JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

TRANSFORMER INCIPIENT FAULT PREDICTION USING NAÏVE BAYES (NB) ALGORITHM

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Abstract

Transformers is an important equipment in Electrical Power System. Failure of transformer can cause huge financial loss to industries. The ratio of key gases dissolved in the transformer oil can be used to predict Transformer incipient fault. Four types of incipient faults can be identified based on the key gas ratio, viz, Low Temperature Thermal fault, High Temperature Thermal fault, Low Intensity Discharge fault, High Intensity Discharge fault, and . A data set, with key gases concentration, is considered by using which prediction efficiency of fault classification is attempted using machine learning algorithms. In this work Naïve Bayes (NB) algorithm is used for prediction of transformer incipient fault more precisely.

Key words

Dissolved Gas Analysis (DGA), Transformer Incipient fault, IEC 60599, NB classifier.

1. Introduction

Transformers are most important equipment in the existence of power system. Failure of a transformer, can result in huge financial loss, depending on the duration of outage. Key gases are evolved in a transformer during its operation and can be used to predict incipient faults. It dissolves in insulation oil. These dissolved gases acts as an indicator of incipient fault. The various gases evolved in transformer during fault is exhibited in Table 1.

Table 1: Transformer faults and key gases

Key Gas	Chemical representation	Fault type
Hydrogen	H_2	Corona
Carbon monoxide and carbon dioxide	CO / CO_2	Cellulose insulation breakdown
Methane and Ethane	CH_4 / C_2H_6	Low temperature oil breakdown
Acetylene	C_2H_2	Arcing
Ethylene	C_2H_4	High temperature oil breakdown

The incipient faults can be predicted using these dissolved gases.

2. Dissolved Gas Analysis (DGA) and IEC 60599-2015

A reliable method to predict incipient faults in oil-filled transformer is DGA [1]. It is used as indicator to identify deteriorating insulation, partial discharge, over heating hot spots, and arcing [2]. Standards used for DGA are IEC60599-2015 and IEEE C57-104TM. An early detection can lead to an opportunity for suitable remedial action [3]. During fault, based on type of fault, a key gases are evolved in the transformer oil. The key gases found during DGA are carbon-di-oxide (CO_2), methane (CH_4), ethane (C_2H_6), hydrogen (H_2), acetylene (C_2H_2), carbon monoxide (CO), and ethylene (C_2H_4). Gas concentration in parts per million (ppm) can be found using gas chromatography Dornenberg, Rogers, Duval triangle and key gases method are used for interpretation of transformer faults using DGA. The current work uses key gas ratio method based on IEC standard 60599-2015 for DGA and exhibited in table 2.

Table 2: DGA based fault prediction as per IEC 60599-2015 standard

	IEC 60599	C_2H_2 / C_2H_4	CH_4 / H_2	C_2H_4 / C_2H_6	
	Ratios of characteristic gases < 0.1 0.1 - 1 1 - 3 >3	0 1 1 2	1 0 2 2	0 0 1 2	
Case No.	**Characteristic Fault**				**Typical examples**
0	No fault	0	0	0	Normal ageing.
1	Partial discharges of low energy density	0 but not significant	1	0	Discharges in gas filled cavities resulting from incomplete impregnation or super saturation or cavitations or high humidity.
2	Partial discharges of low energy density	1	1	0	All above but leading to tracking or perforation of solid insulation.
3	Discharge of low energy	1-2	0	1-2	Continuous sparking in oil between bad connections of different potential. Breakdown of oil between solid materials.
4	Discharge of high energy	1	0	2	Discharges with power follow through. Arcing breakdown of oil between windings or coils, or between coil to earth. Selector breaking current.
5	Thermal fault of Low temperature < 150°C	0	0	1	General insulated conductor overheating.
6	Thermal fault of Medium temperature range 150°C - 300°C	0	2	0	Local overheating of the core due to concentrations of flux. Increasing hot spot temperatures, varying from small hot spots in core, overheating of copper due to eddy currents, bad contacts/joints (pyrolitic carbon formation) up to core and tank circulating currents
7	Thermal fault of Medium temperature range 300°C - 700°C	0	2	1	
8	Thermal fault of high temperature > 700°C	0	2	2	

3. NB Algorithm

Several classification algorithms are available for fault classification [4-11]. The current work is an attempt to use Naïve Bayes machine learning algorithm for fault classification. It is a Generative Classification Algorithm. The probability of an object belonging to certain class is calculated using Bayes theorem. In case of 'm' classes, to predict the class of a new object Bayes theorem with certain approximations are used 'm' times as shown in the equations 3.1 through 3.3.

$$P(y_a|X) = P(X|y_a) \qquad (3.1)$$

$$P(y_b|X) = P(X|y_b) \qquad (3.2)$$

$$P(y_m|X) = P(X|y_m) \qquad (3.3)$$

The class 'i' with the highest probability value, **$P(y_i|X)$** is assigned to the object 'X' .

