer to the normal operating position. Overall, these prevalent approaches have reduced the efficiency and reliability of the electricity network in Nigeria. In addition, they increase operating costs, especially as the reactive maintenance approach involves the procurement of the damaged equipment in the network [8], [9], [10].

2. LITERATURE REVIEW

A number of related approaches as well as other strategies have been suggested with respective to failure rates of transformers and how these failures can be mitigated through the utilization of maintenance models. The authors in [11], [12], [13], [14], carried out survey of Artificial Intelligence (AI) and Internet of Things (IoT) applications with respect to PdM of transformers while [15] suggested a novel framework based on multimodal information fusion. On the other hand, the use of AI for transformer PdM was the core focus of [16] study. Reference [17] utilized a Deep Learning (DL) approach in estimating transformer aging and it was based on operational data. It should be noted that complex aging factors still make transformer life management challenging. For [18], the authors developed a lightweight DL model using Multi-Head Attention (MHA) for Remaining Useful Life (RUL) prediction on IoT devices with minimal memory and computational needs. The study sought to address important Industry 4.0 issues. Reference [19] introduced an effective technique for transformer fault detection. The acoustic emission signals obtained by non-contact microphones served as the foundation for the authors' approach. An IoT-based transformer monitoring system was suggested by [20]. In the meantime, [21] suggested an edge-cloud mixed framework to address the shortcomings of traditional PdM systems in managing high-volume, real-time sensor network data. K-Nearest Neighbors (KNN) model-based edge devices were utilized for continuous data transmission to the cloud and real-time anomaly detection. In order to detect transformer faults, [22] proposed a mixed monitoring system. The hybrid fault detection system was designed using Fuzzy Logic (FL) and DGA based strategies. For [23], the authors utilized Adaptive Neuro Fuzzy Inference System (ANFIS) technique in predicting hotspot temperature of transformers. Estimated also in the study, is the feasibility of optimizing top oil of transformers. Reference [24] evaluated the reliability of transformers within three feeders located in a particular community. The idea behind the study was to present the diverse factors responsible for the failure rate of the transformers within the feeders' network. This is because, such will enable the concerned utility to act more promptly to minimize downtime as a result of the failure of transformers. Reference [25] carried out a comparative examination of diverse thermal frameworks for estimating the top oil and hotspot temperatures of power transformers.

The transmission substation that was utilized as a case study in this research work, is a critical power transmission hub in Nigeria, serving millions of customers and industries. The 300 MVA power transformer in this substation plays a significant role in ensuring a stable power supply. However, frequent faults and failures due to aging equipment, overloading, and environmental conditions have highlighted the need for developing a maintenance framework which will reduce the failure of the transformers therein. The current maintenance framework in the substation is based on reactive approach and random maintenance schedule. These approaches are not effective as there are unexpected failures of the transformers in the substation. To avoid frequent failure of the transformers in this substation, it is necessary thus to develop a PdM model to enhance the maintenance schedules, reduce failure rates, and improve power system reliability. This is thus, the idea behind this study. Gradient boosting was utilized in this study because of its ability in dealing with sophisticated relationships within data, providing robustness and high accuracy in the process.

3. METHODOLOGY

This section describes the methodical process used to develop and test a PdM model for a 300-MVA power transformer at a 330/132 kV Transmission Substation situated in Lagos State, Nigeria. The procedure entails gathering and cleaning pertinent data, developing pertinent features, constructing the GB Machine (GBM) model, evaluating its performance, and then executing simulations. The goal here is to deliver a robust, evidence-based tool that forecasts transformer issues and steers maintenance actions, thus boosting grid reliability and cutting the number of unexpected outages.

3.1 Problem Formulation

The problem is to develop and simulate a PdM model for a 300-MVA, 330/132 kV transformer at a Transmission Substation with the aid of Gradient Boosting Algorithm, to forecast the transformer faults, evaluate the health condition, and get the most suitable maintenance plan for the improvement of the reliability, and reduction of unplanned outages.

3.2 Objective Function

The aim of this study to create a Gradient Boosting-driven PdM model that will aid in reducing the likelihood of transformer failure and, is capable of efficiently prompting the planning of maintenance tasks. The objective function is represented mathematically as Equation (1) [26], [27].

$$min_{f(X)}\ L(Y, \hat{Y}) \tag{1}$$

Where: $L(Y, \hat{Y})$ given as $-\sum_{j=1}^{m} y_{ij} \log(p_{ij})$, is the loss function that indicates the extent of the correspondence between the actual transformer condition (y_{ij}) and the result of the prediction of the condition (p_{ij}). While $f(X)$ is the Gradient Boosting-based predictive maintenance model, which relates input features X (for instance, concentration of gases, temperature, load profile) to fault diagnosis or condition monitoring results.

3.3 Constraints

The practical and technical constraints listed below also affect the model development and operation:

(i). Temperature Limits: Transformer oil and winding temperatures must remain within manufacturer recommended limits to prevent accelerated aging or damage. This limit is indicated as Equation (2).

$$T_{min} \leq T_{op} \leq T_{max} \tag{2}$$

(ii). Load Limit: Transformer loading should definitely not be more than the rated capacity. This is indicated as Equation (3).

$$L_{op} \leq L_{rated} \tag{3}$$

3.4 The Transmission Substation Power Transformer

The 330/132 kV Transmission Substation situated in Lagos State, Nigeria, is a major transmission facility managed by the transmission company of the given location in the country. It acts as a crucial node for receiving and distributing bulk electrical power from the national grid to Lagos and neighbouring states. The substation is the place where several high-capacity power transformers are installed, among them is the 300-MVA, 330/132 kV power transformer, which is the main focus of this research. This transformer reduces the input voltage from 330 kV to 132 kV for further transmission and distribution. Due to the fact that this transformer is the main element in the grid, its failure may cause power outage and economic losses of a large scale. Therefore, there is a need for a smart predictive maintenance system to be put in place that will enable the detection of possible failure at an early stage and thus, prompt the schedule of interventions.

