Transformer Incipient fault prediction using Support Vector Machine (SVM)

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Abstract: *Power transformer is an important link in power system. Utilities will face a huge loss if a fault occurs transformer. The outage can cause loss to industry sector. Transformer incipient fault can be predicted using Dissolved Gas Analysis (DGA) based on gas ratios. The current work is an effort to use SVM to predict transformer incipient fault more precisely. DGA data of various transformer oil samples were collected and analyzed to select the best SVM kernel function and kernel factor to be used and to observe the prediction accuracy.*

Key words: DGA, Transformer Incipient fault, IEC 60599, SVM classifier.

1. Introduction

Transformers form a crucial link in power system. It is one of the major asset of utilities. With increased demand for electric energy, transformers are being overloaded to cope with the demand. Failure of a transformer in-service, can result in loss of millions of dollars, based on the duration the transformer is out of duty. It is time consuming and costly to replace faulty transformers. Hence it is important to monitor the gases in the transformer condition. Due to various operating conditions in the transformer gasses are evolved in the transformer oil. These gases dissolve in insulation oil and can be used as indicator of incipient fault. Key gases evolved during the operation of transformer are shown in table 1.

Table 1: Key gases evolved during fault

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

Monitoring gases evolved in the transformer oil can help in predicting the possible faults and this can be achieved by using DGA.

2. Dissolved Gas Analysis and IEC 60599

One of the most acceptable method to identify incipient fault in transformer is DGA [1]. The combustible concentration limits vary between different countries, continents and

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transformers. Hence setting the concentration limits is not easier. The incipient faults in oil-filled power transformer can be detected using DGA, which is more reliable. DGA is not science, but an art. It is the most prominent test in determining the state of a transformer. It acts as a first indicator to identify partial discharge, deteriorating insulation & oil, over heating hot spots, and arcing [2]. IEC60599 and IEEEC 57-104TM standards are used as standard for DGA. It helps in early diagnosis and provides opportunity to find suitable cure [3]. A characteristic amount of gas is produced in the transformer oil based on type of fault. There is a significant increase in the individual gas concentration, Total Dissolved Combustible Gas (TDCG). Gas chromatography is used to detect the gases as parts per million (ppm). It is used to identify, separate, and quantify mixtures of gases. The key gases found during DGA are hydrogen (H_2), methane (CH_4), acetylene (C_2H_2), ethylene (C_2H_4), ethane (C_2H_6), carbon monoxide (CO), and carbon-di-oxide (CO_2). By using DGA incipient faults in a transformer can be predicted. Certain gases are formed in transformer oil even under normal transformer operational conditions. Therefore, large sampling is required to build concentration norms. The cost of unplanned outages can be reduced by the early detection of such internal faults in transformer. The interpretation of transformer faults using dissolved gases analysis is produced using some techniques that are assumed by Dornenberg, Rogers, Duval triangle and key gases methods. All the techniques mentioned above have its own pro's and con's. All the techniques do not arrive at same conclusion. The accuracy depends upon the expertise of the person handling the analysis. IEC standard 60599 for ratio method of DGA shown in table 2.

Table 2: IEC 60599 for fault prediction based on DGA

	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. SVM Algorithm

Support Vector Machine" (SVM) is a supervised machine learning algorithm which is suitable for both classification and regression challenges [4][5]. In the SVM algorithm, a n-dimensional space is plotted where n is the number of features in data set. The value of each feature being the value of a particular coordinate. A hyper-plane is determined that differentiates the two classes the classification is done. The hyperplane should divide the set of samples such that all the points with the same label are on the same side of the hyperplane [6]-[11].

4. MATLAB simulation and analysis

For the experimentation and testing a data set of 200 samples were used. The data used were concentration of various gases like C_2H_2, CH_4, C_2H_6, C_2H_4 and H_2. The experimentation was conducted in two stages. In the first investigation various kernel function and kernel factors of SVM was used and predictions were done. The purpose was to identify the model best suited for fault prediction. The second investigation was done by varying the Kernel Scale and observing the impact on the prediction accuracy for the model selected. MATLAB version R2020a was used for the investigation. Table 3 shows sample data.