4. NB algorithm simulation using MATLAB

Testing and experimentation was carried out with a data set of 200 samples. Gas concentration of C_2H_2, CH_4, C_2H_6, C_2H_4 and H_2 were used as attributes. In the initial investigation Kernel NB and Gaussian NB algorithms were used and prediction accuracy was identified. The aim was to identify suitable model for transformer incipient fault prediction. In the next stage, investigation and analysis was done by considering the best algorithm selected from initial investigation. Experimentation was carried out using MATLAB version R2020a. Table 3 exhibits sample data with gas concentration in ppm.

Table 3: Sample data set.

Sl. No.	Gas Concentrations ppm					Fault type
	H_2	CH_4	C_2H_2	C_2H_4	C_2H_6	
1	2238	826	537988	335279	4008	High intensity discharge
2	2373	817	669150	447061	4284	High intensity discharge
3	2394	754	673175	360327	4049	High intensity discharge
4	6729	323	2	45353	2323	Low intensity discharge
5	10000	800	40	9	222	Low intensity discharge
6	9900	780	35	10	150	Low intensity discharge
7	10000	769	36	11	180	Low intensity discharge
8	30	80	3	220	675	Thermal fault
9	4000	6076	2	23232	4544	Thermal fault
10	100	200	1212	3222	188	No Fault

5. Results and Discussion

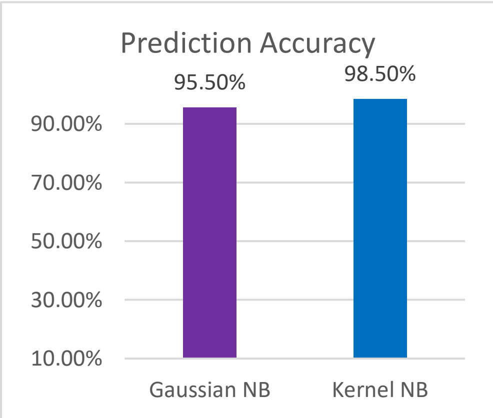
5.1. NB Algorithm Selection

Gaussian and Kernel NB algorithms were considered for analysis. Prediction accuracy and training time were selected as the parameters for comparison to select between the two algorithms. The results are tabulated in Table 4 and represented in figure 1a and 1b.

Table 4: Prediction accuracy for different NB algorithm

Algorithm	Prediction Accuracy	Training time in sec
Gaussian NB	95.5%	6.93
Kernel NB	98.5%	7.18

The results obtained depicted that Kernel NB algorithm has a better prediction efficiency of 98.5% over Gaussian NB algorithm with prediction efficiency of 95.5%. Although the training time was slightly higher in case of Kernel NB algorithm, the difference was 3.6%. Hence Kernel NB algorithm was selected for future analysis. The confusion matrix of Kernel NB algorithm is shown in figure 2.