3.4.1 Technical Parameters of the 300-MVA, 330/132 kV Power Transformer

The typical technical parameters of the 300-MVA, 330/132 kV, 3∅ power transformer are given in Table 1.

Table 1. Technical Parameters of the 300-MVA, 330/132 kV Power Transformer

Parameter	Specification
Transformer Type	3∅, 2-winding, Oil-immersed, Outdoor Transformer
Power Rating (Base MVA)	300-MVA
Main Voltage (HV)	330 kV
Secondary Voltage (LV)	132 kV
Frequency	50 Hz
Vector Group	YNd1 (Star-Delta)
Cooling Method	ONAN/ONAF
Rated Current (HV side)	≈ 525 A
Rated Current (LV side)	≈ 1311 A
Impedance	12% - 15% (Typical, depends on design)
Tap Changer	On-load Tap Changer (OLTC) with ±10% in 1.25% steps
Insulation Class	Class A (Oil-paper insulation)
Cooling Oil Type	Mineral Oil
Temperature Rise (Oil/Winding)	55°C / 65°C
Short Circuit Withstand Duration	2 seconds
Neutral Earthing	Solid or through Neutral Earthing Resistor (NER)
Total Weight (including oil)	Approximately 200 - 250 metric tons
Core Material	High-grade Cold Rolled Grain Oriented (CRGO) Silicon Steel

3.5 Predictive Model Development Using Gradient Boosting

Power transformers that operate continuously and reliably are crucial for power system stability. Predictive maintenance, led by data analytics and ML methods, offers a proactive approach to the detection of early symptoms of failure. The work presented here introduces a method for constructing a predictive maintenance model (Gradient Boosting - GB algorithm) which will aid in evaluating the condition of a 300-MVA, 330/132 kV power transformer of a transmission substation. The model combines various operations and data to calculate failure probability and thus, prompts a suitable maintenance plan. The system architecture as illustrated in Figure 1 involves several important steps which includes data collection, data preprocessing, feature selection, training of the model, and maintenance prediction.

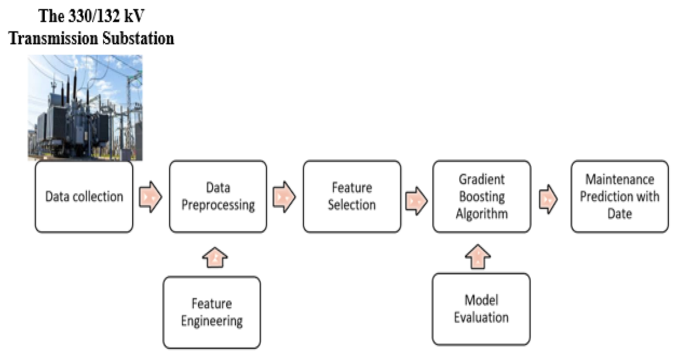

Fig. 1. Architecture of the Proposed Predictive Maintenance Model

3.5.1 Data Collection

Data was gathered from diverse sources (DGA reports, oil and ambient temperature reports, load current and voltage report, insulation resistance, fault and maintenance logs, manufacturer specifications, real-time monitoring data) between May to July 2025. The number of gases such as H_2, CH_4, and C_2H_2 in ppm, temperature in degrees Celsius, and the insulation resistance in megaohms were some of the collected data (see Tables 2, 3 and 4 for details). Load data gathered from Supervisory Control and Data Acquisition (SCADA) systems was complemented by insulation tests and fault logs obtained from maintenance records (see Table 5 for details). These inputs allowed monitoring of the transformer's condition continuously. Table 6 shows the description of each data source.

3.5.2 Data Preprocessing and Feature Selection

The raw data was pre-processed for quality and consistency. Missing values were imputed using the mean imputation method, and features such as gas ratios (for example C_2H_2/H_2), load ratio (actual versus rated current), and thermal stress (oil temperature above the baseline) were created. The numerical features were brought to the same scale with minimum-maximum scaling, and the categorical values like fault types were converted into numbers. These processed inputs were then utilized to train the GB model, which allowed the prediction of the transformer's health condition or fault risk from the past and the present situation, thus making it possible to perform proactive maintenance and decrease the risk of failure. Thus, the following points are noteworthy:

(i). Data Integration: All relevant values were combined into one structured dataset based on timestamp. The information from the SCADA systems as well as diagnostic logs were matched by date.

(ii). Handling Missing Values: Insulation resistance data was not recorded on June 15th and 16th. This missing data was substituted with the average of the existing values. However, the mean imputation technique employed for filling in the gap in the insulation resistance data could be said to have contributed slightly to some level of bias within the modelling process.

