

# Software Defect Prediction Models for Quality Improvement: A Literature Study

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## Abstract

In spite of meticulous planning, well documentation and proper process control during software development, occurrences of certain defects are inevitable. These software defects may lead to degradation of the quality which might be the underlying cause of failure. In today's cutting edge competition it's necessary to make conscious efforts to control and minimize defects in software engineering. However, these efforts cost money, time and resources. This paper identifies causative factors which in turn suggest the remedies to improve software quality and productivity. The paper also showcases on how the various defect prediction models are implemented resulting in reduced magnitude of defects.

**Keywords:** *Software Defects, Defect Prediction, Defect Prediction, Software Quality, Machine Learning Algorithms, Defect Density.*

## 1. Introduction

Software metrics has been used to describe the complexity of the program and, to estimate software development time. "How to predict the quality of software through software metrics, before it is being deployed" is a burning question, triggering the substantial research efforts to uncover an answer to this question. There are number of papers supporting statistical models and metrics which profess to answer the quality question. Typically, software metrics elucidate quantitative measurements of the software product or its specifications. Defects can be defined in a disparate ways but are generally defined as aberration from specifications or ardent expectations which might lead to failures in procedure. Defect data analysis is of two types; Classification and prediction that can be used to extract models describing significant defect data classes or to predict future defect trends. Classification predicts categorical or discrete, and unordered labels, whereas prediction models predict continuous valued functions. Such analysis can help us for providing better understanding of the software defect data at large.

A software defect is an error, flaw, bug, mistake, failure, or fault in a computer program or system that may generate an inaccurate or unexpected outcome, or precludes the software from behaving as intended. A project team always aspires to procreate a quality software product with zero or little defects. High risk components within the software project should be caught as soon as possible, in order to enhance software quality. Software defects always incur cost in terms of quality and time. Moreover, identifying and rectifying defects is one of the most time consuming and expensive software processes. It is not practically possible to eliminate each and every defect but reducing the magnitude of defects and their adverse effect on the projects is achievable.

In year 2008 and 2009, SANS institute conducted a study to identify the most common and dangerous 25 software bugs or defects. About 30 organizations gave their contribution for the study. Commercial software organizations like Apple, Aspect Security, Breach Security, CERT, Homeland Security, Microsoft, MITRE, Oracle, Red Hat and Tata; academic institutes like University of California, Perdue University etc were among these organizations. These 25 security problems were classified into three domains [14] shown in figure 1.

Therefore, defect prediction is extremely essential in the field of software quality and software reliability. Defect prediction is comparatively a novel research area of software quality engineering. By covering key predictors, type of data to be gathered as well as the role of defect prediction model in software quality; the interdependence between defects and predictor can be identified. This paper gives you intensive insights and future research avenues about software defect prediction.

Interactions	Resource Management	Defense Leakages
<ul style="list-style-type: none"> <li>Poor input validation</li> <li>Poor encoding of output</li> <li>SQL query structures</li> <li>Web page structures</li> <li>Operating system command structures</li> <li>Open transmission of sensitive data</li> <li>Forgery of cross-site requests</li> <li>Race conditions</li> <li>Leaks from error messages</li> </ul>	<ul style="list-style-type: none"> <li>Unconstrained memory buffers</li> <li>Control loss of state data</li> <li>Control loss of paths and file names</li> <li>Hazardous paths</li> <li>Uncontrolled code generation</li> <li>Reusing code without validation</li> <li>Careless resource shutdown</li> <li>Careless initialization</li> <li>Calculation errors</li> </ul>	<ul style="list-style-type: none"> <li>Inadequate authorization and access control</li> <li>Inadequate cryptographic algorithms</li> <li>Hard coding and storing passwords</li> <li>Unsafe permission assignments</li> <li>Inadequate randomization</li> <li>Excessive issuance of privileges</li> <li>Client/server security lapses</li> </ul>

Fig. 1 Security Problems

Preemptive discovery of software defects in a software project empowers managers to make appropriate decisions and plan limited project resources in a more structured and systematic way. In general, we should focus on the following different aspects of the problem.

- Defect prevention;
- Defect detection;
- Defect correction;

Since defect prediction is a relatively new domain of research, in this paper we will be discussing various prediction models which have been proposed. In the current prediction models, complexity and size metrics are used in order to preempt any defects that might occur during operation or testing phase of the project. In another model of defect prediction, reliability based models use the operational profile of a system to predict failure rate that the project will face. Also in most projects, information collected in the testing and defect detection is analyzed to help predict defeats for similar types of projects. However, since all models of defect prediction have areas where they come up short, the search for one model that can predict defects in a wide range of projects has been on. The multivariate model of defect prediction have been touted as the model that can solve this issue but still no all encompassing model has been uncovered as of now. With the importance of enforcing the highest levels of quality in systems, it has become imperative to improve defect prediction techniques so that they can anticipate more defects at an early stage leading to a quality project delivery.