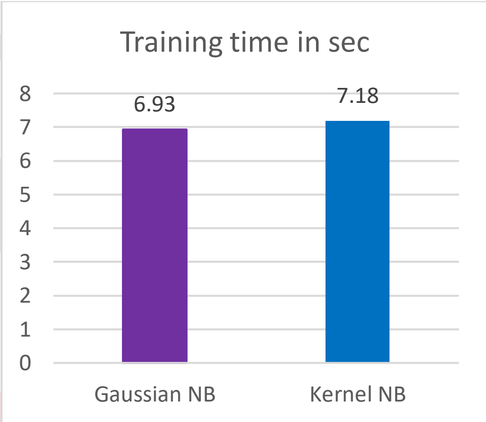


Fig 1a: Prediction accuracy Fig 1b: Training timing

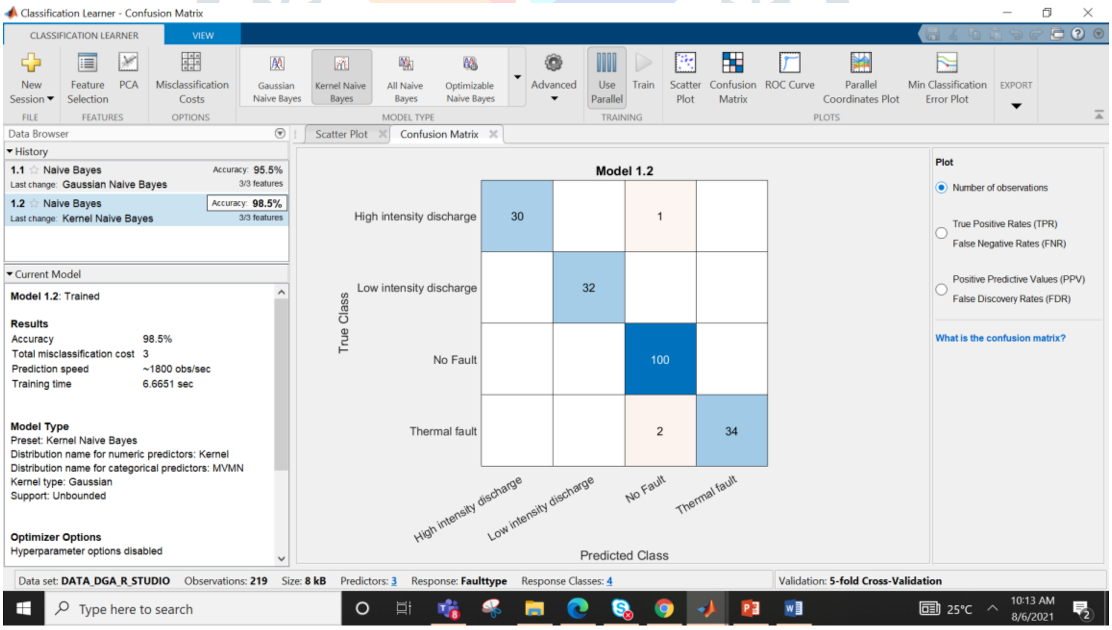


Figure 2: Confusion matrix for Kernel NB Algorithm

The accuracy of prediction is indicated by confusion matrix. It represents pictorially true class with respect to predicted class. It can be seen from the confusion matrix that the selected model has one incorrect prediction in the "High Intensity Discharge" and 2 incorrect prediction in the "Thermal Fault" case.

5.2. Transformer Incipient Fault Prediction

By using Kernel Naïve Bayes algorithm, prediction accuracy for all the classes i.e. No fault, Thermal fault, Low intensity fault and High intensity fault, was identified using Region of Conversion (ROC). ROC provides the prediction accuracy as a plot of true positive predictions v/s false positive predictions. Accuracy is indicated by the area under curve (AUC). If the AUC is 0.98 it indicates 98% accuracy of prediction. The ROC curve for the four classes mentioned above are shown in figure 3 to figure 7.