(iii). Feature Engineering: Gas Ratio (C_2H_2/H_2) was designed to find potential arcing. Then, load ratio was also compared to the rated full-load current. Furthermore, the following gas ratios: C_2H_2/H_2, C_2H_2/C_2H_4, C_2H_4/C_2H_6, CH_4/H_2, from the DGA dataset were utilized to enhance the model's discriminatory ability.

(iv). Encoding Categorical Data: For a model to process categorical data that is not numeric efficiently, it must be changed into the numerical format. The main categorical variable in this research was the "Fault Type", which came from the maintenance records. Some of the category names are "None", "Arcing", "Short Circuit".

(v). Output Labeling: In a classification model, the transformer health status is represented by numbers where 0 means Normal, 1 means Warning, and 2 means Critical, and these are decided based on key diagnostic thresholds. To illustrate, when hydrogen (H_2) is above 150 ppm or insulation resistance (IR) is lower than 600 MΩ, the situation is referred to as a Warning. When acetylene (C_2H_2) concentration goes beyond 10 ppm, which is a sign of arcing, the status becomes a Critical one. Such limits enable the model to identify clearly the different types of the transformer condition as well as the areas where faults are possible. The model then can prompt effective predictive maintenance plans. In addition, the ppm criteria for classifying a transformer state into 0, 1, and 2 such as H_2 >150 is not done randomly. Rather, these classifications are made based on established industry standards such as IEEE (C57.104), IEC (60599) [28], and experiments conducted within the realm of DGA. Thus, when H_2 >150, this indicates unusual electrical condition in the insulation of transformers. And further suggests a transition from 0 to 1 status.

3.5.3 Gradient Boosting Algorithm

The GB Algorithm is an advanced supervised machine learning method that is designed for regression and classification issues. It creates a collection of weak learners, usually decision trees, one after another where each novel model learns to fix the mistake residuals of the previous model [29]. The step for the gradient boosting algorithm is stipulated and elaborated below [30], [31].

Let the training dataset be:

$$D = \{(x_1, y_1), (x_2, y_2), \dots .(x_n, y_n)\} \tag{4}$$

Where: x_i is the feature vector and y_i is the target value (classification label or continuous value).

Let the objective be to reduce a differentiable loss function L(y,F(x)), where F(x) is the predictive function.

Step 1: Initialize the model

Set the model parameters with a constant value in order to minimize the loss function:

$$F_0(x) = \text{argmin} \sum_{i=1}^{n} L(y_i, \gamma) \tag{5}$$

Step 2: For m = 1 to M (number of boosting iterations), repeat:

i. Compute the negative gradients (residuals)

These serve as the pseudo-response values:

$$r_i^{(m)} = -\left[\frac{\partial L(y_i, F(x_i)}{\partial F(x_i)}\right]_{F(x) = F_{m-1(x)}} \tag{6}$$

ii. Fit a regression tree $h_m(x)$ to the residuals $r_i^{(m)}$

This tree partitions the data and outputs a leaf value for each region R_{jm}, where j = 1, 2,…J (number of terminal nodes/leaves). Then compute the optimal value γ_{jm} for each terminal node region R_{jm} using Equation (7).

$$\gamma_{jm} = argmin \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma) \quad (7)$$

iii. Update the model using Equation (8).

Table 2. DGA Dataset

Sample ID	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	CO	CO_2	TDCG	Condition Label
1	71	24	1.5	17	9	252	3621	374.5	0
2	94	20	1.7	8	12	280	4161	415.7	0
3	72	11	1.4	18	10	279	3691	391.4	0
4	79	10	0.6	10	13	198	3974	310.6	0
5	78	19	0.1	16	7	257	4066	377.1	0
6	83	12	1.7	11	9	222	3666	338.7	0
7	37	13	1.9	18	6	158	3845	233.9	0
8	72	11	1.4	19	11	157	3534	271.4	0
9	97	26	0.5	12	8	151	3889	294.5	0
10	73	19	1.1	17	6	193	3661	309.1	0
11	93	13	1.2	19	12	189	4224	327.2	0
12	99	22	0.5	9	12	273	3992	415.5	0
13	60	24	0.3	13	11	158	3843	266.3	0
14	20	21	0.6	19	7	230	3891	297.6	0
15	54	12	1.5	9	14	190	3527	280.5	0
16	26	18	1.2	6	5	197	4002	253.2	0
17	42	14	1.5	12	10	184	4238	263.5	0
18	66	23	1.7	9	14	291	4294	404.7	0
19	28	24	0.9	14	7	212	4242	285.9	0
20	71	13	1.8	11	11	292	3670	399.8	0
21	179	28	9.5	26	17	436	4477	695.5	1
22	192	37	5.1	24	20	378	3927	656.1	1
23	194	36	5.9	29	21	442	4372	727.9	1
24	189	38	3.8	28	23	466	4158	747.8	1
25	189	30	6.6	28	19	401	4133	673.6	1
26	194	32	9.5	25	22	463	4396	745.5	1
27	162	38	7.8	22	15	451	3980	695.8	1
28	199	26	6.5	25	21	479	4302	756.5	1
29	152	29	6.4	25	21	418	4338	651.4	1
30	161	32	4.7	25	22	419	4097	663.7	1
31	172	35	8.7	20	23	474	4086	732.7	1
32	156	37	8.9	23	17	440	4410	681.9	1
33	169	28	7.5	23	23	478	4450	728.5	1
34	168	32	4	28	23	392	4162	647	1
35	166	34	9.8	23	15	352	4203	599.8	1
36	212	44	23.5	38	33	599	4507	949.5	2
37	203	59	23.3	30	32	616	4886	963.3	2
38	272	43	23.5	49	38	612	4809	1037.5	2
39	289	42	24.6	47	38	582	4462	1022.6	2

