Transformer Health Monitoring

By

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A Thesis submitted to

Pakistan Navy Engineering College (PNEC), Karachi

National University of Sciences and Technology (NUST), Islamabad

In partial fulfillment of requirements for the degree of

Master of Science (MS) in **Electrical Engineering**

With specialization in Control Systems

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Declaration

I, *Muhammad Salman Khan* declare that thesis titled **"Transformer Health Monitoring"** also, the work introduced are my own particular and has been created by me accordingly my own unique research.

I endorse that:

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3. Where ever I have consulted the published work of others, this is always clearly referenced
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This thesis is dedicated to *my beloved parents*

and siblings

Abstract

Realtime fault detection and identification can increase the reliability of a system. Key to this is online monitoring, classification and characterization of such faults. Deviations in performance of a system under normal conditions without any internal or external parameter changes can be classified under faults. These deviations start as minor disturbances or changes, if left unchecked, may alter the operations of a system. These alterations may cripple the system or lead to its failure.

Diagnosis is the detection and identification of faults in the system. The goal of this project is to develop a structure for fault diagnosis which can detect and categorize the condition of an electrical system. to fulfill this requirement, methods are presented for identification of transient faults and stationary faults using time-frequency analysis. The fault features are extracted from the transformer current using Short Time Fourier Transform and Wavelet Transform,. The existence of a fault is analyzed using spectrum energy density analysis and subsequently categorization is performed by the pattern recognition classifiers; ensemble classifier. The efficiency of each classifier is compared for determination of an optimal classification technique.

Probable faults in an electrical system, their effects and their manifestation in the system parameters are included. Also included is an experimental setup whereby which data for diagnosis is collected.

Keywords: *Transformers, Short-circuit Faults, Transient Faults, LDC, QDC, SVM,Ensemble*

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Abbreviations

MCSA	Motor Current Signature Analysis
DWT	Discrete Wavelet Transform
TD	True Detection
FD	False Detection
ACC	Accuracy
SEN	Sensitivity
PPV	Positive Predicted Value
NPV	Negative Predicted Value
LDC	Linear Discriminant Classifier
QDC	Quadratic Discriminant Classifier
ONAN	Oil Natural Air Natural

Chapter 1

Introduction

1.1 Electrical Faults

In the age of transformation of traditional electrical networks into smart grids, demand for online monitoring of grid system components has been identified.Critical operations of complex system is now possible while being cost-effective, reliable and maintaining safe operation. To accomplish this goal, early diagnosis of faults has become one of the key issues of interest for research.

Deviations in performance of a system under normal conditions without any internal or external parameter changes can be classified under faults. These deviations start as minor disturbances or changes, if left unchecked, may alter the operations of a system. These alterations may cripple the system or lead to its failure.Diagnosis is the early detection of such faults in the system in real time and the identification and assessment of its type and severity. In this thesis, fault diagnosis and its assessment are referred to as fault analysis.

1.2 Social Impacts for Transformer Faults In Pakistan

Demand for electricity usually outweighs its supply in Pakistan. While most of this is due to "circular debt" wherein the government is unable to manage its power tariff recoveries against the cost of generation and transmission. Inefficiencies in the transmission and distribution network with power losses up-to 40 % also play a major factor in the smooth supply of electricity. Coupled with the enormous increase in energy demand emanating from population growth and industrial development, a power crisis has emerged. Increase in power generation capacity may take years into making, network downtime can certainly be reduced, providing a much needed relief to the struggling power sector.

Network breakdowns are largely due to outdated transmission and distribution infrastructure. To better manage an ailing network infrastructure, maintenance activity is required. However even with carrying out such routine activity, detection of faults in realtime is not widely available, resulting in power supply interruptions.

1.3 Problem Statement

A critical component of the power distribution infrastructure is the electrical transformer. Power and distribution transformers work with different dynamics and cater to different roles. Distribution transformers form the lower chain of electrical power distribution and are heavily impacted with frequently changing dynamics. These dynamics result from transients produced during different transformer loading.

During the life cycle of a transformer, it is subjected to varying loading. Changes between loading levels produces transients in the network and impact the transformer. Reactance of a transformers dampens these transients and ensure safe operation. Over the period of operations, internal aging including degradation of oil and insulation, reduce the ability to sustain these transients.

A fault may occur unwarned and may cause temporary downtime or in some cases result in irreversible damage. Such faults cannot always be prevented during regular maintenance cycles. To ensure timely detection of faults, the need for online monitoring is now ever needed. Such faults can be detected non intrusively using electrical current. Despite with advancement and expansion in the technology of conditional monitoring of transformers, detection and classification of faults is still a grey region that requires to be explored for further enhancement.

Modern research has examined the possibility of detecting transformer faults. Investigation of transformer current signals signatures has provided that changes occur in a when subjected to faults. Therefore pattern recognition and machine learning approach can be applied for training and fault detection of a system in realtime.

1.4 Goal Of Thesis

Present study goal is to develop a system that can detect in realtime the changes occurring in a transformers current signature. This system is built to be non intrusive and if required, will easily be deployed in the field without the need of modifications to an existing transformer. This will also help in reducing maintenance costs and preventing unscheduled downtime which inadvertently result in losses of production and financial incomes, and are the priorities of any electrical power distribution utility. The use of current signature analysis for transformer signature profiling has been adapted from work done in the field of Motor Current Signature Analysis (MCSA) [1]. For the scope of this thesis, transformer current signature can be classified into three states as follows:

- Healthy Data sampling: TCS during normal operation
- Fault 1: Transformer subjected to fault 1
- Fault 2: Transformer subjected to fault 2

Typically each transformer carries its own unique current signature and this is inherent to its design and the materials used for its construction. Deviations are expected between transformers current signatures under identical conditions and identical operational parameters. This is true even the said transformers are part of the same production model with similar design and construction type.

The use of AI applied via Machine learning will aid in real time identification of a detected fault. The identification of the fault will be determine the transformer state to be either healthy or of the two faulty states stated above.

1.5 Thesis Outline

Thesis comprises of eight major chapters.

- Chapter 1 contains the overview , problem statement, goal and proposed approach.
- Chapter 2 contains literature review about trend in transformer maintenance, techniques and previous implemented methods of transformer health state monitoring .

- Chapter 3 briefly explains the transformer faults, the severity of such faults and effects of transients.
- Chapter 4 contains theoretical description of feature extraction and classification.
- Chapter 5 describes the hardware test setup and software platform.
- Chapter 6 encloses methodology of the proposed framework.
- Chapter 7 explains the results in detail.
- Chapter 8 draws conclusion regarding the proposed framework.

Chapter 2

Literature Review

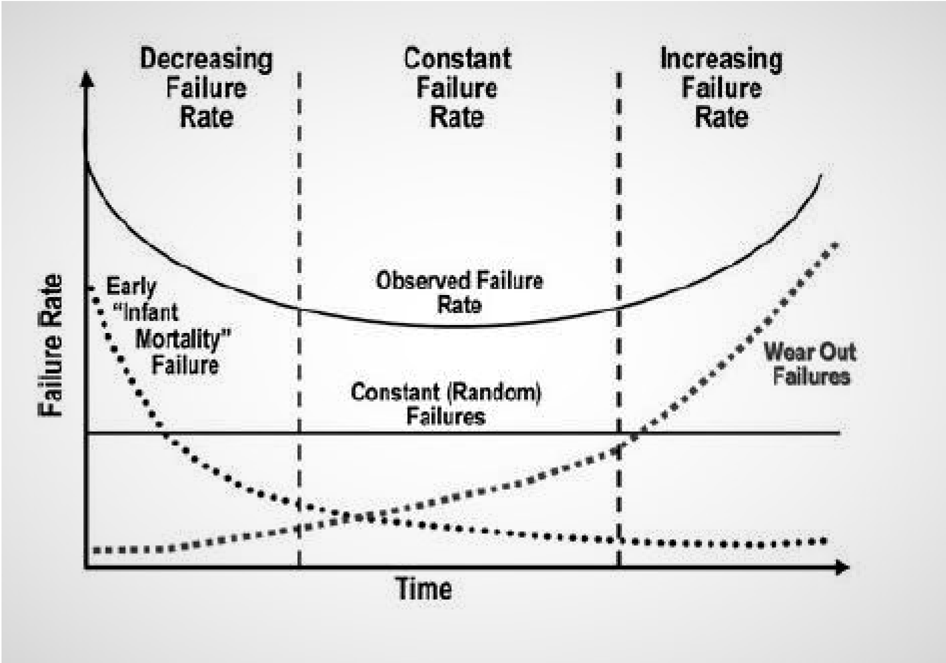
2.1 Scope and Objective of the Chapter

This chapter provides highlights on studies which have been conducted or proposed during previous years. It explains the different methods for identification of transformer faults and the methods and their classification accuracy achieved for correct classification of transformer failure events.

2.2 Transformer Failure Pattern

Literature review is composed of two sections. First section briefs about different transformer faults. The second section focuses on short circuit faults.

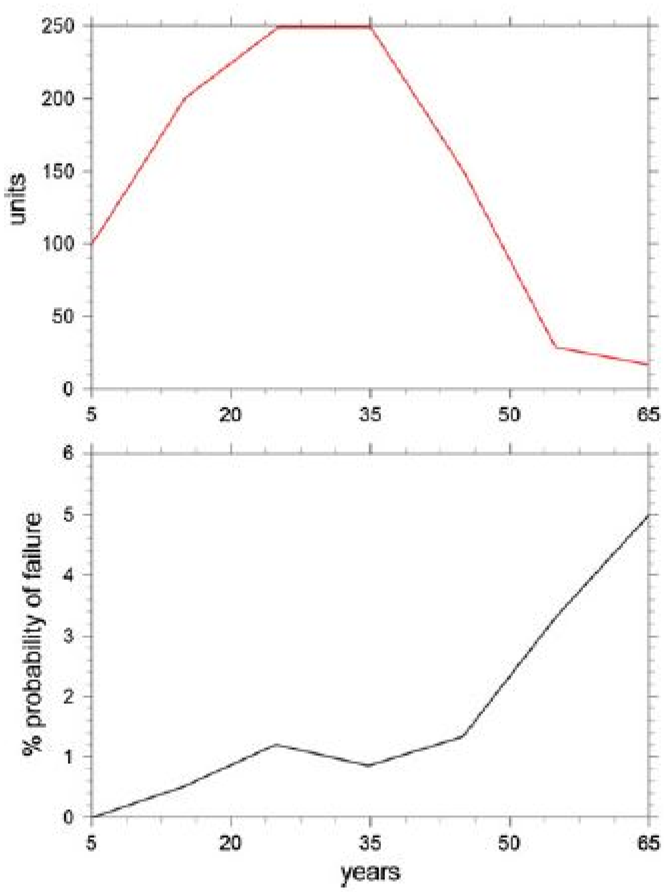
The transformer failure pattern has been found to follow the bath tub curve. The bath tub curve is divided in three stages. The first stage is where the transformer is most likely to fail early on in its operational life, this stage has a decreasing failure ratio. The second stage witch covers the most part on the curve exhibits a constant failure ratio. In the final stage, an increasing failure ratio exhibiting a period of wear out. An increasing failure ratio in the first stage of the curve, indicate manufacturing defects including material and workmanship inadequacies.



Growth in the industrial sector, paved the way for expansion of the power utilities. The increase in consumption of electrical energy from 1 trillion to 11 trillion kWh was due to utilization of a substantial number of transformers [2]. The number of transformers installed in the USA in three decades are shown, in the figure. In the UK's Grid system, the majority of transformers were installed between the years 1995 & 1975 [2]. A transformer reliability report for Australia and New Zealand, showed the average age of transformers in 1995 to be 28.6 years [2]. A large number of these transformers have had a functional life far greater than their natural life and most of them are ONAN based transformers. These transformers are now in the third stage of the bath tub curve and are will be prone to an increasing failure ratio in the near future [2].

2.3 Failure by Aging

In the 3rd stage of the bath tub curve, the transformers failure ratio depicts an increasing trend over time. In the final quarter of the transformers life, failure ratio is expected to increase up to 5 times compared to a normal transformer failure ratio. The failure probability against age distribution is shown in figures [2].



2.4 Transformer Insulation System

The transformer insulation is mostly comprised of :

- Insulation between the High Voltage (Primary for step down) winding and the active part containment tank
- Insulation between the High Voltage and the Low Voltage (Secondary for step down) windings
- Insulation between individual turns of a winding.

These insulation components are the mist susceptible to failure due to the marginal clearances in dielectric strength. Monitoring of such insulation whether solid or liquid is crucial for maintaining insulation integrity.

Defects reported frequently in transformer insulation are [2]:

- Buildup of moisture in cellulose based insulation
- Contamination of oil with water, particles and insulation aging products
- Insulation surface contamination, which occurs mainly due to adsorption of polar aging products on a cellulose surface or due to deposition of conducting particles and insoluble aging products and
- Partial Discharges in weaker sections of cellulose based paper insulation. Moisture and impurities changes dielectric parameters of run down components, viz. their conductivity, permittivity and dissipation factor, particularly with temperature, which in turn result in related changes in the dielectric characteristics of the whole transformer.

Defects in minor insulation, e.g. inter turn or coil insulation, such as moisture in cellulose insulation, overheating leading to accelerated aging and insulation surface contamination, have only a small impact on overall dielectric characteristics of the whole transformer, due to relatively high capacitance of turn insulation. Thus detection of a defective condition of minor insulation of a winding is very difficult until a critical PD or noticeable gas generation occurs [2].