### 1.1 A General Defect Prediction Process:

To construct a prediction model, we must have defect and measurement data collected from actual software development efforts to use as the learning set. There exist compromise between how well a model fits to its learning set and its prediction performance on additional data sets. Therefore, we should evaluate a model's performance by

comparing the predicted defectiveness of the modules in a test set against their actual defectiveness [20].

Sunghun Kim et al. [18] have described a common defect prediction process shown in the figure 2.

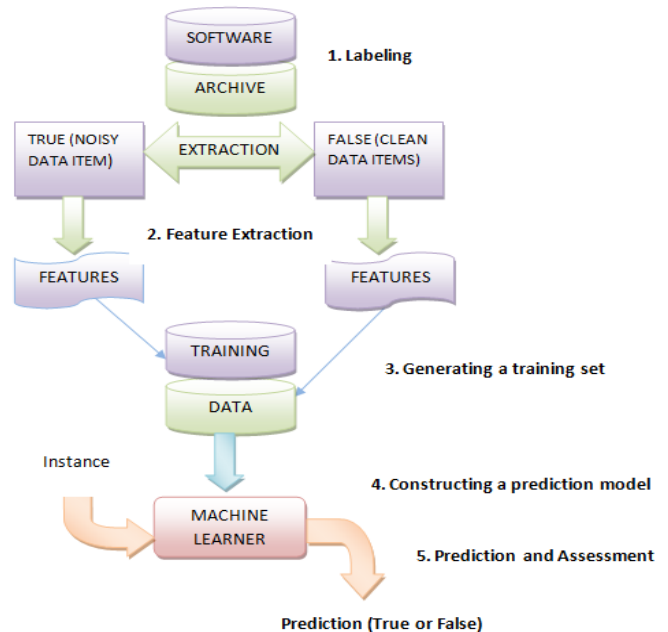


Fig. 2 General Defect Prediction Process

**Labeling:** Defect data should be gathered for training a prediction model. In this process usually extracting of instances i.e. data items from software archives and labeling (TRUE or FALSE) is done.

**Extracting features and creating training sets:** This step involves extracting of features for prediction of the labels of instances. General features for defect prediction are complexity metrics, keywords, changes, and structural dependencies. By combining labels and features of instances, we can produce a training set to be used by a machine learner to construct a prediction model.

**Building prediction models:** General machine learners such as Support Vector Machines (SVM) or Bayesian Network can be used to build a prediction model by using a training set. The model can then obtain a new instance and predict its label, i.e. TRUE or FALSE.

**Assessment:** The evaluation of a prediction model requires a testing data set besides a training set. The labels of instances in the testing set are predicted and the prediction model is evaluated by comparing the prediction and real labels. 10-fold cross-validation is broadly used to separate the training and testing sets.

## 2. Problem Definition

As we have discussed upon earlier, defect prediction is vital in nature. Our prime objective is to predict defects without overrunning the estimated cost as well as without delaying scheduled delivery of software. However, the main issue related to this is mainly the plethora of models which can be used for the same. All models of defect prediction have their own set of advantages and disadvantages which makes it hard to understand which fault prediction model should be used and more importantly in what type of project. Since every project tends to be unique, this is hard from a decision making standpoint. However, we believe thorough model evaluation can enable project managers to make a more informed decision.

In our study, we will cover the popular models of defect prediction and evaluate the pros and cons of each model along with the situations where the models can be used. We will evaluate the models based a varied set of criteria depending on the model being discussed. After evaluation, we will also include our personal observations and interpretations on why we think certain decision models are useful along with substantiating case studies of real world usage wherever possible.