40	280	48	12.7	33	25	642	4576	1040.7	2
41	248	59	15.6	37	31	695	4700	1085.6	2
42	233	55	11.5	48	30	619	4321	996.5	2
43	230	45	24.7	48	30	508	4582	885.7	2
44	227	41	15.3	30	36	611	4780	960.3	2
45	269	55	14.3	32	25	517	4471	912.3	2
46	292	53	23.7	32	36	537	4579	973.7	2
47	293	56	18.3	32	36	616	4490	1051.3	2
48	285	40	14.8	47	33	554	4869	973.8	2
49	267	47	11.1	47	39	586	4454	997.1	2
50	202	56	22.7	38	35	676	4338	1029.7	2

Table 3. Transformer Oil Temperature Dataset

Sample ID	Timestamp	Ambient_ Temp	Top Oil_ Temp	HotSpot_ Temp	Load_Percent	Condition_ Label
1	10/05/2025 12:00	34	73	72	62	0
2	11/05/2025 12:00	34	61	89	70	0
3	12/05/2025 12:00	31	69	71	60	0
4	13/05/2025 12:00	29	74	85	69	0
5	14/05/2025 12:00	28	74	70	75	0
6	15/05/2025 12:00	29	63	84	64	0
7	16/05/2025 12:00	28	60	74	77	0
8	17/05/2025 12:00	35	63	72	80	0
9	18/05/2025 12:00	35	62	85	84	0
10	19/05/2025 12:00	33	60	77	69	0
11	20/05/2025 12:00	31	72	76	61	0
12	21/05/2025 12:00	33	66	72	61	0
13	22/05/2025 12:00	32	68	73	70	0
14	23/05/2025 12:00	33	60	81	62	0
15	24/05/2025 12:00	30	70	83	78	0
16	25/05/2025 12:00	32	71	82	80	0
17	26/05/2025 12:00	34	73	89	76	0
18	27/05/2025 12:00	34	74	77	71	0
19	28/05/2025 12:00	34	67	71	71	0
20	29/05/2025 12:00	30	65	88	80	0
21	30/05/2025 12:00	28	61	82	78	0
22	31/05/2025 12:00	29	61	89	72	0
23	01/06/2025 12:00	33	69	86	84	0
24	02/06/2025 12:00	31	61	73	63	0
25	03/06/2025 12:00	31	65	77	69	0
26	04/06/2025 12:00	36	78	93	88	1
27	05/06/2025 12:00	34	81	99	92	1
28	06/06/2025 12:00	36	81	93	94	1
29	07/06/2025 12:00	36	81	96	86	1
30	08/06/2025 12:00	35	78	94	88	1

31	09/06/2025 12:00	35	75	95	93	1
32	10/06/2025 12:00	35	81	98	94	1
33	11/06/2025 12:00	35	76	90	88	1
34	12/06/2025 12:00	35	76	93	89	1
35	13/06/2025 12:00	36	82	96	86	1
36	14/06/2025 12:00	34	78	93	92	1
37	15/06/2025 12:00	36	83	96	89	1
38	16/06/2025 12:00	34	82	90	85	1
39	17/06/2025 12:00	35	83	98	89	1
40	18/06/2025 12:00	36	83	96	86	1
41	19/06/2025 12:00	42	91	109	102	2
42	20/06/2025 12:00	38	97	113	104	2
43	21/06/2025 12:00	38	96	102	102	2
44	22/06/2025 12:00	41	97	112	96	2
45	23/06/2025 12:00	43	94	109	102	2
46	24/06/2025 12:00	43	86	104	96	2
47	25/06/2025 12:00	36	99	108	100	2
48	26/06/2025 12:00	37	87	106	97	2
49	27/06/2025 12:00	38	99	114	104	2
50	28/06/2025 12:00	39	87	112	109	2

Table 4. Transformer Insulation Resistance Dataset

Sample ID	Test Voltage (kV)	IR Phase A-B (MΩ)	IR Phase B-C (MΩ)	IR Phase C-A (MΩ)	Ambient Temp (°C)	Humidity (%)	Condition Label
1	5	1200	1180	1195	32	45	0 (Normal)
2	5	950	940	960	34	48	0 (Normal)
3	5	680	700	690	35	52	1 (Warning)
4	5	540	510	530	36	55	1 (Warning)
5	5	400	420	410	37	60	2 (Critical)
6	5	1150	1130	1120	30	42	0 (Normal)
7	5	700	730	720	34	50	1 (Warning)
8	5	380	360	370	38	65	2 (Critical)
9	5	1280	1260	1250	29	40	0 (Normal)
10	5	1050	1020	1040	33	47	0 (Normal)
11	5	580	560	570	36	53	1 (Warning)
12	5	420	430	440	37	59	2 (Critical)
13	5	980	970	965	32	46	0 (Normal)
14	5	690	710	705	35	51	1 (Warning)
15	5	350	340	330	39	68	2 (Critical)