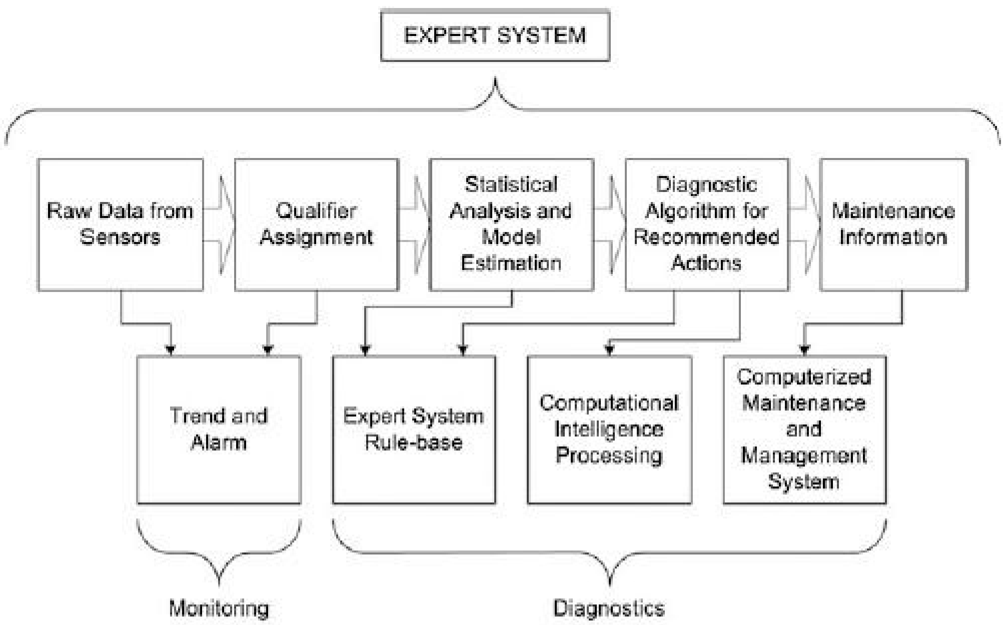
The above discussion indicates that there are several ways of diagnosing defects in transformer insulation system:

- Detection of Partial Discharges
- Detection of distortion of winding geometry
- Detection of aging products by chemical methods
- Detection of changes in dielectric characteristics, which can be performed in time domain and also in frequency domain

2.5 Monitoring and Diagnostics

Monitoring is the collection of data from a set of sensors, combined with local control features and early warning detection of failure symptoms. It acts as the first responders when the behaviour of a transformer is not as it should be. This is through measuring against a reference value periodically or continuously. The type and sophistication of system employed determines the fault scanning frequency.

Diagnostics is the application of complex analysis that outputs a reliable assessment report for the test subject, indicating whether if any action is required. On a basic level, a diagnostic system uses data transformation techniques and applies onto raw data from the sensors for credible and realizable information. Modern diagnostics systems are automated and perform data collection on site. Current innovations in diagnostic systems field are focused towards development of a system which uses data collected from sensory devices and coupled with the operational performance parameters of the equipment turn data into providing a diagnostic engine. The use of intelligent analytical tools has garnered a lot of attention from power utilizes which are seeking greater reliance on automated fault detection. A diagram showing use of information in monitoring and diagnostics.



Chapter 3

Transformer Condition Monitoring

3.1 Scope and Objective of the Chapter

The flaws that can be recognized by visual investigation of transformers after the fault events have been documented in the IEC 60599. Five characteristics faults are detailed and are [2]:

- Partial discharges which create small punctures due to carbonization, in paper,
- Discharges of Low intensity that cause larger punctures in paper,
- Discharges of High intensity discharges with power follow through, the evidence of which are extensive carbonization, metal fusion and possible tripping of transformer,
- Faults due to thermal activity occurring below 300 C which cause the paper insulation to turn brown,
- Faults due to thermal activity occurring above 300 C observed through carbonization of paper and
- Faults due to thermal activity occurring above 700 C indicate oil carbonization, metallic joints fusion.

3.2 Transformer End-of-Life

Factors influencing the life and future opeartional status of transformers are known, nor are generally legitimately comprehended. Be that as it may, all in all, the accompanying are noteworthy [2]:

- The underlying thermal, electrical and mechanical properties of protecting materials utilized. It is to be noted here that distinctive materials lose their properties at different rates and in the midst of the aging procedure a comparative material may lose assorted properties at different rates,
- Thermal, electrical and mechanical burdens. Thermal stresses emerge because of over-load current, localized overheating, flux leakages and additionally break down of cooling system. Electrical stresses are caused by system and in addition transient over-voltages, winding resonances and etc. Mechanical stresses between leads, conductors and windings are created by short circuits and inrush-currents. Their relative significance is dictated by the requirement to keep the physical stresses to a minimum while getting efficient utilization of the material utilized,
- Normal load cycle along with the environmental factors like ambient temperature and
- Allowable level of deterioration. Disintegration to complete failure of transformers isn't satisfactory practically. The level of deterioration that can be allowed is resolved to a great extent by degree of safety and service continuity conditions and furthermore by the likelihood of event of irregular working conditions.

There is no very much specific moment that a transformer will need to be replaced, but there an increasingly likelihood that the transformer will eventually fail. Mechanical and dielectric withstand strength of the transformer is diminished by slow aging and deterioration of its insulation system.

Amid the operational life of a transformer, it is subjected to various faults which cause radial and compressive powers. With systematic development the operational stresses on transformer increase with the increase in loading.For an aged transformer, ordinarily the conductor insulation is weakened enough to not being able to support any further mechanical stresses of a fault. As such, the insulation is withered to the point that any fault or dense vibrations may cause significant harm. When the dielectric failure occurs in the inter turn insulation, or the windings are loosened, the ability of the transformer to withstand short circuit failures are loosened, at that point the transformer's capacity to withstand failure is exhausted.

3.3 Aspects of Transformer Condition Monitoring

3.3.1 Thermal Modelling

The typical task life of a transformer is in part associated with the decay of its protection through thermal ageing, which is resolved mostly by its day by day loading cycles. Transformer loading guides provide direction for choosing proper transformer evaluations for given loading and cooling conditions and especially for conditions with loading proportions over the nameplate rating of a transformer. For oil-inundated power transformers, the International Electrotechnical Commission (IEC) loading guide 60354 can be utilized, while IEC60905 considers dry type transformers. In the Institute of Electrical and Electronics Engineers (IEEE) loading guide , an indistinguishable computation techniques from announced in IEC60354 are embraced, which are additionally like the loading guides detailed by the American National Standards Institute (ANSI)and National Electrical Manufacturers Association (NEMA) [3] .

The improvement of a precise thermal model is constantly viewed as a standout amongst the most fundamental issues of transformer condition monitoring. For the most part accepted techniques, reported by IEC [4] and IEEE [5], can be utilized to anticipate the zones of hot-spot temperature in a transformer as the sum of the ambient temperature. The two consistent state temperature rises of top-oil and bottom-oil above ambient can be evaluated independently. There are additionally a couple of enhanced thermal models established on the conventional thermal arrangements. A precise and important thermal model is exceedingly required practically speaking to manage transformer thermal ratings.

3.3.2 Dissolved Gas Analysis

Oil-immersed power transformers are filled with a fluid that serves various purposes. The fluid acts as a dielectric media, an insulator and a heat transfer agent. The most common type of fluid used in transformers is of a mineral oil origin. During normal operations, there is usually a slow degradation of the mineral oil to yield certain gases that are dissolved in the oil. However, when there is an electrical fault within a transformer, gases are generated at a much more rapid rate. DGA is probably the most widely employed preventative maintenance technique in use today to monitor on-line transformer operations, and a number of DGA interpretation guidelines have been developed by different organisations, e.g. IEC60559 [6], IEEE C57.104-1991 [7], CIGRE TF 15.01.01 [8] and GB7252- 87 [9]. By applying a DGA interpretation technique on an oil sample, dissolved gases can be determined quantitatively. The concentration and the relation of individual gases allow a prediction of whether a fault has occurred and what type it is likely to be. For nearly forty years, DGA and its interpretation have been a useful and reliable tool for monitoring conditions of oil-filled transformers and other oil-filled electrical equipment. However, based upon the conventional DGA interpretation methods, it is an arduous task to determine malfunction types and oil sampling intervals, due to various fault conditions and other interfering factors. Moreover, determining the relationships between gas levels and decline conditions is a perplexing task, because of complex gas combination patterns. Many attempts have been made to tackle DGA interpretation problems with a few recent developed computational intelligence (CI) techniques, among which artificial neural networks (ANNs) are the most widely used fault classifiers for DGA.

3.3.3 Frequency Response Analysis

These days, the breadth FRA (SFRA) strategy has gotten overall consideration for transformer winding condition evaluation slowly supplanting the low voltage impulse (LVI) system. FRA [**?**] is an exceptionally sensitive strategy for identifying winding movement faults caused by loss of bracing weight or by short circuit forces. Varieties in frequency responses may uncover a physical change inside a transformer, e.g. winding development caused by loosened clamping structures and twisting winding deformation due to shorted turns. In modern practice, FRA is a standout amongst the most appropriate winding diagnostic tools that can give a sign of displacement and deformation faults. It can be connected as a non-intrusive procedure to maintain a strategic distance from interruptive and costly tasks of opening a transformer tank and leading oil de-gasification and dehydration, which can limit the effect on system operations and loss of supply to clients and subsequently spare a large number of revenue in timely maintenance. There are a few global guidelines and proposals for testing power transformers utilizing SFRA, e.g. DL/T 911-2004 [10], CIGRE WGA2.26-2006 [11] and IEEE PC57.149 (draft) [12].

3.3.4 Partial Discharge Analysis

Electrical protection assumes a critical part in any high voltage control device, particularly power transformers. Partial discharge (PD) happens when a nearby electric field surpasses an threshold value, bringing about a partial breakdown of the surrounding medium as detailed by IEC60270 [33]. Its aggregate impact prompts the debasement of insulation. PDs are started by the nearness of deformities amid its manufacture, or the decision of higher stress directed by design contemplations. Estimations can be gathered to identify these PDs and screen the soundness of protection amid the service life of a power transformer. PDs show as sharp current pulses at transformer terminals, whose nature relies upon the sorts of protection, deformities and estimating circuits and identifiers utilized. The ordinary electrical estimation of PDs is to identify PD current pulses with a testing circuit. In any case, given that the test information dependably comprise of PD signals, sinusoidal waveforms and background noise, the extraction of valuable data from PD signals is an exceptionally troublesome issue. The location of PDs can be performed by an assortment of procedures, most usually electrical, acoustical [13], optical [14] and compound methods [15]. There are three kinds of PD investigation techniques, i.e. the time-settled fractional release examination [16], the intensity spectra based PD investigation [17] and the phase resolved partial discharge investigation [16]. In light of the unique attributes of PDs, conventional computerized flag handling strategies are not reasonable for dissecting PD signals. Other helpful time-frequency tools, e.g. Fourier change (FT) and Wavelet change (WT), can be utilized to investigate PDs for de-noising, characteristic extraction and information characterizations.

3.4 Disadvantages of traditional Techniques

3.4.1 Inaccuray of Thermal Modelling

The for the most part acknowledged temperature estimation methods,reported in the IEC and IEEE guides [4], [5], can be utilized to foresee problem area temperatures (HSTs), topoil temperatures (TOTs) and bottom-oil temperatures (BOTs). The aides give mathematical models for deciding the result of various loading ratios utilizing an arrangement of conditions with empirical thermal parameters. In any case, the regular calculation of inward transformer temperatures with exponential conditions isn't just a confounded assignment yet additionally prompts a conservative estimate, acquired based on a few assumptions of operational conditions [1, 4]. In addition, these observational conditions are chiefly settled on thermal profiles of a particular transformer, and this point by point data isn't likely accessible or dependably shifts with time. Its capacity to predict transformer temperatures under realistic loading conditions is to some degree constrained (e.g. the conventional model can't represent the varieties of encompassing temperatures and warm progression when a transformer's cooler is on or off). In this manner, the improvement of a more significant and precise warm model for transformers is constantly viewed as an imperative issue.

3.4.2 Uncertainity of Dissolved Gas

As known, not every one of the blends of gas proportions presented in a fault can be mapped to a fault type as depicted in a diagnostic criterion. Distinctive transformer DGA finding procedures may give differed examination results, and it is troublesome for engineers to settle on a ultimate conclusion when looked with so much various data. It is likewise realized that some DGA techniques, for example, the Rogers ratio strategy, neglect to clearly recognize faults in transformers in marginal cases, while other DGA strategies can distinguish these cases. In this manner, the integration of the accessible transformer DGA conclusions to give an adjusted general condition appraisal is extremely necessary. Moreover, transformer determination elucidations are done by human specialists applying their experience and standard strategies, and numerous endeavors have been settled on to refine choice procedures used to guide DGA analysts for assessing transformer conditions. Such endeavors incorporate EPSs [18] and the analysis of data utilizing ANNs [19] or fuzzy logic [20], [21], which are constrained in their portrayal of DGA interpretation as a characterization or pattern recognition problem. In addition, diverse transformer test strategies, i.e. TM, DGA, FRA and PDA, have diverse points of interest and impediments making it hard to dispose of one and select another. Consequently a more instinctive thought is to consolidate every one of the outcomes got from real test techniques and incorporate these data to frame a general assessment. As test outcomes are now and again loose and even inadequate, a reasonable data mix strategy is required to process DGA information for managing such vulnerabilities.

3.4.3 Intricate issues in winding deformation analysis

Among different procedures connected to control transformer condition observing, FRA is the most reasonable one for solid evaluation for identifying winding dislodging and misshaping. It is set up upon the way that frequency responses of a transformer winding in high frequencies rely upon changes of its inside separations and profiles, which are worried about its deviation or geometrical deformation. In this manner, the estimation of inward parameters plays a vital part in exact reenactments of transformer winding frequency practices. Demonstrating of a genuine winding with a specific end goal to get frequency responses, being near experimental ones, is a to a great degree multifaceted task since a detailed transformer show must consider each turn or segment of a winding independently. In any case, in industry practice it isn't generally conceivable to lead extra tests for exact estimations of transformer geometry or insulation parameter estimation.

3.5 Maintenance Strategy

Prevention of failure and keeping the transformers in great operational condition is a critical issue for power utilities. Customarily time-based maintenance (TBM) was completed in which transformers were kept up at standard time interims regardless of the need of the upkeep. Today, be that as it may, power utilities are performing condition-based upkeep (CBM) instead of TBM.