Table 3: Sample data of gas concentrations in ppm.

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. Selection of Algorithm

Based on the kernel function, there are 4 types of SVM algorithm available for fault classification. They are Linear SVM (LSVM), Quadratic SVM (QSVM), Cubic SVM (CSVM) and Fine Gaussian SVM (FGSVM). In the initial experimentation fine tuning of the kernel factor with all the 4 cases was taken up to identify the most suitable kernel function and the value of kernel factor. The results are tabulated in Table 4 and represented in figure 1.

Table 4: Prediction accuracy for different kernel function and kernel values

Kernel Scale	0.1	0.25	0.4	0.5	0.6	0.75	1	2
LSVM	84.4	69.8	61.8	59.8	60.3	60.3	70.9	84.4
QSVM	92.0	89.9	86.9	85.4	84.9	85.4	70.9	73.4
CSVM	67.8	61.3	91.5	91.5	91.5	81.4	70.9	73.4
FGSVM	88.4	88.9	87.9	86.9	85.9	83.9	87.9	72.9

The results obtained depicted that CSVM gave a consistent prediction efficiency of 91.5% over a kernel scale of 0.4 to 0.6. The prediction efficiency of other methods was found to be not at the range of CSVM and was also not consistent. Hence CSVM was selected for the analysis in this work. The kernel scale was fixed at 0.55. The confusion matrix of CSVM with kernel factor of 0.55 is shown in figure 2.

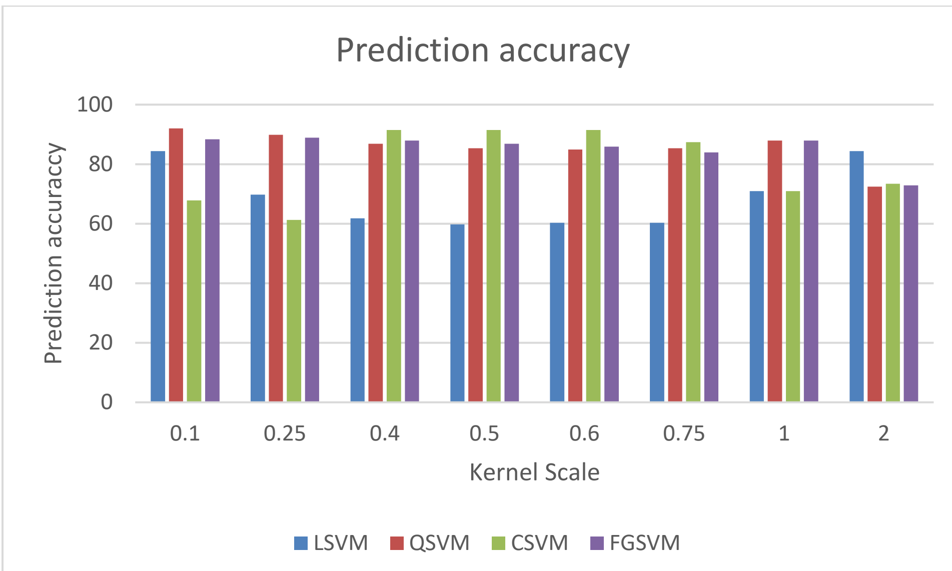

Figure 1: Prediction accuracy of various SVM function with the variation of kernel scale