Table 5. Load Data and Fault Log Obtained from Maintenance Record

Entry	Date	Load (%)	Voltage (kV)	Current (A)	Fault Type	Fault Location	Action Taken	Condition
1	2025-06-01	78	132	820	None	-	Routine Inspection	Normal
2	2025-06-02	83	132	865	None	-	Oil level checked	Normal
3	2025-06-03	87	130	890	Overheating	Top Oil	Cooling fan activated	Warning
4	2025-06-05	93	129	940	Insulation Degrade	Phase A-B	IR test and cleaning	Warning
5	2025-06-07	97	128	990	Short Circuit	Phase B-C	Replaced bushings	Critical
6	2025-06-09	81	132	850	None	-	Status Normal	Normal

Entry	Date	Load (%)	Voltage (kV)	Current (A)	Fault Type	Fault Location	Action Taken	Condition
7	2025-06-11	76	133	800	None	-	Load within limits	Normal
8	2025-06-12	89	130	880	Oil Leak	Radiator	Seal replaced	Warning
9	2025-06-14	96	128	1010	Overload	Secondary Side	Load shedding	Critical
10	2025-06-15	84	132	860	None	-	IR values acceptable	Normal
11	2025-06-17	92	129	930	Partial Discharge	HV Winding	Monitoring continued	Warning
12	2025-06-18	98	127	1050	Arcing	Tap Changer	Internal inspection	Critical
13	2025-06-20	80	132	845	None	-	Load normal	Normal
14	2025-06-22	86	130	875	Moisture Detected	Insulation	Oil filtration	Warning
15	2025-06-23	95	128	1000	Overheating	Hot Spot	Fan setting changed	Critical
16	2025-06-25	79	132	825	None	-	IR within limits	Normal
17	2025-06-27	88	131	885	Thermal Stress	Core	Load balancing	Warning
18	2025-06-28	90	129	910	Loose Connection	Bushing A	Tightened	Warning
19	2025-06-29	99	127	1060	Flashover	HV Terminal	Isolation & Repair	Critical
20	2025-06-30	82	132	835	None	-	Condition normal	Normal

Table 6. Description of Data Sources

Data Type	Source
DGA Reports	Transmission Substation & Transmission Company Archives
Temperature Readings	On-site Sensors & Historical Logs
Load Profiles	Grid Control Room Records
Fault Logs and Incident Reports	Substation Maintenance Team
Maintenance Records	Transmission Company Maintenance Documentation
Manufacturer Specifications	OEM (Original Equipment Manufacturer) Technical Manuals
Real-Time Monitoring Data	Online Sensors
Expert Opinions	Substation Engineers and Operators

$$F_m(x) = F_{m-1}(x) + \alpha \sum_{j=1}^{j} \gamma_{jm} \cdot 1_{\{x \in R_{jm}\}} \quad (8)$$

Where: $\alpha \in (0.1)$ is the learning rate and $1_{\{x \in R_{jm}\}}$ is an indicator function (1 if $x \in R_{jm}$, otherwise 0)

Step 3: Final model

After M iterations, the final predictive model is given as Equation (9).

$$F_m(x) = F_0(x) + \sum_{m=1}^{M} \alpha \sum_{j=1}^{J} \gamma_{jm} \cdot 1_{\{x \in R_{jm}\}} \quad (9)$$

Furthermore, the pictorial representation of the GB algorithm is depicted in Figure 2.

3.5.4 Model Evaluation

The dataset was divided into two segments: 70% for training the GB model and 30% for evaluating the model's performance based on new data. Moreover, 5-fold cross-validation was utilized throughout the training phase to ensure that the model accurately represents the data and to mitigate overfitting by checking the model's performance over several parts of the training set. After the GB model was trained to identify the transformer health conditions (Normal, Warning, Critical), it was tested to confirm that it works reliably on new data. Model evaluation means checking for accuracy, stability, and the ability to adapt to new situations through different performance measures. These measures are stated below:

(i). Accuracy: this is the ratio of the number of right predictions to the total number of predictions.

Accuracy is illustrated mathematically as Equation (10).

$$Accuracy = \frac{Number\ of\ Correct\ Prediction}{Total\ prediction} \ x\ 100 \quad (10)$$

(ii). Precision, F1 – score and Recall: These were calculated for each class and then averaged. Precision measures how many of the predicted labels ("Warning" or "Critical") are correct, while recall assesses how well the model identified actual faults. When class distributions are unbalanced, the F1-score is particularly helpful since it strikes a balance between recall and precision. Equations (11) – (13) [32] are the mathematical representations of precision, recall and F1 – score.

$$Precision = \frac{True\ Positives\ (TP\ [correctly\ predicted\ labels])}{TP + False\ Positives\ (FP\ [incorrectly\ predicted\ labels])} \quad (11)$$

$$Recall = \frac{TP}{TP + False\ Negatives\ (FN\ [actual\ faults\ not\ identified])} \quad (12)$$

$$F1 - score = 2 * \frac{(Recall * Precision)}{(Recall + Precision)} \quad (13)$$

(iii). Confusion matrix: this is the primary instrument to assess the efficiency of a classification algorithm, especially in the case of multi-class problems such as a transformer health classification (Normal, Warning, Critical). It lays out in an understandable way the extent to which the model can correctly identify the classes.

(iv). ROC (Receiver Operating Characteristic)-AUC: the ROC-AUC score is utilized when class probabilities are predicted. It has a score between 0 and 1, with a score close to 1.0 denoting exceptional class distinction and a score close to 0.5 indicating the model is doing no better than random assumption.