The foundations of this advancement can be found in the rebuilding and deregulation of electric power industry. In the changed situation, the free power makers, transmission organizations, framework administrators and distribution organizations are compelled to cut expenses in support and activity without imperiling steady supply of electrical power. In the event that the genuine state of the hardware is dependably known, at that point expenses can be decreased in CBM via completing support just when the state of transformer requires it. Therefore, solid symptomatic instruments are essential prerequisites of CBM and there is an expanding requirement for noninvasive checking and indicative apparatuses for evaluation of interior state of transformers.

Chapter 4

Feature Extraction & Classification

4.1 Scope and Objective of the Chapter

This chapter describes data analysis techniques. A brief overview of the use of different techniques to process the data and the classification of such data to generate relevant information.

4.2 Time Frequency Domain Analysis

4.2.1 Discrete Wavelet Transform (DWT)

Current Signals with under fault conditions contain transients which are non linear in nature and have high frequency components. For a signal, when analysed under short duration lengths, appear to be stationary. Signals when examined for long periods appear as non-stationary as in there original form. For a precise information interpretation of transformer current signals, wavelet transform is applied.Wavelet transform tracks the standard of superposition, alike Fourier transforms.Wavelets makes it perceptibly simpler to assess uneven signs with noisy and jerky spikes when contrasted with Fourier change.As sine and cosine waves are infinite, it is difficult to evaluate a spike.Wavelets have limited provision, so an impulse in signal can be easily assessed by differing the magnitude of basic functions.For instance, discrete wavelets will breakdown time domain signal into smaller stationary function, called fundamental functions, which are formed scaling and deciphering a singular function of a particular structure, known as the mother wavelet. The wavelet basis is on a very basic level the same as the Fourier basis, with the exclusion of the wavelet being limited in time. For a wavelet transform the fundamental function can be described over a particular time windows and is zero for everywhere else.

4.3 Dimensional Reduction

4.3.1 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is an analytical system that converts a groups of correlated or possibly correlated variables in a group of variables with no correlation using orthogonal transformation. These variables are called principal components. For p variables related to n observations, the unique principal components are given by

This transformation is characterized such that the primary component segment has the biggest conceivable difference (that is, represents however much of the changeability in the information as could reasonably be expected), and each succeeding part thus has the most elevated variance conceivable under the requirement that it is orthogonal to the preceding components.

4.4 Pattern Recognition Classifiers

4.4.1 Linear Discriminant Classifier

Linear discriminant classifiers (LDC) [22] is trained on input feature vectors of an arrangement of known classes. In current study it has two classes transformer faults and normal transformer operation . The element space was separated in C sub-regions, where C is the number of classes, each class corresponds to transformer faults and normal transformer operation respectively. Weighting coefficients was recorded for each class that maximize linear discriminant function for input vectors. LDC draws a decision region between given classes while maintaining the location of data. In current study LDC holds two distinguishable classes for classification. Therefore Discriminant function for our specified two class category can be written as:

$$D(x) = \sum_{i=1}^{\infty}(s_p w_1) + \sum_{i=1}^{\infty}(n_p w_2) \tag{4.4.1}$$

Where s, n are seizure and normal samples and âĂŸwâĂŹ is the weighted co-efficient. Two category lda implements decision as follows:

$$for\ w_1\ decide\ if \quad D(x) > w_0 \tag{4.4.2}$$

$$for\ w_2\ decide\ if \quad D(x) < w_0 \tag{4.4.3}$$

The equation D(x)=0 declares the decision boundary which separates the point of two classes. On the basis of given conditions LDC classifies whole data sets into the predefined class. Figure 4.1 illustrates hyper-plane separation for two classes.

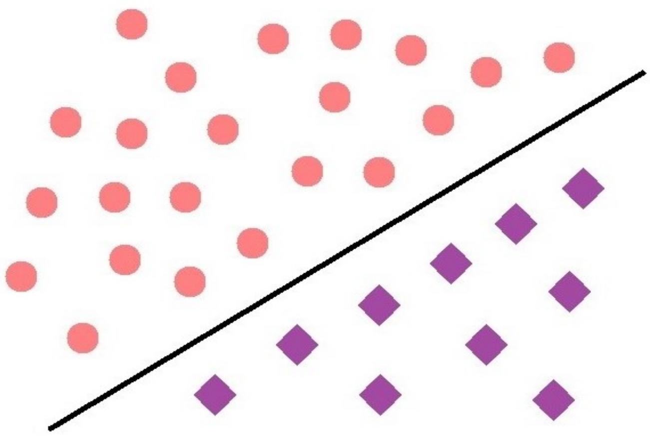


Figure 4.1: LDC class separation by a hyper-plane

4.4.2 Quadratic Discriminant Classifier

Quadratic discriminant investigation (QDC) [23] is firmly identified with linear discriminant analysis (LDA), where it is expected that the estimations from each class are normally distributed. Not at all like in case of LDA, in QDA there is no supposition that the covariance of each classes is equal. To evaluate the factors essential in quadratic discrimination more calculation and information is required unlike in case of linear discrimination. Quadratic Discrimination is the general type of Bayesian separation. Figure 4.2 illustrates hyper-plane separation for two classes.

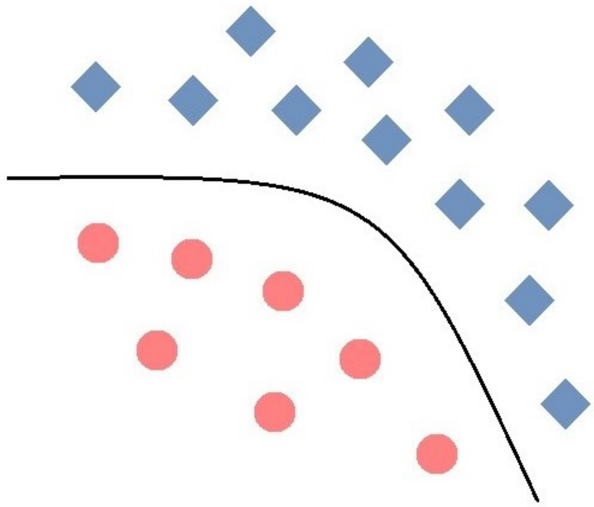


Figure 4.2: QDC class separation by a hyper-plane

4.4.3 Support Vector Machine

Support Vector Machine (SVM) presently the utmost prevalent approach in supervised machine-learning. SVM was presented by Vapnik and his associates [24] as a precise method for generic pattern classification hitches.

SVM depends on basic hazard minimization guideline, and build a Optimal Separating Hyperplane(OSH) in the feature space. The OSH can characterize both the training sets and the concealed samples within the test set with the least misclassification possibility. Classes are disjointed by optimal separating hyperplane (OSH), SVM fits OSH in between class samples that resides at the edge of class boundary. SVM generalize more precisely on unnoticed cases with respect to classifiers that aim to limit the training error, for example, neural networks. In this way, with SVM grouping just a portion of the training data that lie at the edge of the class boundary in feature space are required in formation of decision plane. [24].

They are extensively applied on diversified real-world applications involving detection and classification jobs. SVM applications shelter applications like automatic biomedical signal processing, image analysis, text classification, hand-written alphabets recognition, speech recognition, bio-informatics etc. Figure 4.3 illustrates hyper-plane separation for two classes.

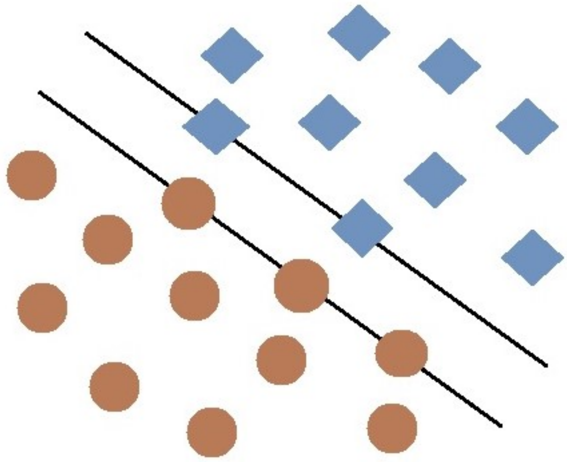


Figure 4.3: SVM class separation by a hyper-plane

4.4.4 Bayes optimal classifier

The Bayes Optimal Classifier is a classification technique. It is an ensemble of all the hypotheses in the hypothesis space. On average, no other ensemble can outperform it.[25] Naive Bayes Optimal Classifier is a version of this that assumes that the data is conditionally independent on the class and makes the computation more feasible. Each hypothesis is given a vote proportional to the likelihood that the training dataset would be sampled from a system if that hypothesis were true. To facilitate training data of finite size, the vote of each hypothesis is also multiplied by the prior probability of that hypothesis. The Bayes Optimal Classifier can be expressed with the following equation:

$$y(x) = argmax \sum P(c_j|h_i)P(T|h_i)P(h_i) \tag{4.4.4}$$

where Y is the predicted class, C is the set of all possible classes, H is the hypothesis space, P refers to a probability, and T is the training data. As an ensemble, the Bayes Optimal Classifier represents a hypothesis that is not necessarily in H. The hypothesis represented by the Bayes Optimal Classifier, however, is the optimal hypothesis in ensemble space (the space of all possible ensembles consisting only of hypotheses in H).

4.4.5 Boosting (machine learning)

Boosting is a machine learning ensemble meta-algorithm for primarily reducing bias, and also variance [26] in supervised learning, and a family of machine learning algorithms that convert weak learners to strong ones.[27] Boosting is based on the question posed by Kearns and Valiant (1988, 1989)

Chapter 5

Experimental Setup

5.1 Scope and Objective of the Chapter

This chapter delves upon the experimental setup created for transformer fault detection. Transformers current signals are sampled under normal conditions and while ensuring the exact same sampling parameters, into the same transformers, faults are injected. The hardware setup required to perform this task is details in this chapter.

5.2 Transformer Setup

Transformers selected for the experimental setup have the following specifications;

- Rated Capacity: 10kVA, 3Ø
- Primary Voltage (Phase to Phase): 420V,
- Secondary Voltage (Phase to Phase): 400V,
- Frequency: 50Hz,
- Delta - Wyve with a floating neutral,
- Aluminium Winding with laminated steel core design

5.3 Protection Setup

Safety being paramount to all operations and studies, was ensured throughout the design and development of transformer faults. Dual protection miniature circuit breakers in accordance with transformer loading capacity and sufficient instantaneous current cutoff were selected and installed on the primary phases of the transformers. Each phase of the transformer was added to a phase selector, for each switching On/Off of a transformer phase. Since the transformer was to be subjected to short circuit faults, which do not perform well when circuit breakers are installed, hence were bypassed ont the secondary terminal of the transformer.

5.4 Load Setup

A suitable resistive load was setup for three phase transformer loading. Each phase was loaded with a resistive load of 1.5kW. This load was kept unchanged during both the sampling of transformer under normal conditions and under fault conditions. Balanced transformer loading on all phases of testing was ensured, to avoid any parameter changes.

5.5 Data Acquisition Setup

The primary and secondary current signals were acquired from the individual phases of the transformers. This was done via use of current transformers with a step down ratio of 30:5 A. Identical current transformers were used to minimize ingress of noise or random signals due to the design deviations. Each current transformer was sampled and sorted out to ensure random noise signals impact was at a minimum or displayed constant variance in tests.

Current Signals from the secondary terminal of the current transformer were fed to a National Instruments data acquisition hardware interface. The signals were continuously sampled with a sampling speed of 20KS/s for each phase of the transformer. The duration of each sampling session was kept at 10 seconds. A shunt resistor of 1 ohms was used as a short between terminals of each current transformer.

5.6 Fault Setup

The transformers were subjected to two different fault conditions.

5.6.1 Internal Short Circuit Fault

For Fault 1, secondary phases, Yellow Phase and Blue phase along with the floating neutral from the RYBn based configuration of the transformer were shorted. This was to simulate an internal fault in the transformer. The current transformers on the secondary phases were placed after the short was placed in the transformer. This was done to mimic an internal fault of the transformer. This fault was repeated till completed failure or the transformer was achieved. Each sampling session recorded the transformer current signal before the internal short circuit current exceeded the safe working value of the installed primary protection or before the sampling session period was completed. While the transformer was subjected to faults, all operational parameters of the transformer were kept similar to sampling under normal conditions. All operational changes observed were due to fault activity in the transformer.

5.6.2 External Short Circuit Fault

For Fault 2, all secondary phases of the transformer were shortened and the floating neutral was disconnected. This fault was used to represent an external fault. The secondary terminals to the load were shortened after passing through the current transformers. Each transformer phase was loaded in balanced sequence. Similar to the fault 1 of the transformer, all operational parameters of the transformer were kept similar to as when sampled under normal loading conditions. Any changes observed were directly related to the fault induction in the transformer.

Chapter 6

Fault Detection & classification Methodology

6.1 Scope and Objective of the Chapter

The principle focus of the chapter is to define the issues tended to in the thesis.It portrays the data acquired, genuine impediments and limitations for fault recognition and detection systems. The second objective of the segment is to conjecture the best approach to manage addressed problem. In light of the selected approach, a layout of the distinctive stages for the development of detection and classification algorithm is presented.

6.2 Methodology Overview

In order to develop detection and classification algorithm, proposed framework has two parts. First part addresses creation of faults of the transformer . Second sections focus on testing of algorithm for detection, recognition and classification.

6.2.1 Faults Creation

Transformers current signals are sampled under two different conditions, Normal operation and operation under influence of fault. Source voltage , transformer loading, source frequency and other operational parameters are kept identical. Any deviation which may occur are a result of the two different conditions under which the current signals are sampled.

The current signals are sampled at 20KS/s for ten seconds of length. Sampling of healthy condition was performed ten times. Sampling of fault condition was performed for the same length at the same sampling speed. Fault 1 - External short circuit was sampled for ten times. Fault 2 - Internal short circuit was sampled multiple times till the transformer attained complete failure.