## 3. Study of Software Defect Prediction Models

### 3.1 Prediction Model using size and complexity metrics

Among the popular models of defect prediction, the approach that uses size and complexity metrics is fairly well known. This model uses the program code as a basis for prediction of defects. More specifically, lines of code (LOC) are used along with the concept of complexity model developed by McCabe. Using regression equations, simple prediction metrics estimates can be obtained using a dependent variable (D) defined as the sum of defects found during testing and after 2 months post release. Famously, Akiyama made 4 equations. We have illustrated the equation that includes the LOC metric:

$$Defect (D) = 4.86 + 0.018 \text{ Lines of Code } (L) \quad (1)$$

Gaffney deduced above equation (1) into another prediction equation. He argued that LOC was not language dependent owing to optimal size for individual modules with regards to defect density. The regression equation is given below:

$$D = 4.2 + 0.0015 L_{4/3} \quad (2)$$

The size and complexity models presume that defects are direct function of size or defects are occurred due to program complexity. This model ignores the underlying casual effects of programmers and designers. They are the human factors who actually commence the defects, so any attribution for flawed code depends on individual(s) to certain extent. Poor design capability or problem difficulty may result in highly complex programs. Difficult problems might require complex solutions and naive programmers might create 'spaghetti code' [6].

### 3.2 Machine Learning Based Models

Machine learning (ML) algorithms has demonstrated great practical significance in resolving a wide range of engineering problems encompassing the prediction of failure, error, and defect-impulsions as the system software grows to be more complex. ML algorithms are very useful where problem domains are not well defined, human knowledge is limited and dynamic adaption for changing condition is needed, in order to develop efficient algorithms. Machine learning encompasses different types of learning such as artificial neural networks (ANN), concept learning (CL), Bayesian belief networks (BBN), reinforcement learning (RL), genetic algorithms (GA) and genetic programming (GP), instance-based learning (IBL), decision trees (DT), inductive logic programming (ILP), and analytical learning (AL)[3].

G. John, P. Langley [4] employed RF method for prediction of faulty modules with NASA data sets. Prediction of software quality was introduced by Khoshgafaar et al. [5] by using artificial neural network. In this model they classified modules as fault prone or non fault prone, using large telecommunication software system. They compared their end results with another non-parametric model achieved from discriminant method. Fenton et al. [6] suggested the use of Bayesian belief networks (BBN) for the prediction of faulty software modules. Elish et al. [7] recommended the use of support vector machines for predicting defected modules with context of NASA data sets. This model compares its prediction performance with other statistical and machine learning models. We have discussed few models in detail to enhance the understanding of Machine learning based prediction models.

#### 3.2.1 The Probabilistic Model for Defect Prediction using Bayesian Belief Network

Fenton, Krause and Neil [6] proposed a probabilistic model for defect prediction. They recommended a holistic model rather than a single issue (for e.g. size, or complexity, or testing metrics, or process quality data) model, by combining the different factors of casual

evidence in order to successful defect prediction. The model uses Bayesian Belief Network (BBN) as the suitable practice for representation of this evidence. The Bayesian approach causes statistical conclusion to be improved by expert judgment in those parts of a problem sphere where empirical data is scattered. Additionally, the causal or influence organization of the model better reflects the series of real world events and relations than any other practice.

BBN can be exploited to support effective decision making for SPI (Software Process Improvement), by executing the following steps.

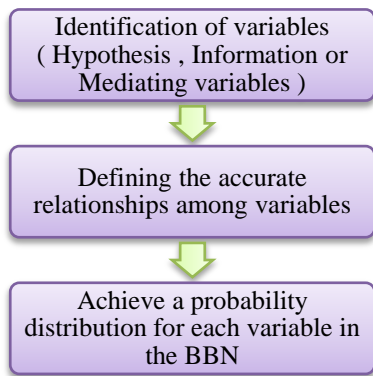


Fig. 3 Bayesian Approach

A BBN represents the joint probability distribution for a set of variables. This is achieved by defining Directed acyclic graph (DAG) and Conditional probability tables. A BBN can be employed to deduce the probability distribution for a target variable (e.g., “Defects Detected”), which indicates the probability that the variable will obtain on each of its possible values (e.g., “very low”, “low”, “average”, “high”, or “very high” for the variable “Defects Detected”) given the observed values of the other variables [8, 9].

N. Fenton, M. Neil and D. Marquez [17] reviewed the use of Bayesian networks to overcome impediments of using BN’s for predicting software defects and software quality. BN tools and algorithms suffered from ‘Achilles’ heel. This compelled modelers to predefine discretization intervals in advance and resulted in inadequate predictions for large set of data. To improve this ‘dynamic discretization’ algorithm was used. This algorithm exploits entropy error as the basis for approximation allowing more accuracy.