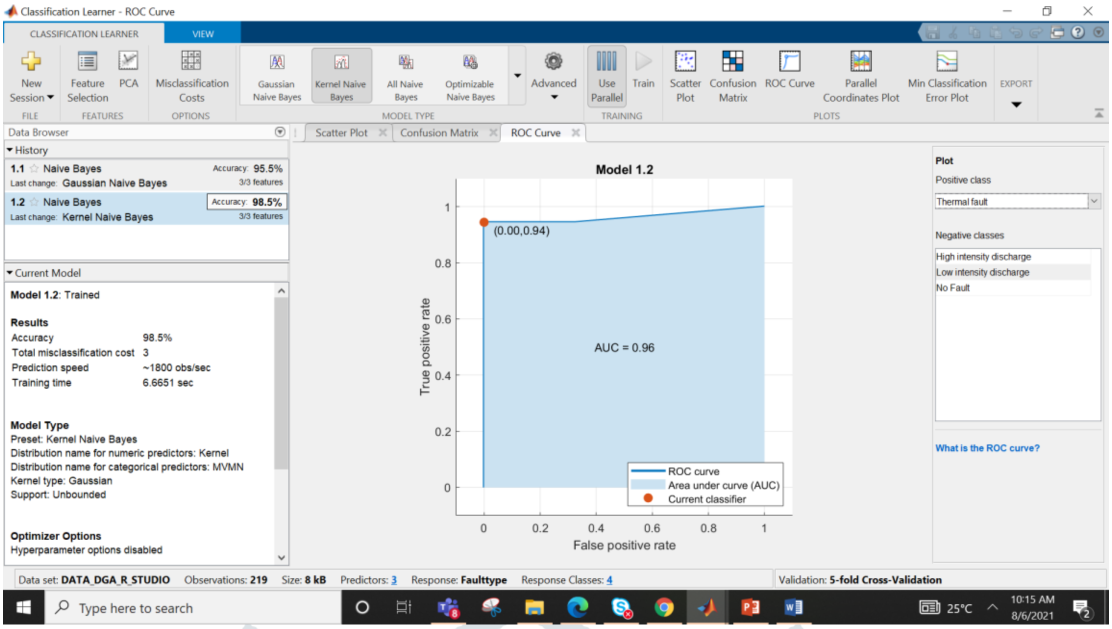


Figure 3: AUC = 0.96 (Fault type: Thermal fault)

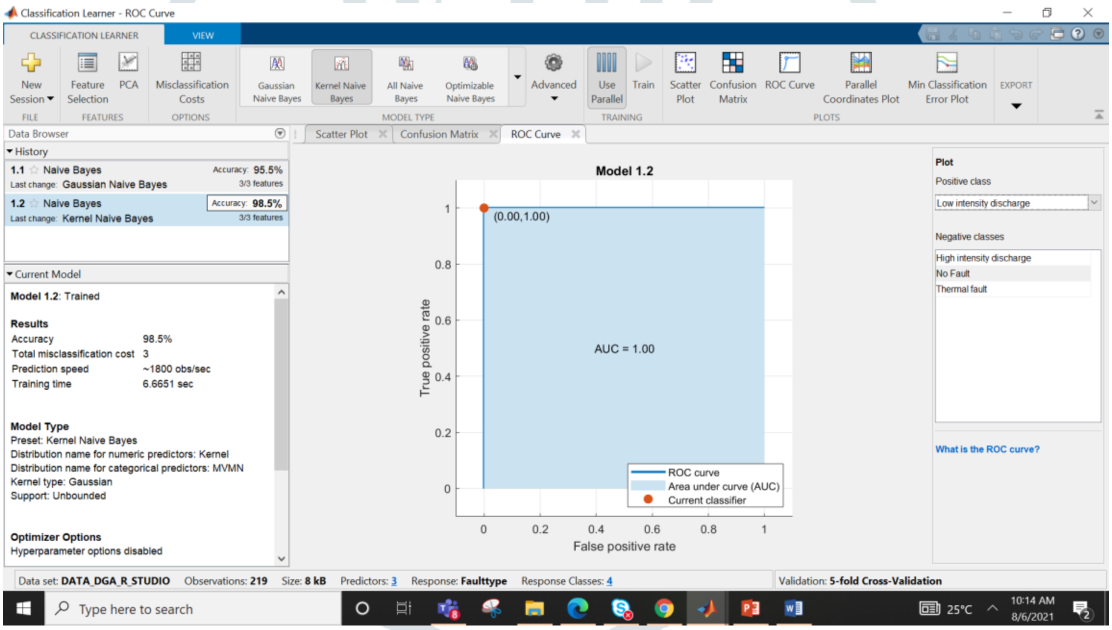


Figure 5: AUC = 1.0 (Fault type: Low intensity discharge)