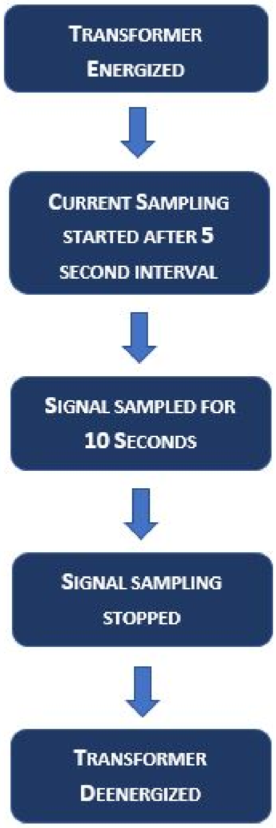


Figure 6.1: Algorithm Flow - Normal Sampling

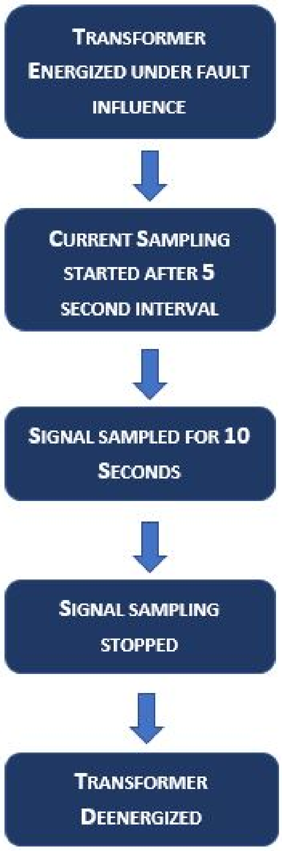


Figure 6.2: Algorithm Flow - Fault Sampling

6.2.2 Classification

On the acquired current signals, Wavelet decomposition was applied on each of the six phases of the signal. The decomposition was performed using Daubechies-4 with 6 level decomposition. Feature extraction was performed using principal component analysis (PCA), for dimensional reduction of decomposed data matrix. Feature classification was performed using Ensemble Classifier,Linear Discriminant Analysis (LDC), Quadratic Discriminant Analysis (QDC) and Support Vector Machine (SVM).

Based on the classification accuracy the classifiers are evaluated. Classifier with high accuracies are tested against multiple scenarios involving single or multiple faults. These test results help in selecting the optimal classifier.

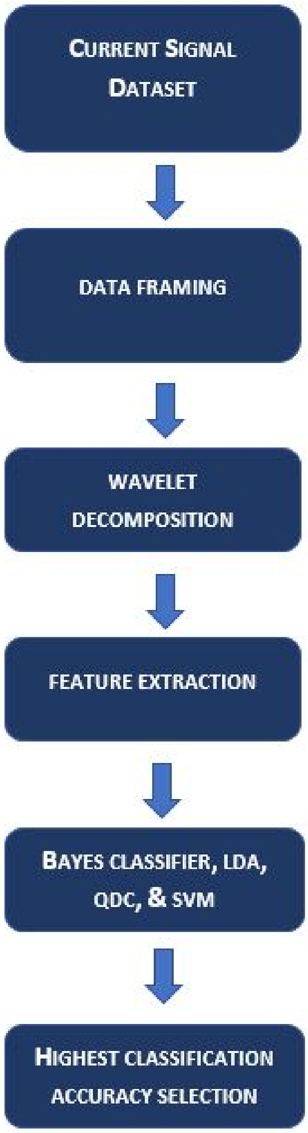


Figure 6.3: Algorithm Flow - Classification

6.3 Current Signal Processing

6.3.1 Current Signal Data Import

Data set were created upon end of each sampling session by Lab View. These data sets are in excel format and can be directly imported into matlab. No data manipulation is performed at any step during data import.

6.3.2 Current Signal Segmentation

Current signal obtained under Fault induced operation and under normal operation were extracted from the data set. For each of the fault data and the normal operation data, classes were defined.

Chapter 7

Methodology Results

7.1 Scope and Objective of the Chapter

This chapter delves upon the results obtained upon implementation of the proposed methodology in the previous chapter. This chapter details the performance of all classifiers that were put to test. For all the results, confusion matrix, ROC plots and scatter plots of the current signal data are featured in the later part of this chapter.

7.2 Classifiers - Parameters and Performance

The selection of a classifier is based on a set of parameters and is not limited to the accuracy of classification results obtained by the classifiers in question. These parameters are

- Accuracy,
- Prediction speed
- Training time.

For a classifier to be deemed feasible, the major factor is its accuracy in classifying the results, not only in a distinctive variations between data classes, but also in events where these classes are closely related. For the work detailed in this thesis, performance of various classifiers are evaluated at and for wavelet decompostion of primary phase current signal under level '6'. The performance is determined where the true classes and the predicted classes for a set of observations converge to a high confidence level and where repeatability is ensured for each iteration in the observation classes.

The True Positive Rates (TPR) and True Negative Rates (TNR) are data samples which have been accurately identified as positive samples and negative samples respectively. The False Positive Rates (FPR) and false negative Rates (FNR) are observation samples that have been inaccurately characterized as under False positive and false negative categories respectively.

Parameters for classification accuracy are as follows;

7.2.1 TRUE IDENTIFICATION RATE(TIR)

Total number of samples classified correctly from all three classes i.e. Transformer Current under normal operation, under internal short circuit and under influence of external short circuit are defined as:

$$TIR = TPR + TNR \tag{7.2.1}$$

7.2.2 FALSE IDENTIFICATION RATE (FIR)

Total number of samples classified incorrectly from all three classes i.e. Transformer Current under normal operation, under internal short circuit and under influence of external short circuit are defined as:

$$FIR = FPR + FNR \tag{7.2.2}$$

7.2.3 CLASSIFICATION ACCURACY (ACRY)

This the measure of precisely classified sample observations out of the total group of sample observation. It is described as:

$$ACRY = \frac{TPR + TNR}{TPR + TNR + FPR + FNR} * 100 \tag{7.2.3}$$

7.2.4 SENSITIVITY(SENS)

Sensitivity is is an estimation which evaluates positive samples distinguished accurately by a classifier and is defined as:

$$SENS = \frac{TPR}{TPR + FNR} * 100 \tag{7.2.4}$$

7.2.5 SPECIFICITY (SPFY)

Specificity is a measure of classifier ability to accurately perceive degree of negative examples viably from pool of negative examples and can be characterized as:

$$SPFY = \frac{TNR}{TNR + FPR} * 100 \tag{7.2.5}$$

7.2.6 POSITIVE PREDICTED RATIO (PPR)

It is the ratio of positive values and total number of positive examples perceived by a classifier and can be characterized as:

$$PPR = \frac{TPR}{TPR + FPR} * 100 \tag{7.2.6}$$

7.2.7 NEGATIVE PREDICTED RATIO (NPR)

It is the ratio of negative values and total number of negative examples perceived by a classifier and can be characterized as:

$$NPR = \frac{TNR}{TNR + FNR} * 100 \tag{7.2.7}$$

7.3 Classification Results

Classification results for each classifier LDC, QDC SVM and Ensemble are explained further.

7.3.1 Linear Discriminant Classifier

7.3.1.1 LDC Confusion Matrix For Internal Fault

LDC correctly classified 149 Internal fault events out of a total of 150 Internal fault events. Correct classification of healthy events was 0 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 82.8%. Confusion Matrix is shown in figure 7.1. True Positive & False Negative Rates are shown in figure 7.2.Positive Predictive Values & False Discovery Rates are shown in figure 7.3

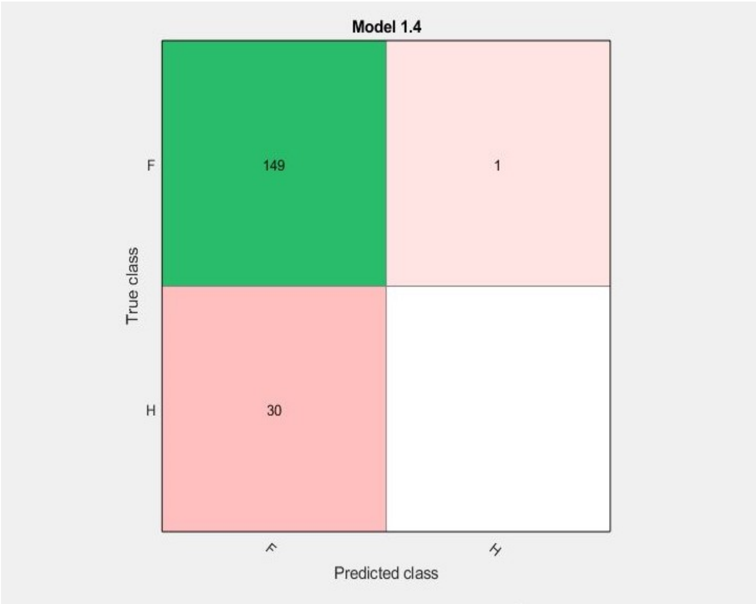


Figure 7.1: Internal Fault - Confusion Matrix of LDC at Wavelet Band-6

7.3.1.2 LDC TP/FN Rates For Internal Fault

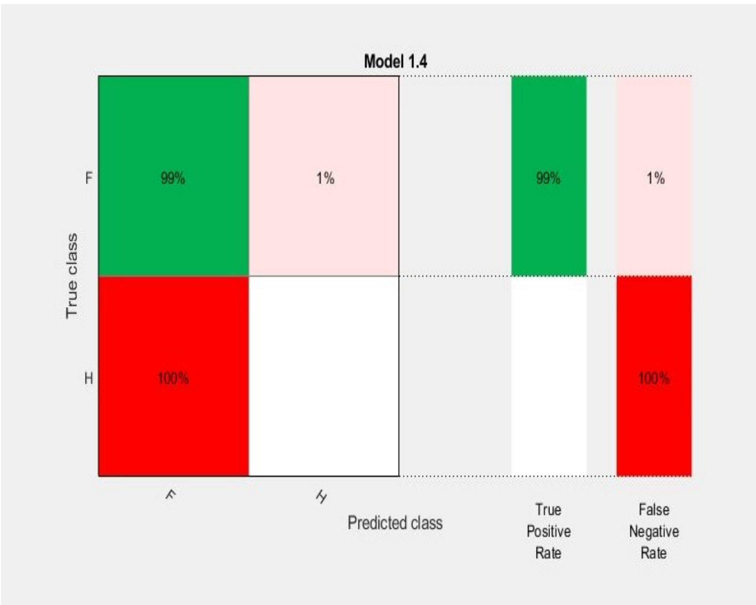


Figure 7.2: Internal Fault - True Positive & False Negative Rates of LDC at Wavelet Band-6

7.3.1.3 LDC PPV/FDR For Internal Fault

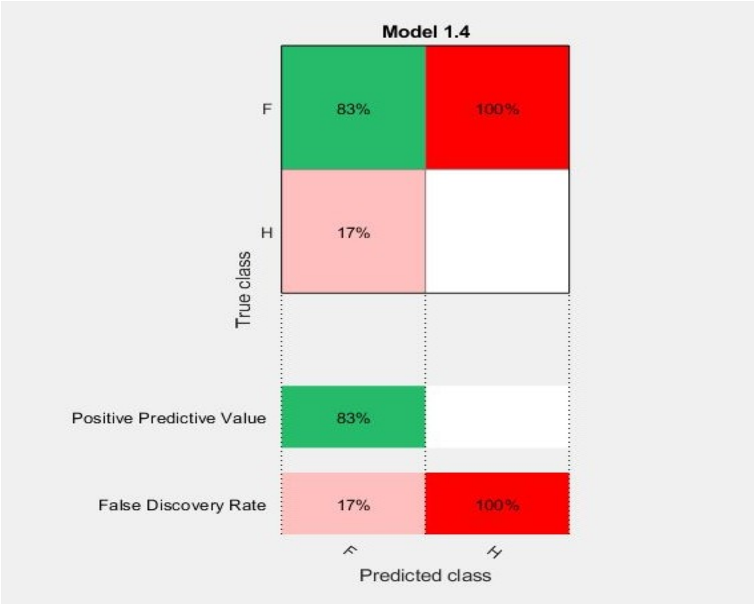


Figure 7.3: Internal Fault - Positive Predictive Values & False Discovery Rates of LDC at Wavelet Band-6

7.3.1.4 LDC Confusion Matrix For External Fault

LDC correctly classified 14 fault events out of a total of 27 faulty events. Correct classification of healthy events was 18 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 59.3%. Confusion Matrix is shown in figure 7.4. True Positive & False Negative Rates are shown in figure 7.5.Positive Predictive Values & False Discovery Rates are shown in figure 7.6