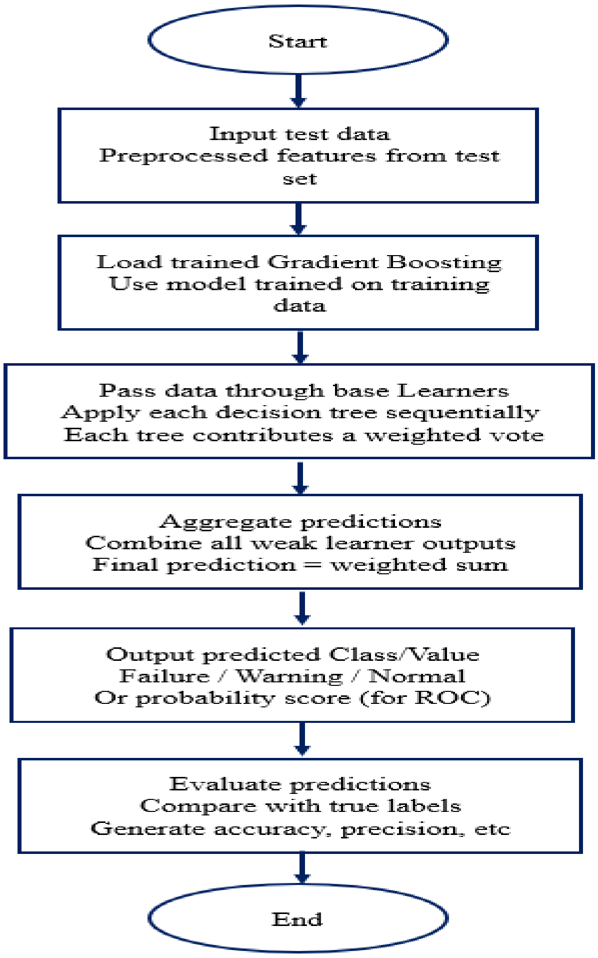

Fig. 2. Gradient Boosting Algorithm

3.6 Simulation and Validation

A simulation of the suggested predictive maintenance model was performed within a computational environment that was created for efficiently executing machine learning, data processing, and model evaluation. This phase is very important as it helps in determining the actual usability, strength, and forecasting capabilities of the GB model developed under realistic conditions.

3.6.1 Tools and Environment for Simulation

A Python code created with the help of XGBoost libraries and Scikit-learn for the GB algorithm's execution was utilized to evaluate the PdM model. The components of the simulation include:

(i). Software: pandas, scikit-learn, matplotlib, XGBoost and python 3x

(ii). Hardware: 16GB RAM with core i7 processor

3.6.2 Simulation Procedure

To ensure that the model used for prediction has been effectively trained, tested, and verified, a structured series of commands were followed. The simulation stages used include:

(i). Data import and preparation: the python environment was utilized to import the pre-processed dataset. At this point, the normalization of data and the treatment of any missing values were checked again.

(ii). Data splitting: to preserve the distribution of different health conditions (such as Normal, Degraded, Faulty), the dataset was separated into training (70%) and testing (30%) groups using stratified sampling.

(iii). Model training using GB algorithm: the GB model was trained with the training subset. Multiple iterations were performed; weak learners (decision trees) were combined in a sequential way to reduce prediction errors. The algorithm repetitively adjusted itself by giving more attention to the misclassified data points at each step. The GB algorithm was empirically tuned to a learning rate of 0.1. By controlling the contribution of each weak learner, this value offers a compromise between model convergence speed and generalization capabilities.

(iv). Hyperparameter tuning: to optimize the model's performance as well as prevent overfitting and enhance model generalization, hyperparameters including number of estimators (trees), learning rate, maximum tree depth, subsampling ratio, and minimum child weight were carefully tuned using grid search and K-fold cross validation (k=5).

(v). Model testing and evaluation: to evaluate the model's predictive power, the unseen test subset was used for validation after the training phase. To measure the performance, a number of evaluation metrics were computed (accuracy, precision, F1-score, AUC-ROC and recall).

(vi). Graphical visualization: visual aids like confusion matrix and ROC curves will be depicted to further enhance understanding of the model performance with respect to the study's goal.

4. Results and Discussion

4.1 Data Summary and Feature Importance

After data preprocessing and feature engineering, important features responsible for identifying the failure of a transformer (in this case, the 300-MVA power transformer) were recognized. The most relevant attributes, according to the GB model are DGA parameters (Hydrogen, Acetylene, Ethylene levels), top-oil temperature, thermal stress, load ratio, and transformer Insulation Resistance and, this is illustrated in Table 7.

Table 7. Feature Importance Table Illustrating Each Input's Contribution to the GB Model's Outputs

Rank	Feature	Importance Score
1.	C_2H_2 (ppm)	0.26
2.	H_2 (ppm)	0.22
3.	Insulation Resistance (MΩ)	0.18
4.	Top-Oil Temperature (°C)	0.12
5.	Load Ratio	0.10
6.	CH_4 (ppm)	0.07
7.	Thermal Stress	0.05

The feature importance table shows that the DGA parameters especially the concentration of Acetylene (C_2H_2) and Hydrogen (H_2), were the most influential variables for the prediction of the target variable. Furthermore, the table shows the contribution of every feature in determining the health of a transformer by the GB model. The parameters such as C_2H_2, H_2, and insulation resistance are the leading ones. Thus, this suggests their strong tie with fault conditions like arcing or insulation failure.