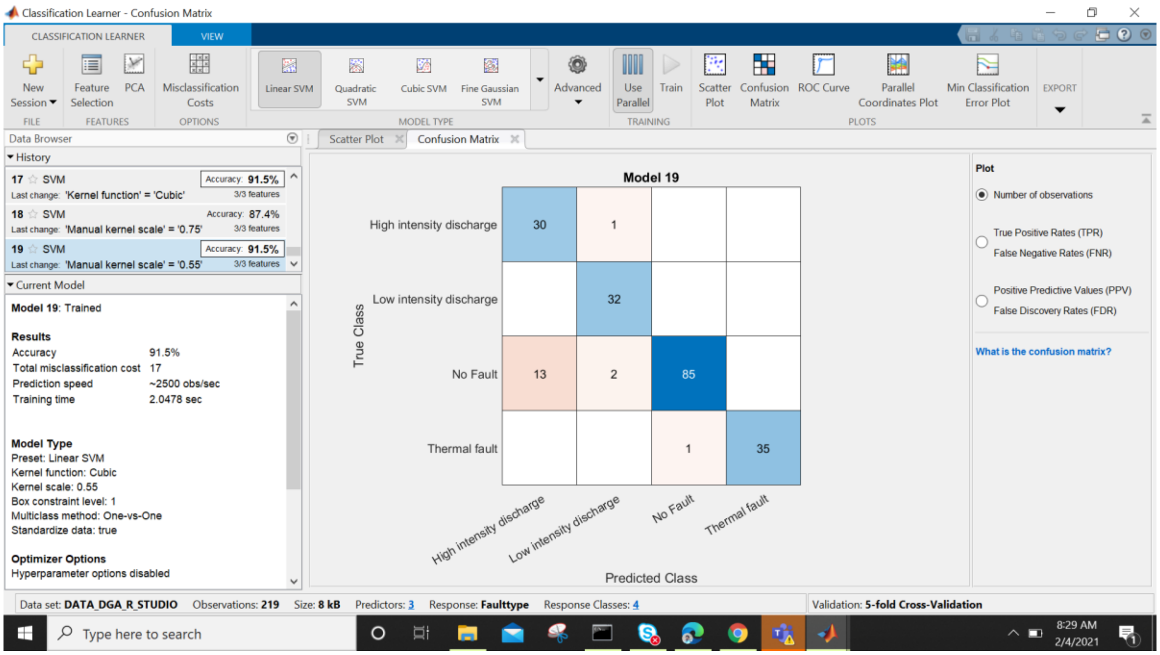

Figure 2: Confusion matrix for CSVM with kernel scale 0.55

The confusion matrix is a matrix of true class versus predicted class. It can be seen from the confusion matrix that the selected model has confusion in the prediction of “No-Fault” case only.

5.2.Transformer incipient fault prediction

From the analysis carried out in 5.1 the CSVM with kernel scale of 0.55 was selected. Region of Conversion (ROC) was used to identify the prediction accuracy for each of the fault type i.e. Low intensity fault, High intensity fault, Thermal fault and No fault cases. The ROC gives the prediction accuracy as a plot of true positive predictions v/s false positive predictions. The area under curve (AUC) is an indicator of accuracy. If the AUC is 0.97 it indicates 97% accuracy of prediction. The ROC curve for the four classes of faults namely Low intensity fault, High intensity fault, Thermal fault and No-fault cases are shown in figure 3 to figure 6.