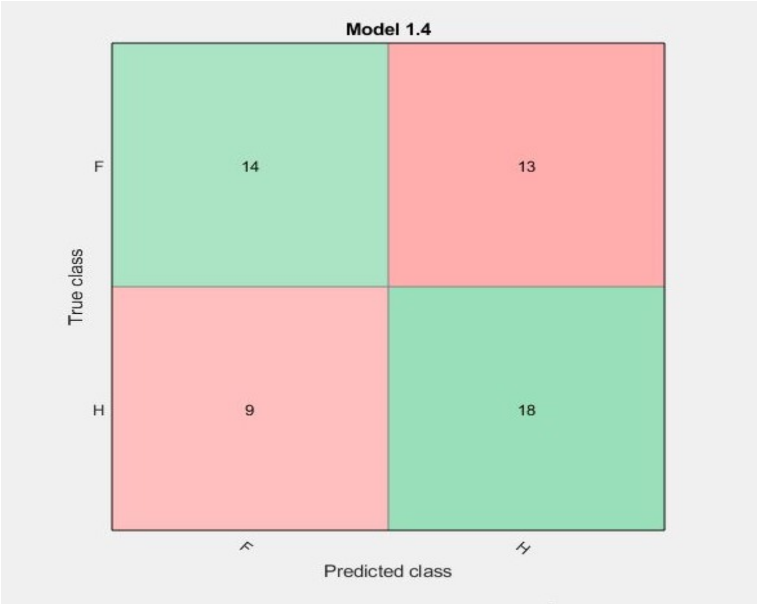


Figure 7.4: External Fault - Confusion Matrix of LDC at Wavelet Band-6

7.3.1.5 LDC TP/FN Rates For External Fault

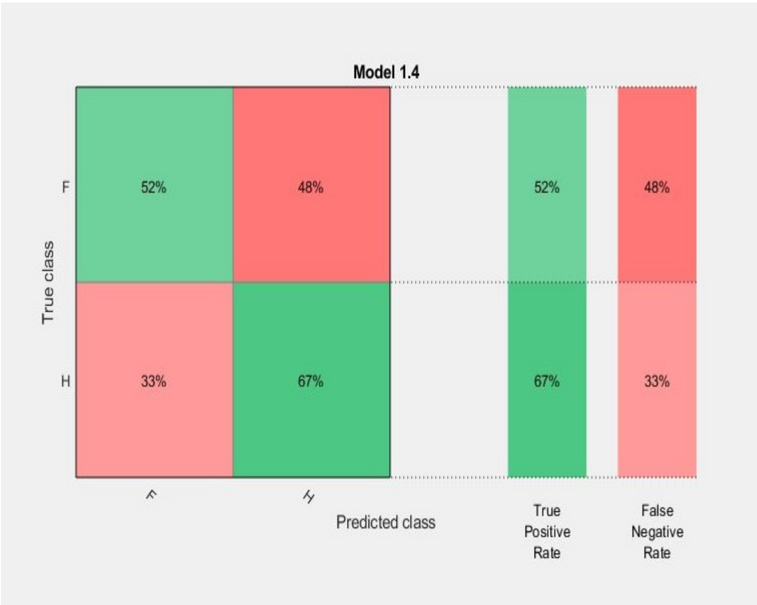


Figure 7.5: External Fault - True Positive & False Negative Rates of LDC at Wavelet Band-6

7.3.1.6 LDC PPV/FDR For External Fault

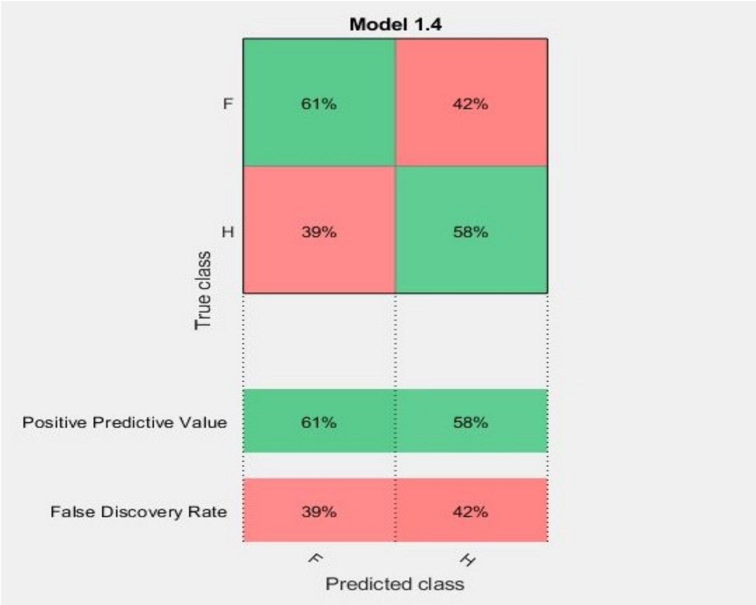


Figure 7.6: External Fault - Positive Predictive Values & False Discovery Rates of LDC at Wavelet Band-6

7.3.1.7 LDC Confusion Matrix For Multiple Faults

Of a pool of 210 events, LDC correctly classified 149 internal fault events out of a total of 150 internal faulty events. Correct classification of external fault events was 0 events out of a total of 30 events and classification of healthy events was 0 events out of a total of 30 events in a pool of 210 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 71.0%. Confusion Matrix is shown in figure 7.7. True Positive & False Negative Rates are shown in figure 7.8.Positive Predictive Values & False Discovery Rates are shown in figure 7.18

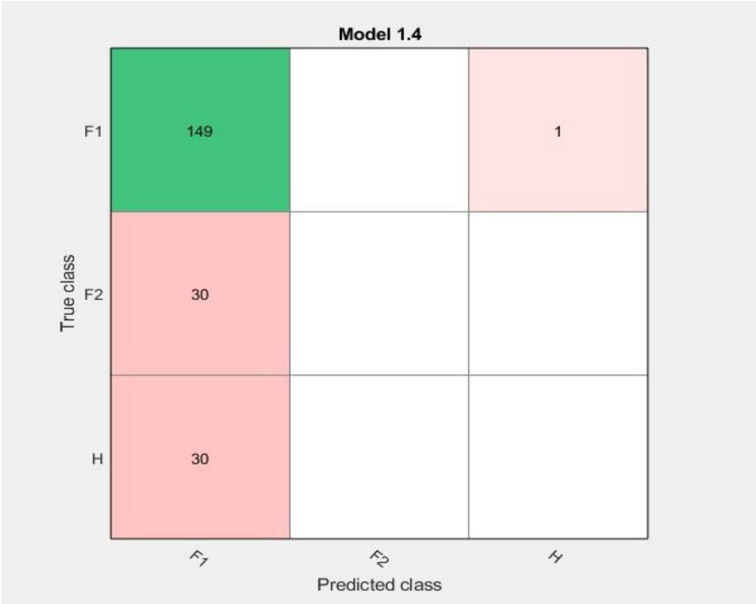


Figure 7.7: Multiple Fault - Confusion Matrix of LDC at Wavelet Band-6

7.3.1.8 LDC TP/FN Rates For Multiple Faults

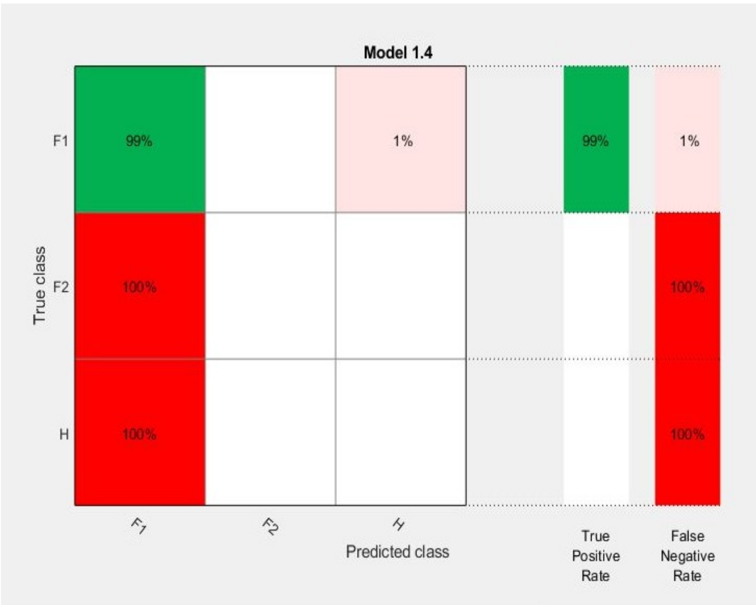


Figure 7.8: Multiple Fault - True Positive & False Negative Rates of LDC at Wavelet Band-6

7.3.1.9 LDC PPV/FDR For Multiple Faults

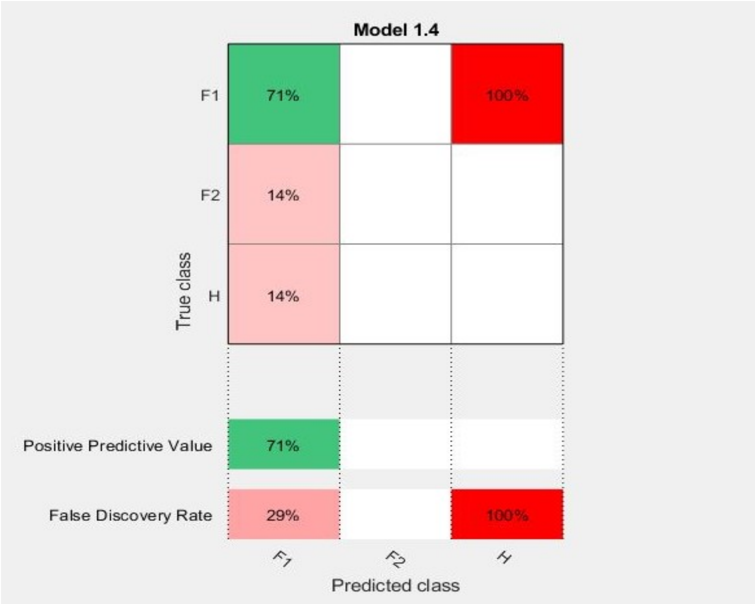


Figure 7.9: Multiple Fault - Positive Predictive Values & False Discovery Rates of LDC at Wavelet Band-6

7.3.2 Quadratic Discriminant Classifier

7.3.2.1 QDC Confusion Matrix For Internal Fault

QDC correctly classified 131 fault events out of a total of 150 faulty events. Correct classification of healthy events was 0 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 72.8%. Confusion Matrix is shown in figure 7.10. True Positive & False Negative Rates are shown in figure 7.11.Positive Predictive Values & False Discovery Rates are shown in figure 7.12

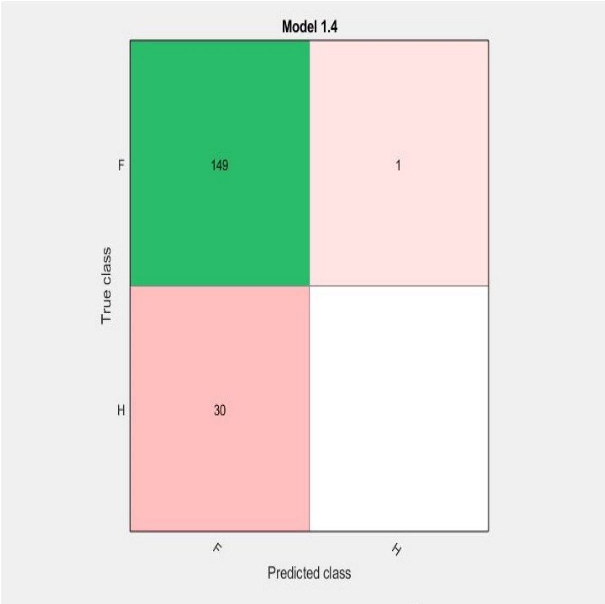


Figure 7.10: Internal Fault - Confusion Matrix of QDC at Wavelet Band-6

7.3.2.2 QDC TP/FN Rates For Internal Fault

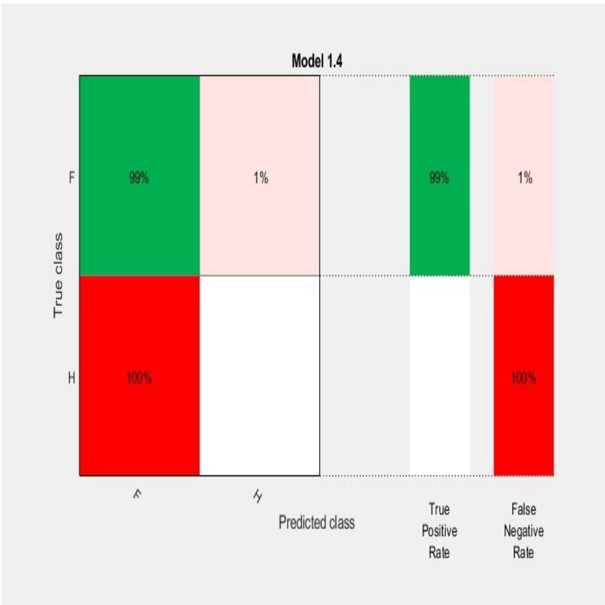


Figure 7.11: Internal Fault - True Positive & False Negative Rates of QDC at Wavelet Band-6

7.3.2.3 QDC PPV/FDR For Internal Fault

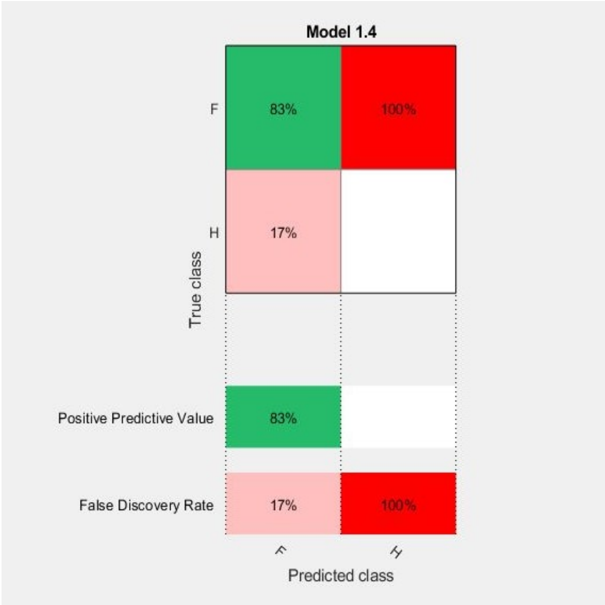


Figure 7.12: Internal Fault - Positive Predictive Values & False Discovery Rates of QDC at Wavelet Band-6

7.3.2.4 QDC Confusion Matrix For External Fault

QDC correctly classified 131 fault events out of a total of 150 faulty events. Correct classification of healthy events was 0 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 72.8%. Confusion Matrix is shown in figure 7.10. True Positive & False Negative Rates are shown in figure 7.11.Positive Predictive Values & False Discovery Rates are shown in figure 7.12