4.2 Confusion Matrix Analysis

The confusion matrix evaluates the effectiveness of the GB model in the task of identifying transformer health in three categories: Normal (0), Warning (1), and Critical (2). This matrix as illustrated in Figure 3 depicts that the model is capable of making trustworthy and reliable classifications, thus reducing the chances of not detecting the critical faults. The confusion matrix indicates that the model performed excellently across all the three classes. Ninety-eight number of true positives and only two false negatives for the Critical class was obtained. Out of the 2 false negatives, one was categorized as Normal and one as Warning. Thus, the recall of the model for the Critical class is approximately 98%, implying that the model has outstanding fault detection ability for critical faults. The Normal category has a total of 95 samples classified into it while the rest is wrongly classified into the Critical (2) and Warning (1) categories. Despite this, the precision of the classification is still relatively good (with a precision level of around 96.9%). As for the Warning category, it manages to classify 56 samples correctly. And the precision score tied to this category is 96.6%.

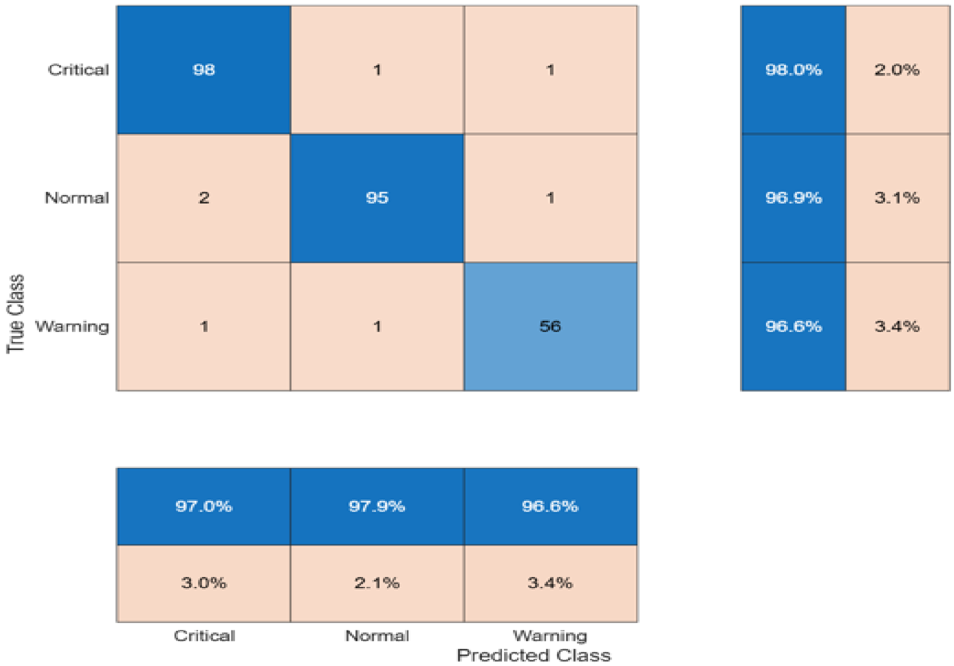

Fig. 3. Confusion Matrix for Transformer Health Classification

4.3 Model Performance Evaluation

The GB-based predictive maintenance model was tested for its efficiency with the aid of various performance indicators to confirm that it can satisfy real-world usage requirements in a monitoring system for transformers in real-time. After preprocessing and feature engineering, the data was divided into 70% for training and 30% for testing. A 5-fold cross-validation approach was used to improve stability, which helps reduce overfitting and ensures that the model performs consistently on various dataset segments. Thus, the pertinent transformer data was used to train and evaluate the PdM model.

On the test set, the model achieved an overall accuracy of 97.3%, indicating a high degree of confidence in its ability to anticipate transformer health conditions. In addition to accuracy, other metrics were assessed to learn more about the model's performance, particularly its capacity to recognize "Critical" and "Warning" states that need to be addressed right away in order for the system to continue operating reliably. Thus, the precision, F1 – score and recall computation result per class is shown in Table 8.

Table 8. Precision, F1-score and Recall Per Class

Class	Precision	Recall	F1-Score
Normal (0)	0.979	0.969	0.974
Warning (1)	0.966	0.966	0.966
Critical (2)	0.970	0.980	0.975

In the case of the Normal class, precision (0.979) and recall (0.969) show that the model is capable of correctly detecting the power transformer health condition with just a few false positive or missing detection errors. Regarding the Warning class, the model attained a recall and precision of 96.6% respectively. This indicates that the model can still mix mild degradation with either normal or severe faults (the assumption here is that a model cannot be 100% accurate). If system reliability is the top priority, then this trade-off is acceptable. Furthermore, the slight decline in performance with respect to this class, is owed to the nature of DGA patterns, which may share some overlapping characteristics between early faults and severe faults. Meanwhile, the model's great capacity to accurately identify severe transformer defects with few false alarms is demonstrated by the Critical class high precision and recall values. Specifically, this class had the highest recall value (98%) and the best detection of the three categories. This is very important from the perspective of power system protection because failure to identify the Critical state would result in severe damage to the transformer. For all classes, the F1-score which weighs the significance of recall and precision, remains high, suggesting that the model is typically robust. The model's PdM capabilities have been demonstrated by these results especially considering the fact that the macro and average precision, recall, and F1-scores are all above 96%. In an early warning scenario, it can consistently identify and understand critical circumstances that call for immediate action while maintaining a satisfactory performance level.