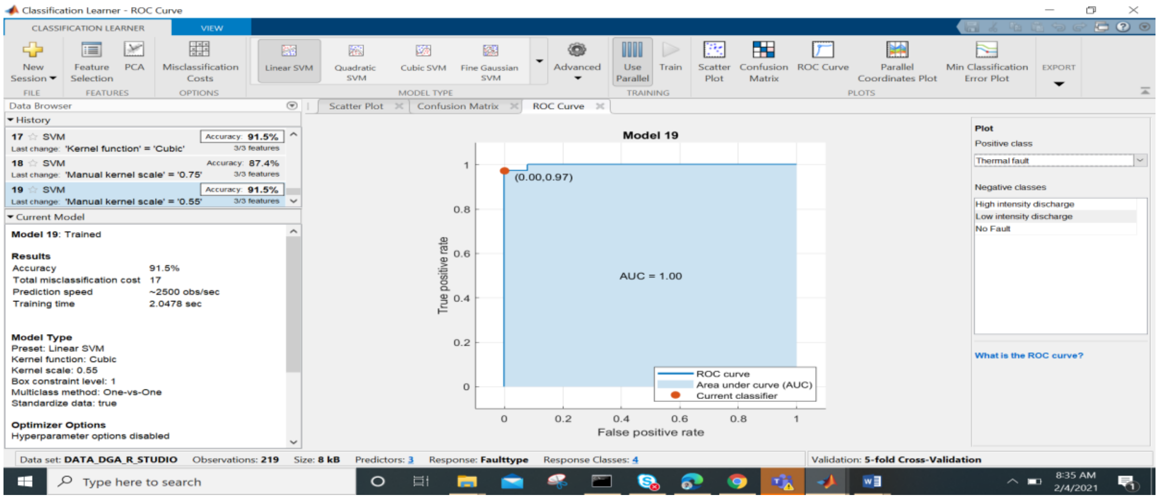

Figure 3: ROC for Thermal fault, AUC = 1.0

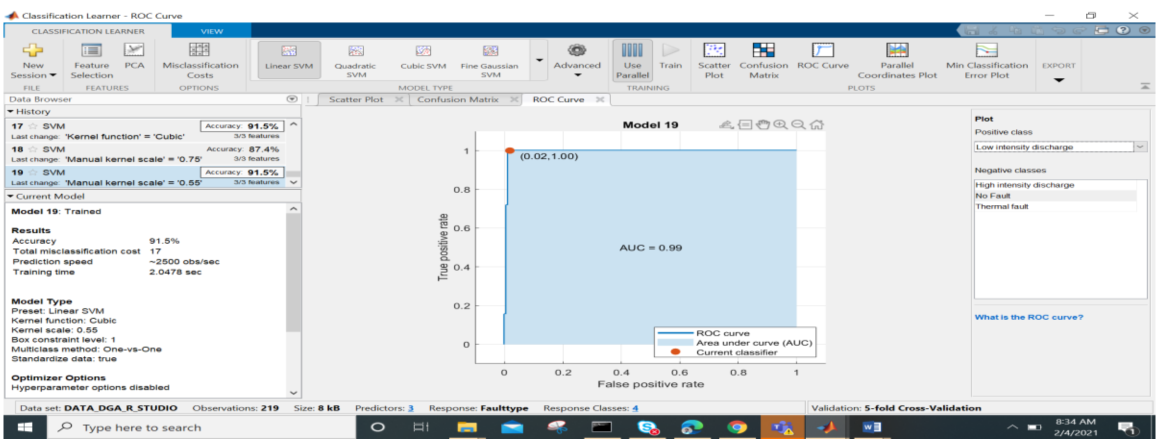

Figure 5: ROC for Low intensity discharge fault, AUC = 0.99

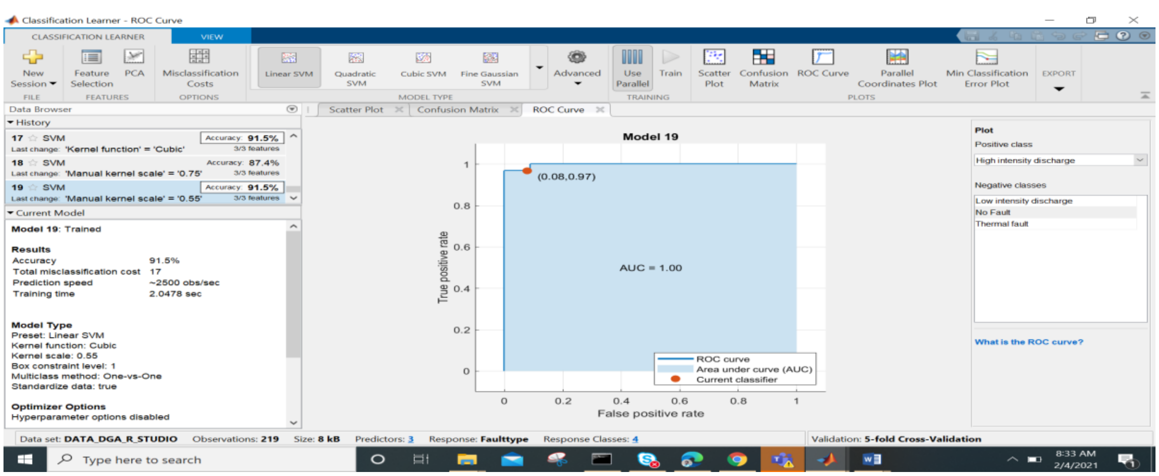

Figure 6: ROC for High intensity discharge fault, AUC = 0.99

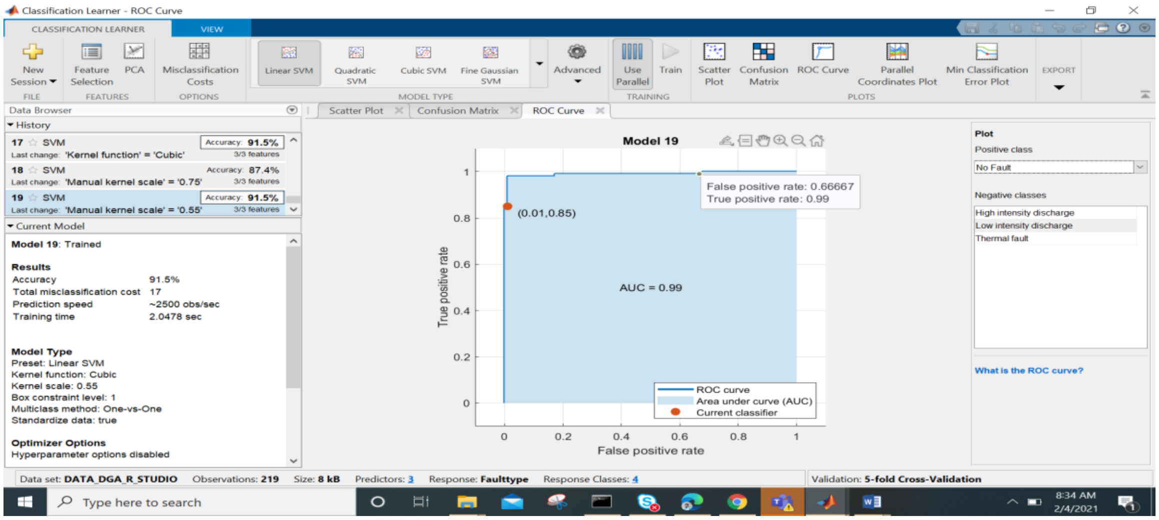

Figure 7: ROC for No-fault, AUC = 0.99

The observations are tabulated in table 5

Table 5: Prediction accuracy of incipient faults using CSVM algorithm.

Sl. No.	Type of incipient fault	AUC	Prediction accuracy
1	Thermal fault	1.0	100 %
2	Low intensity discharge fault	0.99	99%
3	High intensity discharge fault	1.0	100%
4	No-fault	0.99	99%

6. Conclusion

Transformer incipient fault prediction was carried out using SVM machine learning algorithm. It was observed that CSVM model gave better and consistent prediction compared to LSVM, QSVM, and FGSVM. Further the prediction rate is high in CSVM with kernel scale of 0.55.

7. Acknowledgement

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9. Biographies

A. Kumar was born in Karnataka, India, in 1969. He obtained the B.E. degree in Electrical and Electronics Engineering from Bangalore University, Karnataka, in 1993, the M.S. degree in Elctronics and controls from BITS, Pilani, in 1999, the M.Sc (Engg) degree in Electrical Sciences from Visvesvaraya Technological University, India, in 2013 respectively. His area of research includes High voltage Engineering and Machine learning.

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