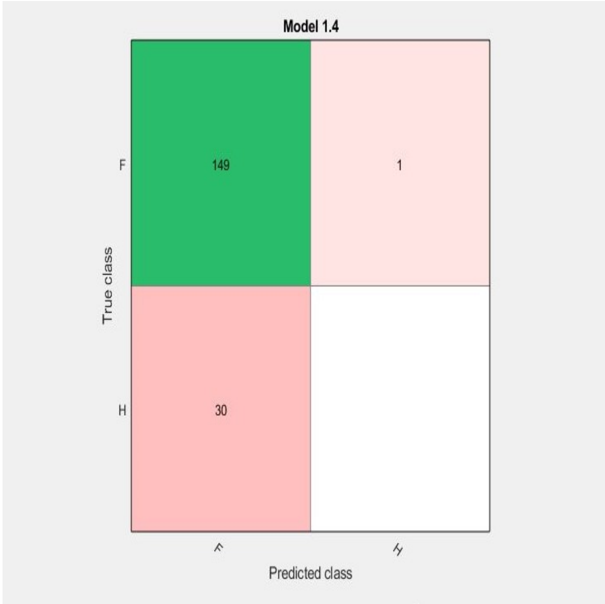


Figure 7.13: External Fault - Confusion Matrix of QDC at Wavelet Band-6

7.3.2.5 QDC TP/FN Rates For External Fault

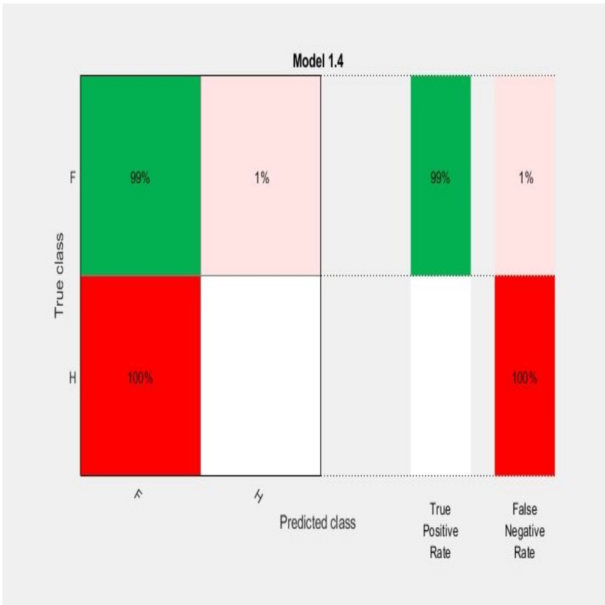


Figure 7.14: External Fault - True Positive & False Negative Rates of QDC at Wavelet Band-6

7.3.2.6 QDC PPV/FDR For External Fault

Figure 7.15: Internal Fault - Positive Predictive Values & False Discovery Rates of QDC at Wavelet Band-6

7.3.2.7 QDC Confusion Matrix For Multiple Faults

Of a pool of 210 events, QDC correctly classified 120 internal fault events out of a total of 150 internal faulty events. Correct classification of external fault events was 0 events out of a total of 30 events and classification of healthy events was 0 events out of a total of 30 events in a pool of 210 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 57.1%. Confusion Matrix is shown in figure 7.16. True Positive & False Negative Rates are shown in figure 7.17.Positive Predictive Values & False Discovery Rates are shown in figure 7.18

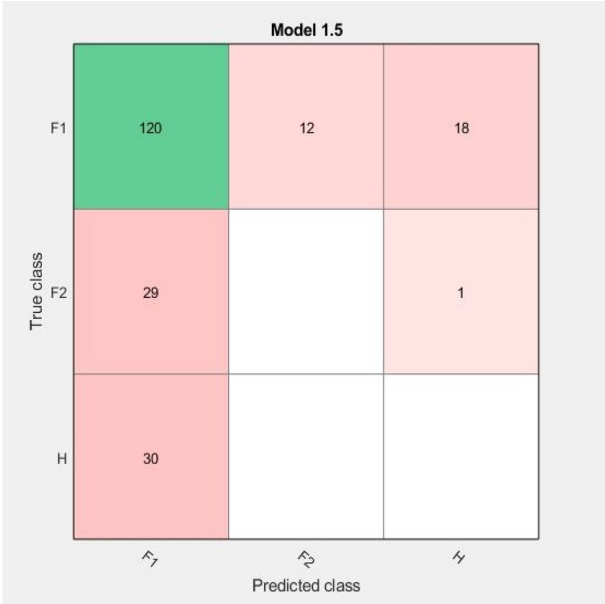


Figure 7.16: Multiple Fault - Confusion Matrix of QDC at Wavelet Band-6

7.3.2.8 QDC TP/FN Rates For Multiple Faults

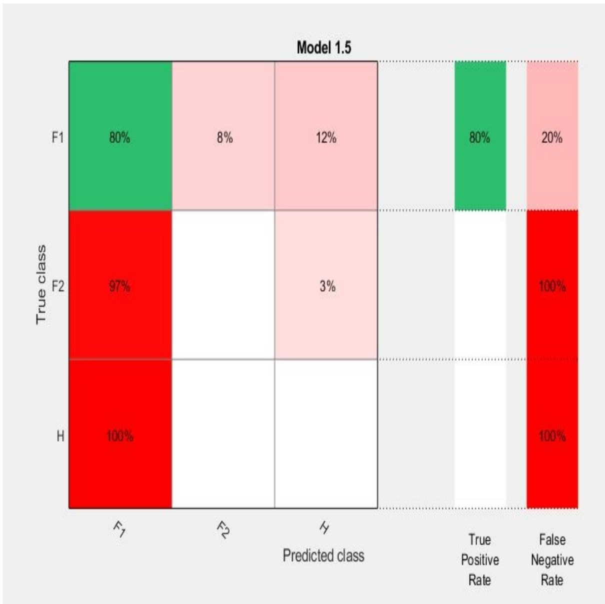


Figure 7.17: Multiple Fault - True Positive & False Negative Rates of QDC at Wavelet Band-6

7.3.2.9 QDC PPV/FDR For Multiple Faults

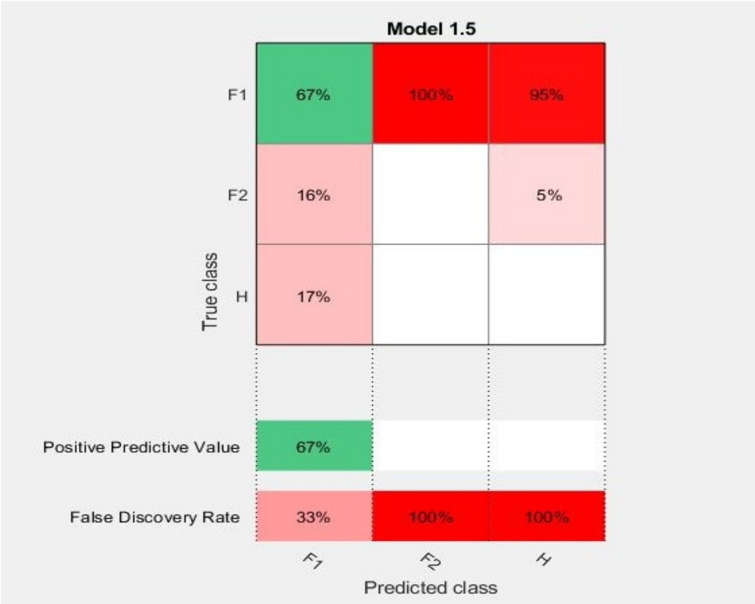


Figure 7.18: Multiple Fault - Positive Predictive Values & False Discovery Rates of QDC at Wavelet Band-6

7.3.3 Support Vector Machine

7.3.3.1 SVM Confusion Matrix For Internal Fault

SVM correctly classified 121 fault events out of a total of 150 faulty events. Correct classification of healthy events was 9 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 72.7%. Confusion Matrix is shown in figure 7.19. True Positive & False Negative Rates are shown in figure 7.20.Positive Predictive Values & False Discovery Rates are shown in figure 7.21

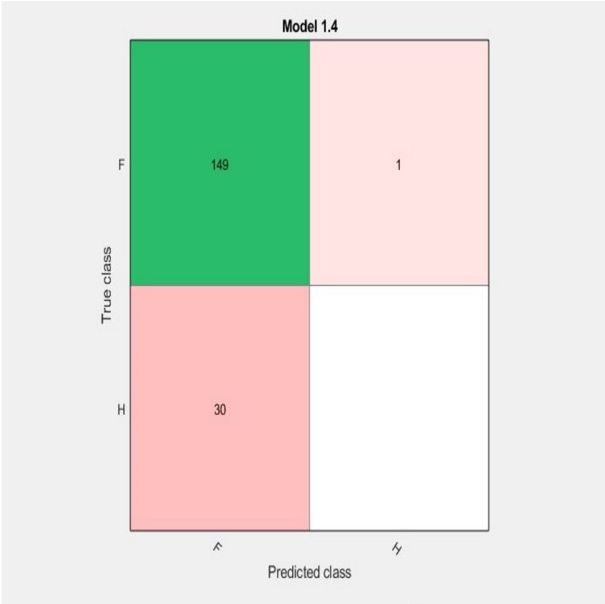


Figure 7.19: Internal Fault - Confusion Matrix of SVM at Wavelet Band-6

7.3.3.2 SVM TP/FN Rates For Internal Fault

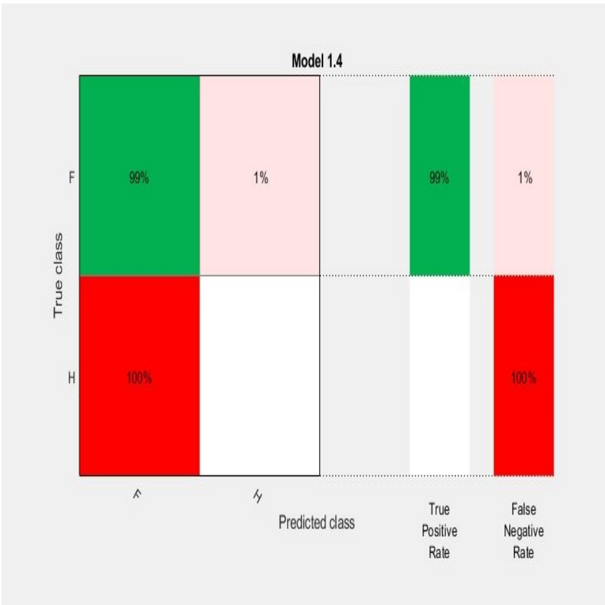


Figure 7.20: Internal Fault - True Positive & False Negative Rates of SVM at Wavelet Band-6

7.3.3.3 SVM PPV/FDR For Internal Fault

Figure 7.21: Internal Fault - Positive Predictive Values & False Discovery Rates of SVM at Wavelet Band-6

7.3.3.4 SVM Confusion Matrix For External Fault

SVM correctly classified 121 fault events out of a total of 150 faulty events. Correct classification of healthy events was 9 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 72.7%. Confusion Matrix is shown in figure 7.22. True Positive & False Negative Rates are shown in figure 7.23.Positive Predictive Values & False Discovery Rates are shown in figure **??**

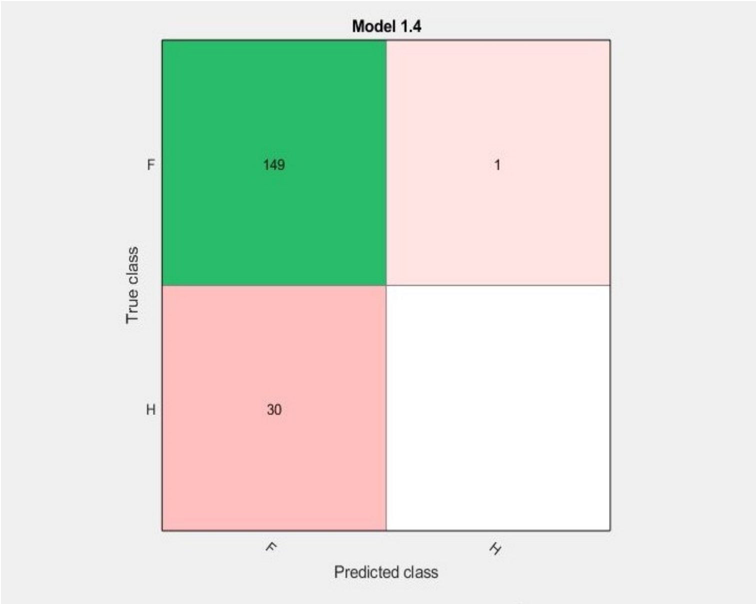


Figure 7.22: External Fault - Confusion Matrix of SVM at Wavelet Band-6

7.3.3.5 SVM TP/FN Rates For External Fault

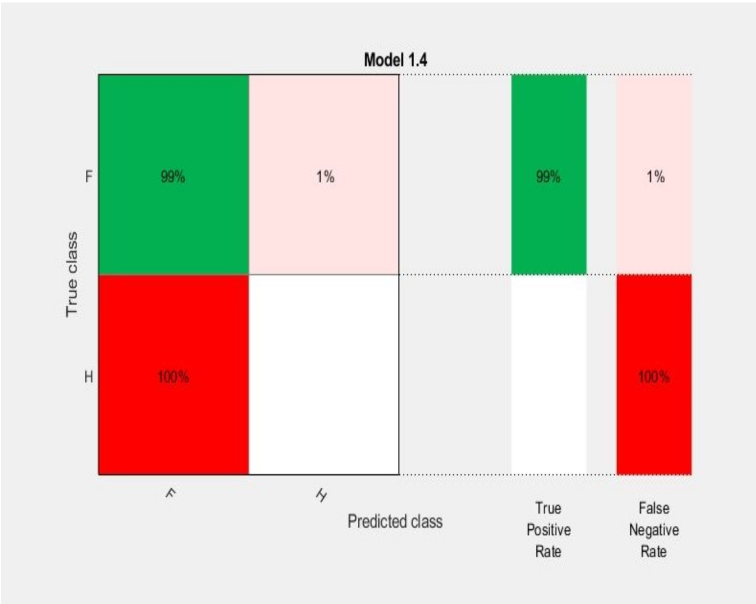


Figure 7.23: External Fault - True Positive & False Negative Rates of SVM at Wavelet Band-6