4.4 ROC Curve

As the decision threshold shifts, the ROC curve in Figure 4 illustrates how well the model maintains the TP and FP rates. The ROC curve analysis highlights the GB model's ability to recognize the three transformer conditions: Normal, Warning, and Critical. The curve of the Normal and the Critical classes are very close in the upper left corner of the ROC space, which means they have the highest TP rates and the lowest FP rates. It shows that the model is especially good at identifying these two classes which is very important for making sure that these conditions of the transformer are not going to be flagged unnecessarily, and serious faults are going to be detected correctly. The corresponding AUC values (above 0.97 for both classes [0 & 2]) indicates the model's high discriminative performance. On the other hand, the Warning class has a lower AUC value (≈0.96). This still illustrates a good classification performance with a little overlap with the Normal and Critical conditions. Overall, the ROC curve shows the model's strong and dependable capability of predicting fault conditions across all classes. These findings suggests that the model can be practically utilized for early fault detection and risk-based maintenance planning of high-voltage power transformers.

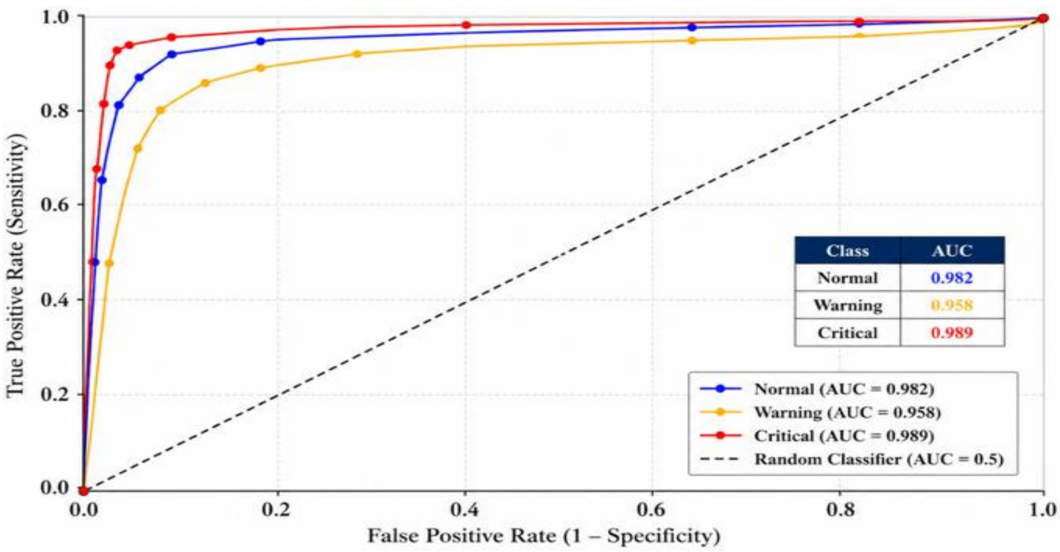

Fig. 4. The GB Model ROC Curve

4.5 Comparative Analysis

On comparison of GB with other ML algorithms as depicted in Table 9, the result show that ensemble methods are clearly better, especially GB for transformer fault classification tasks. An accuracy of 97% was obtained with the GB technique and its average F1-score, recall and precision (0.97 respectively), was the highest amongst the ML algorithms. This demonstrates its capability of being able to accurately diagnose faulty and non-faulty conditions at the expense of keeping the FNs and FPs low. Its sequential learning design and focus on compensating past faults are the main reasons why it is so well adapted at detecting complex nonlinear patterns that occur in maintenance and sensor data.

Coming in second place, is Random Forest (RF) with an accuracy of 88%, and average precision, recall, and F1-score of 0.86, 0.85, and 0.85 respectively. Being an ensemble method too, RF exploits bootstrapping and feature randomness. Therefore, it attains better generalization and less overfitting. Decision Tree, while being simpler, scored moderately with 84% accuracy. However, it is not as good as ensemble methods in terms of robustness and generalization. Logistic Regression and KNN also worked with lower accuracy score of 82% and 80% respectively, and it seems that both methods are actually not capable of discovering underlying patterns in the data. Lower recall and F1-scores of these methods suggest that they are likely to misclassify noisy or imbalanced data.

Table 9. Performance Comparison Considering Other Algorithms

ML Algorithm	Accuracy (%)	Precision (Average)	Recall (Average)	F1-Score (Average)
Gradient Boosting	97	0.97	0.97	0.97
Random Forest	88	0.86	0.85	0.85
Decision Tree	84	0.80	0.79	0.80
Logistic Regression	82	0.77	0.76	0.77
K-Nearest Neighbours	80	0.75	0.74	0.74

5. CONCLUSION

The result of this study discloses that C_2H_2 and H_2 are the top features for determining the condition of the power transformer. The GB machine learning-based predictive maintenance model developed in this study is very dependable and accurate. It prompts a proactive approach for enhancing the dependability of the power transformer of the considered transmission substation, as this will aid in decreasing unplanned outages, maintenance costs, and the hazard of further incidents. The model's implementation on the Nigerian power system, especially in the high-load and high-risk transmission substations will immensely enhance the dependability of the sector. Additionally, this study offers significant insights that may be applied to power transformer reliability management, which would enhance maintenance procedures throughout the Nigerian power system. Other investigations such as exploration of hybrid predictive models, real-time implementation and field testing, development of a web-based PdM dashboard, can be carried out to further enhance the results of this study.

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