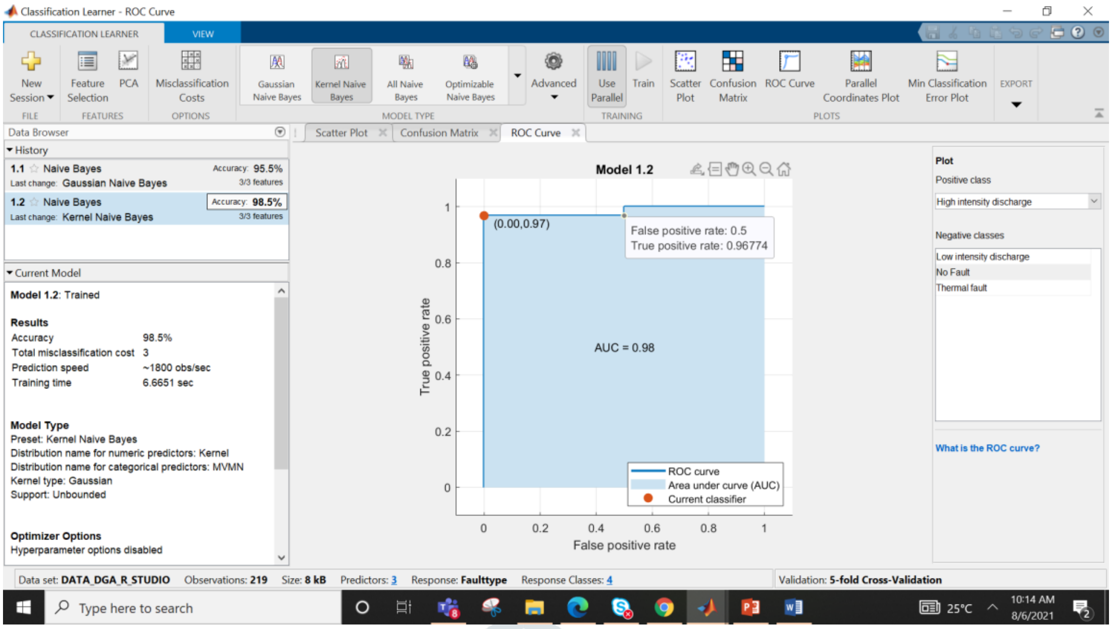


Figure 6: AUC = 0.98 (Fault type: High intensity discharge)

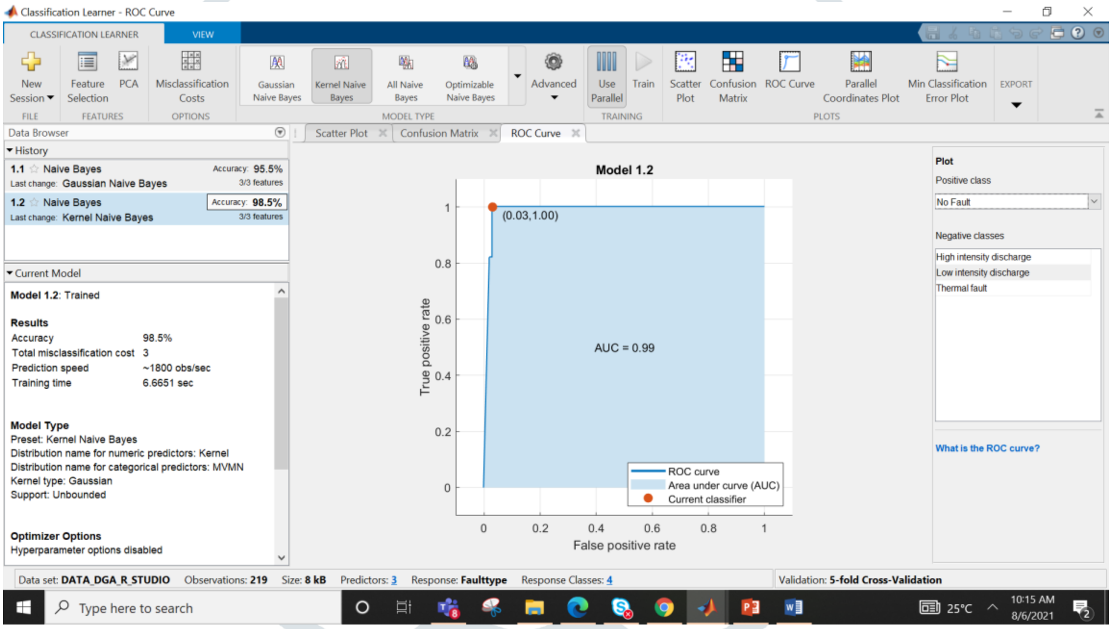


Figure 7: AUC = 0.99 (Fault type: No-fault)

The observations are exhibited in table 5

Table 5: Prediction accuracy of incipient faults using Kernel NB algorithm.

Sl. No.	Type of incipient fault	AUC	Prediction accuracy
1	Thermal fault	0.96	96 %
2	Low intensity discharge fault	1.00	100%
3	High intensity discharge fault	0.98	98%
4	No-fault	0.99	99%

6. Conclusion

In this paper an attempt has been made to predict the incipient faults of a transformer using NB algorithm. In this regard, number of data is recorded with the experimental set up, out of which percentage of data are used for testing purpose. From the study / results and discussions, the following specific conclusions are drawn:

- Prediction accuracy of Kernel NB algorithm and Gaussian NB algorithm is found to be 98.5% and 95.5% respectively.
- It is observed that, Kernel NB algorithm gave better and consistent prediction results compared to the Gaussian NB algorithm.
- Further, by the application of NB algorithm based on the key gas ratios of a transformer, prediction of low intensity discharge fault is found to be 100% accuracy during the thermal fault with accuracy 96%, High Intensity Fault 98% and 99% for No fault Conditions.

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