7.3.3.6 SVM PPV/FDR For External Fault

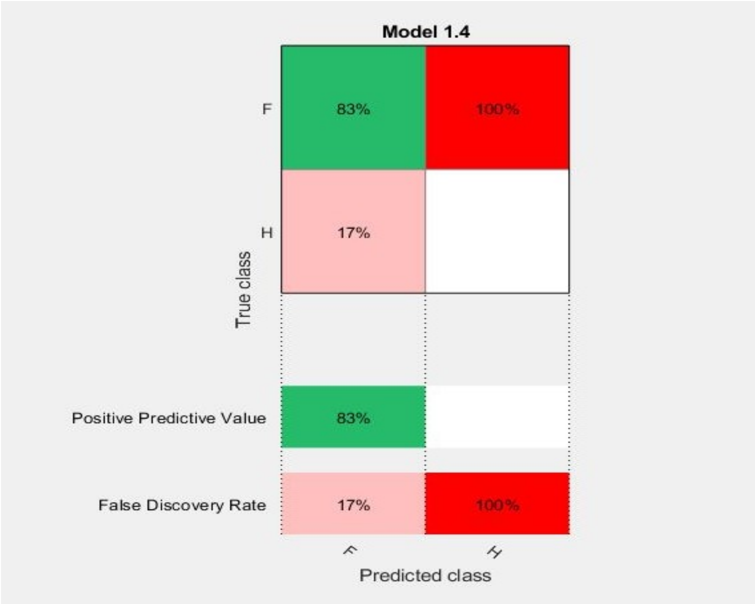


Figure 7.24: External Fault - Positive Predictive Values & False Discovery Rates of SVM at Wavelet Band-6

7.3.3.7 SVM Confusion Matrix For Multiple Faults

Of a pool of 210 events, SVM correctly classified 113 internal fault events out of a total of 150 internal faulty events. Correct classification of external fault events was 8 events out of a total of 30 events and classification of healthy events was 6 events out of a total of 30 events in a pool of 210 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 60.5%. Confusion Matrix is shown in figure 7.25. True Positive & False Negative Rates are shown in figure 7.26.Positive Predictive Values & False Discovery Rates are shown in figure 7.27

Figure 7.25: Multiple Fault - Confusion Matrix of SVM at Wavelet Band-6

7.3.3.8 SVM TP/FN Rates For Multiple Faults

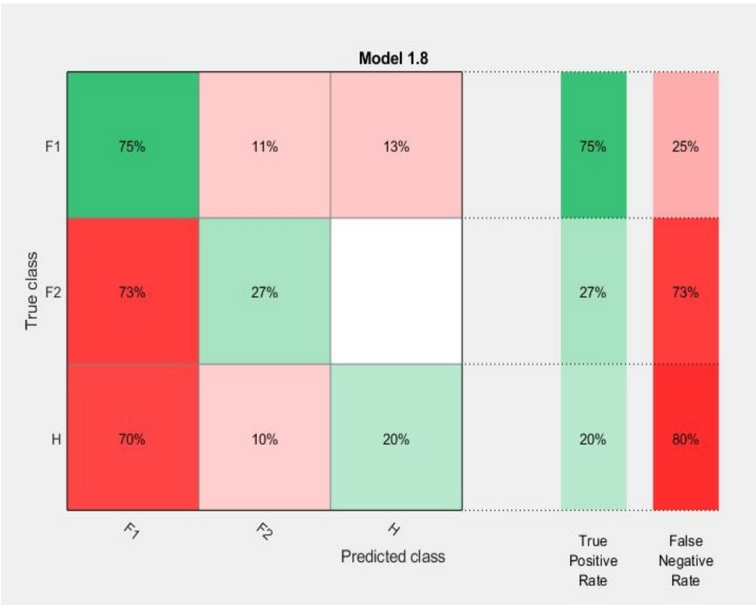


Figure 7.26: Multiple Fault - True Positive & False Negative Rates of SVM at Wavelet Band-6

7.3.3.9 SVM PPV/FDR For Multiple Faults

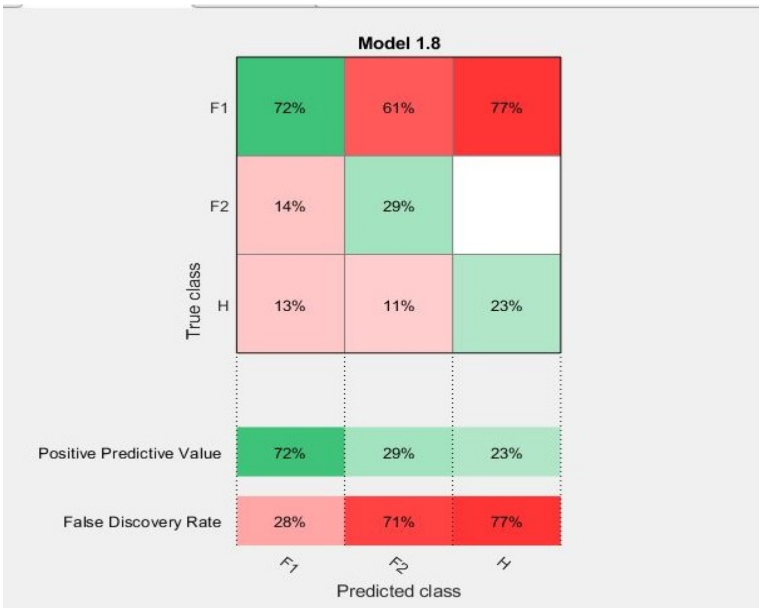


Figure 7.27: Multiple Fault - Positive Predictive Values & False Discovery Rates of SVM at Wavelet Band-6

7.3.4 Ensemble Method

7.3.4.1 Ensemble Method Confusion Matrix For Internal Fault

Ensemble Method correctly classified 133 fault events out of a total of 150 faulty events. Correct classification of healthy events was 24 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 87.2%. Confusion Matrix is shown in figure 7.28. True Positive & False Negative Rates are shown in figure **??**.Positive Predictive Values & False Discovery Rates are shown in figure **??**

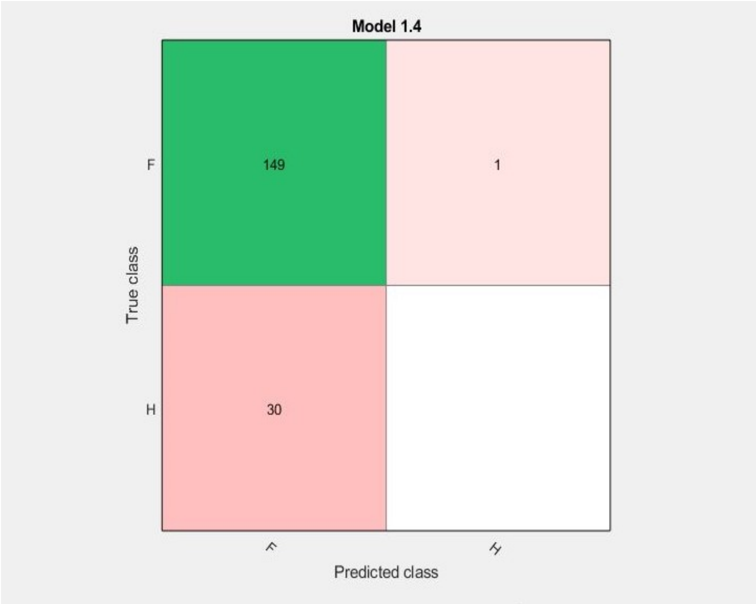


Figure 7.28: Internal Fault - Confusion Matrix of EM at Wavelet Band-6

7.3.4.2 Ensemble Method TP/FN Rates For Internal Fault

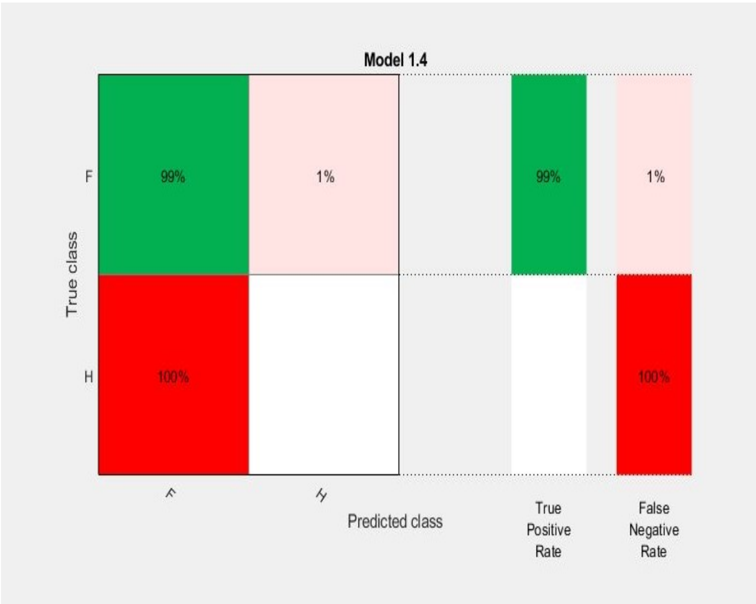


Figure 7.29: Internal Fault - True Positive & False Negative Rates of EM at Wavelet Band-6

7.3.4.3 Ensemble Method PPV/FDR For Internal Fault

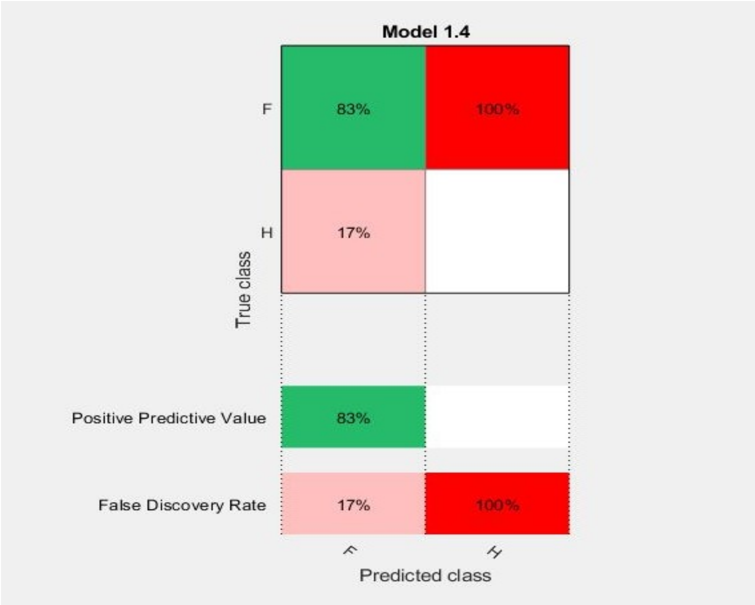


Figure 7.30: Internal Fault - Positive Predictive Values & False Discovery Rates of EM at Wavelet Band-6

7.3.4.4 Ensemble Method Confusion Matrix For External Fault

Ensemble Method correctly classified 133 fault events out of a total of 150 faulty events. Correct classification of healthy events was 24 events out of a total of 30 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 87.2%. Confusion Matrix is shown in figure 7.31. True Positive & False Negative Rates are shown in figure 7.32.Positive Predictive Values & False Discovery Rates are shown in figure 7.33

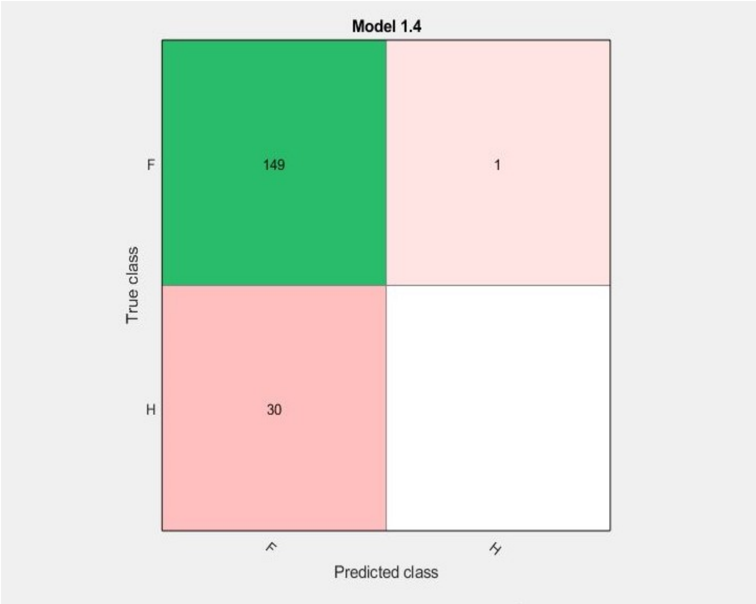


Figure 7.31: Internal Fault - Confusion Matrix of EM at Wavelet Band-6

7.3.4.5 Ensemble Method TP/FN Rates For External Fault

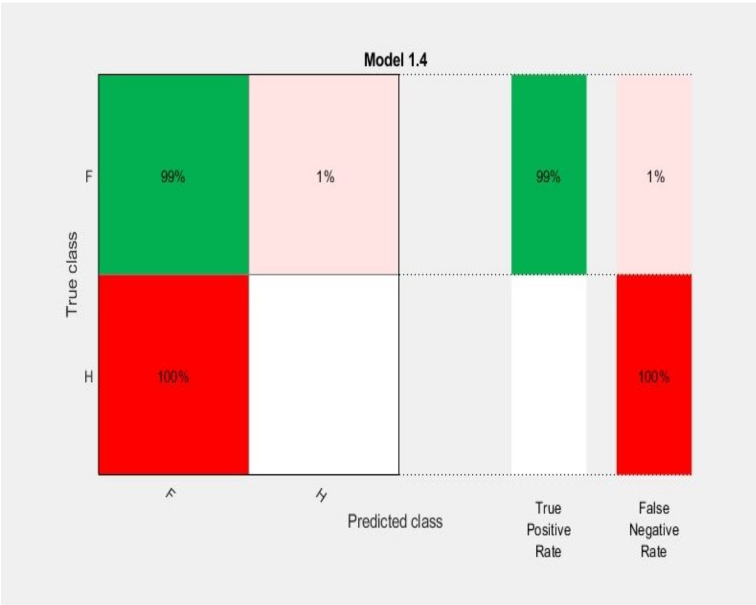


Figure 7.32: External Fault - True Positive & False Negative Rates of EM at Wavelet Band-6

7.3.4.6 Ensemble Method PPV/FDR For External Fault

Figure 7.33: External Fault - Positive Predictive Values & False Discovery Rates of EM at Wavelet Band-6

7.3.4.7 Ensemble Method Confusion Matrix For Multiple Faults

Of a pool of 210 events, Ensemble Method correctly classified 114 internal fault events out of a total of 150 internal faulty events. Correct classification of external fault events was 25 events out of a total of 30 events and classification of healthy events was 26 events out of a total of 30 events in a pool of 210 events. This classification of events was performed on wavelet decomposition of faulty and healthy current signal data at wavelet band-6. Accuracy of classification was 78.6%. Confusion Matrix is shown in figure 7.34. True Positive & False Negative Rates are shown in figure 7.35.Positive Predictive Values & False Discovery Rates are shown in figure 7.36

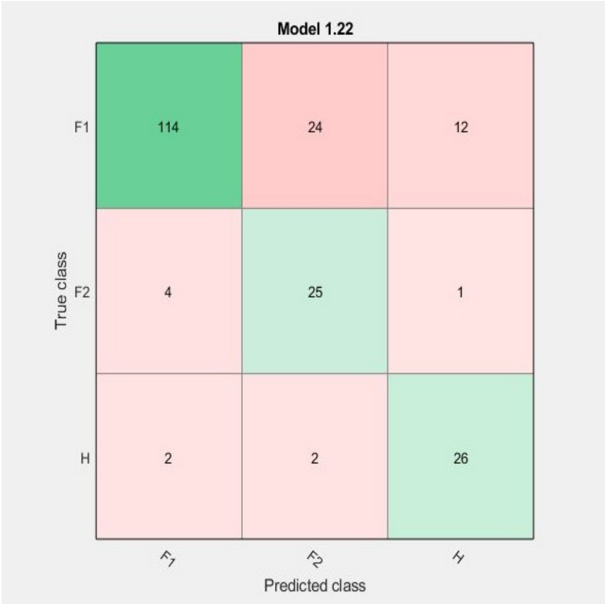


Figure 7.34: Multiple Faults - Confusion Matrix of EM at Wavelet Band-6

7.3.4.8 Ensemble Method TP/FN Rates For Multiple Faults

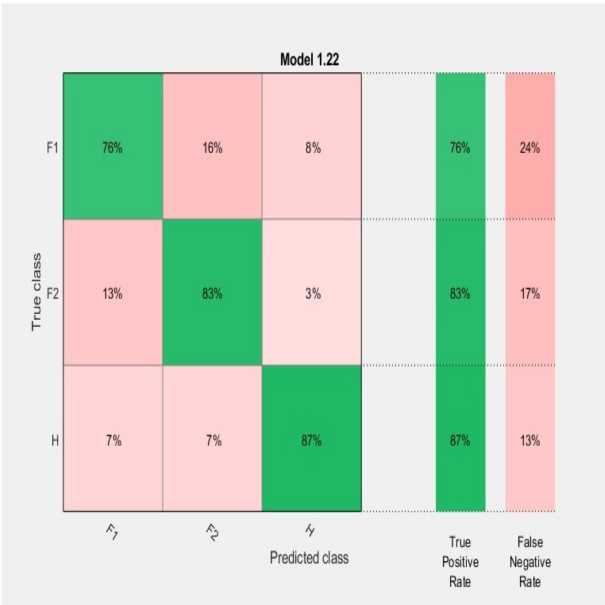


Figure 7.35: Multiple Faults - True Positive & False Negative Rates of EM at Wavelet Band-6

7.3.4.9 Ensemble Method PPV/FDR For Multiple Faults

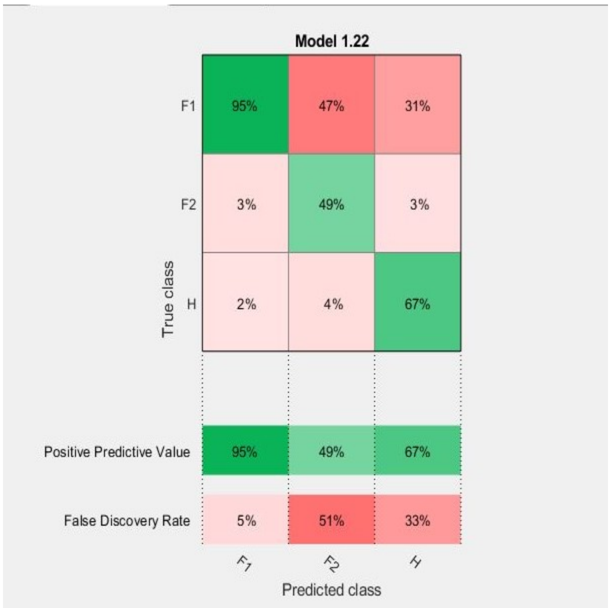


Figure 7.36: Multiple Faults - Positive Predictive Values & False Discovery Rates of EM at Wavelet Band-6

7.4 Classifier Results For Current Study Data-set

Faults classification results are compared based on performance presented by true positive rate **TPR**,true negative rate **TNR**,false positive rate **FPR** and false negative rate **FNR**.

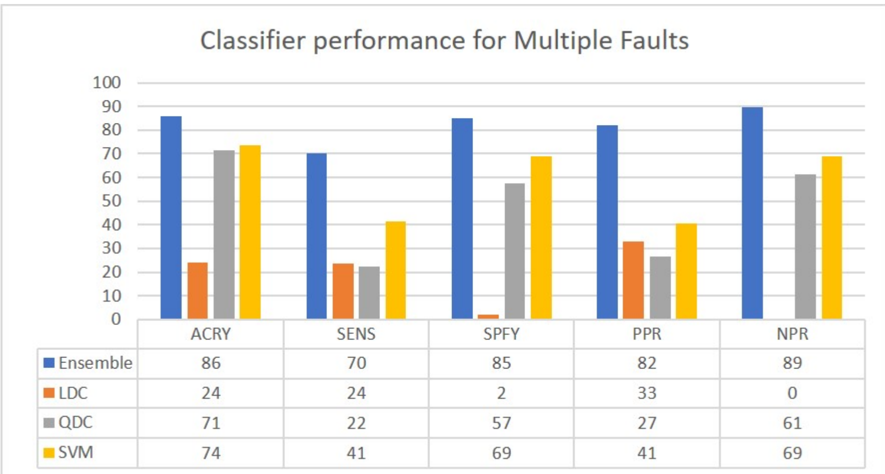


Figure 7.37: Classifier performance for Multiple Faults at Wavelet Band 6

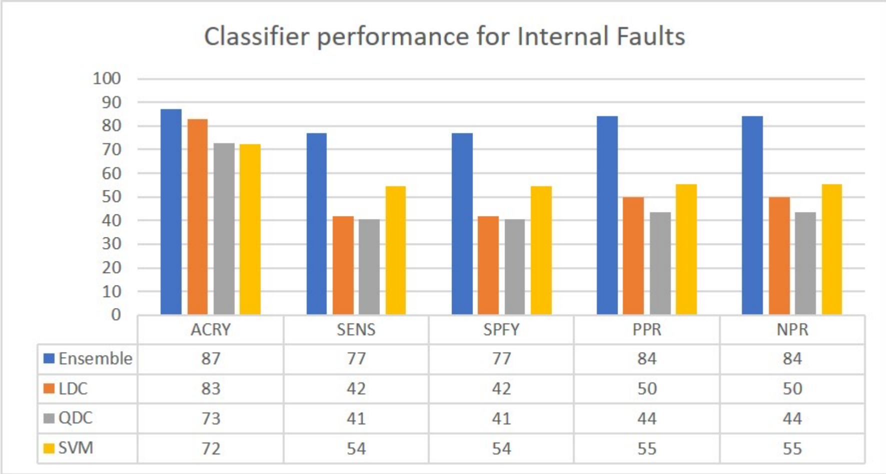


Figure 7.38: Classifier performance for Internal Faults at Wavelet Band 6

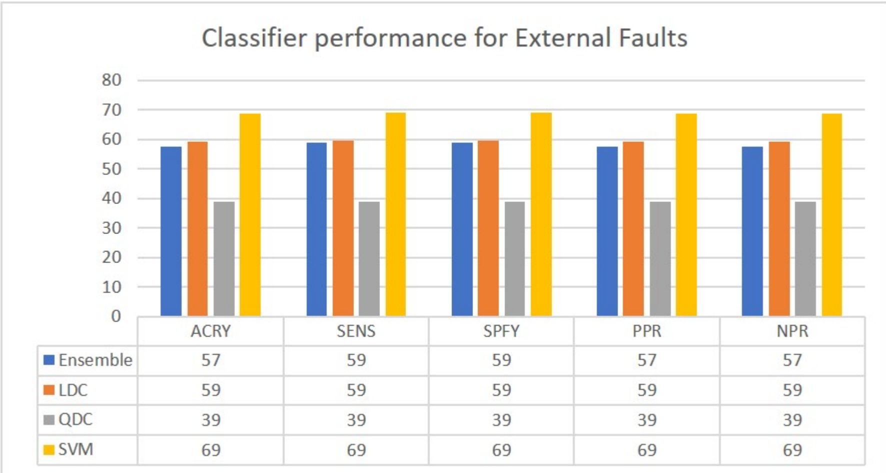


Figure 7.39: Classifier performance for External Faults at Wavelet Band 6

7.4.1 Linear Discriminant Classifier Performance

LDC had an overall accuracy of 55%, average on the lowest of all four classifiers . Performance took a hit during classification of multiple faults. The highest accuracy measured was for Internal faults at 83%. Table 7.1 details each fault classification performance.

Table 7.1: Linear Discriminant Classifier Performance

Type	Wavelet Level	TIR	FIR	ACC	SENS	SPFY	PPR	FDR
Multiple Faults	6	151	479	24%	24%	2%	33%	0%
Internal Faults	6	298	62	83%	42%	42%	50%	50%
External Faults	6	64	44	59%	59%	59%	59%	59%

7.4.2 Quadratic Discriminant Classifier Performance

QDC had an overall accuracy of 72%, at position no. 2 out of the four classifiers . Performance saw a dip during classification of external faults. The highest accuracy measured was for Internal faults at 73%.Table **??** details each fault classification performance.

Table 7.2: Quadratic Discriminant Classifier Performance

Type	Wavelet Level	TIR	FIR	ACC	SENS	SPFY	PPR	FDR
Multiple Faults	6	450	180	71%	22%	57%	27%	61%
Internal Faults	6	262	98	73%	41%	41%	44%	44%
External Faults	6	42	66	39%	39%	39%	39%	39%

7.4.3 Support Vector Machine Performance

SVM had an overall accuracy of 71%, with sensitivity, specificity, positive predictive and negative predictive rates faring better than that of LDC and QDC. Accuracy was constant in all three segments of fault types .Table **??** details each fault classification performance.

Table 7.3: Support Vector Machine Discriminant Classifier Performance

Type	Wavelet Level	TIR	FIR	ACC	SENS	SPFY	PPR	FDR
Multiple Faults	6	464	166	74%	41%	69%	41%	69%
Internal Faults	6	260	100	72%	54%	54%	55%	55%
External Faults	6	74	34	69%	69%	69%	69%	69%

7.4.4 Ensemble Method Classifier Performance

Ensemble Method were the most efficient classifier when compared to LDC. QDC and SVM with sensitivity, specificity, positive predictive and negative predictive rates faring better than the rest of the competition.Accuracy was a respectable 77%, with a high of 83% in multiple faults and a low of 57% in external faults classification. Table **??** details each fault classification performance.

Table 7.4: Support Vector Machine Discriminant Classifier Performance

Type	Wavelet Level	TIR	FIR	ACC	SENS	SPFY	PPR	FDR
Multiple Faults	6	540	90	86%	70%	85%	82%	89%
Internal Faults	6	314	46	87%	77%	77%	84%	84%
External Faults	6	62	46	57%	59%	59%	57%	57%

The results present a clear distinction in classifier performance with, ensemble method classification technique outperforming the four classifier performance comparision.SVM ,QDC, and LDC performed average.

Chapter 8

Conclusion and Future Suggestion

8.1 Conclusion

The current thesis focus was on detection of internal and external faults. Studies on these faults in distribution transformers have not been undertaken as compared to similar studies in power transformers. A new approach to fault detection in the thesis has been presented. The nature of fault is such that, its mere occurrence does not define failure probability and is rather dependent on the intensity of the fault occurrence. However the first step in transformer health monitoring that is the detection and recognition of transformer faults, has been completed as a requirement of the thesis.

In order to detect and recognize transformer faults, a method to achieve this task was proposed. Application of noninvasive technique of transformer current signature analysis, to detect faults was aided via wavelet transformation to achieve relevant signal data extraction. Linear discriminant Classifier (LDC), Quadratic Discriminant Classifier (QDC) and Support Vector Machine (SVM) were utilized for current signal classification. Classification results provided a clear distinction between classification capabilities of transformer faults under various fault conditions. Ensemble method for classification of transformer faults achieved superior performance in all aspects of faults classification. LDC, SVM and QDC achieved less than desired accuracy.

8.2 Future Work Suggestion

Intensity detection and use of intrusive methods for fault detection are next steps in the evolution of transformer condition and health monitoring. Classification of transformer operational parameters to further detail the classification boundaries will aid in producing accuracy and forecasting potential fault occurrences.

An online system can be build for transformer fault detection and prediction. For implementation of this application, use of Field Programmable Gate Array (FPGA) coupled with high accuracy and high resolution OR appropriate Digital Signal Processing (DSP) boards can be considered.

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