### 3.2.1 The Probabilistic Model for Defect Prediction using Bayesian Belief Network

The Fuzzy Logic model is based on the concept of reasoning and works on a value that is approximate in nature. It is a step up from conventional Boolean Logic where there can only be True or False. In case of Fuzzy logic, the truth of any statement is degree and not an absolute number. Modeled on human intuition and behavior, the biggest plus point of Fuzzy logic is that as opposed to the traditional yes – no answers, this model factors in the degree of truth and hence makes allocation for the more human like answers.

Previously in this report, we have elaborated on why it is important to identify software quality issues at an early stage. Ajeet Kumar Pandey and N. K. Goyal [10] suggested the model of Fuzzy Logic and the software metrics as well as process maturity, the model can be constructed as follows:

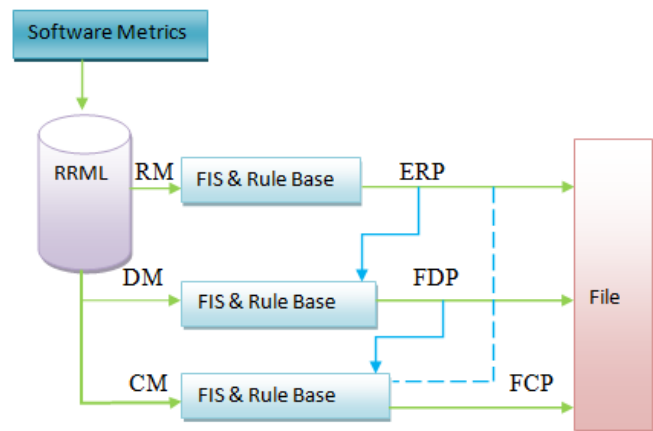


Fig. 3 Fuzzy Logic Approach

This model uses inputs and puts them in a range system. After this, a set of rules is defined that dictates and influences how inputs will be utilized in getting the output as well as finding the definitive value in the fuzzy set. The model has a set of metrics or reliability relevant metric (RRML) list which is made from the available software metrics. The metrics are pertinent to their respective phases in the software development life cycle.

*Requirement Phase Metrics* - As you can see the model has uses three requirements metrics (RM) i.e. Requirements Change Request (RCR), Review, Inspection and Walk through (RIW), and Process Maturity (PM) as input to the requirements phase.

*Design Phase Metrics* – similar to the above phase, three design metrics (DM) i.e. design defect density (DDD), fault days number (FDN), and data flow complexity (DC) have considered as input.



*Coding Phase Metrics* – In this phase, two coding metrics (CM) such as code defect density (CDD) and cyclomatic complexity (CC) have been taken as input at coding phase. The outputs of the model will be the number of faults at the end of Requirements Phase (FRP), number of Faults at the end of Design Phase (FDP), and number of Faults at the end of Coding Phase (FCP).

### 3.2.3 Defect Prediction Models Based on Genetic Algorithms

Genetic Algorithms is an approach to machine learning which behaves similarly to the human gene and the Darwinian theory of natural selection. It is a part of the Evolutionary Algorithms which generate solutions based on the techniques more commonly found in nature like mutation, selection, crossover etc.

Genetic Algorithms are implemented beginning with an individual population that is usually represented in the form of trees. A possible solution is represented by each tree or say chromosome in this case. Nodes on the tree signify particular traits that relates to the problem for which the solution is being searched. Collectively, the set of potential solutions to the problem is (represented by the chromosomes) as known as the population.

Where genetic algorithms come into place is when you need to solve problems which can have many solutions. Here, genetic algorithms are being used to cluster the classes defined as per object oriented metrics into subsystems or commonly known as components of software. As elaborated earlier, genetic algorithm uses an approach akin to Charles Darwin's "Survival of the Fittest" or natural selection. The reason this approach is being considered is because the large solutions set which provide a number of possible solutions to a problem. When applying a genetic algorithm to a problem, there are a few implications which are made. The same are as follows

- a) There must be a fitness function present for the evaluation of whether a solution is a possible one or not
- b) Whenever there is a solution found, there should a representation of it made by a chromosome.
- c) Whichever genetic operators will be applied must be established

Additionally the definition of a solution in this case would be one which would be both complete as well as valid. In terms of a representation, there is the assumption that the possible solutions have been encoded in the solutions space.

### How do Genetic Algorithms work?

In the beginning, the Genetic Algorithms start with a large population. In that population, each individual represents a plausible solution to the problem. These individuals in the population are then encoded in a binary string that is called a chromosome. After that, the group of the individuals will compete so that they can reproduce and then formulate the next generation. However, there is a function called the fitness function that determines which of the competing individuals will gain the right to reproduce. Having the fitness function in place makes sure that only the best individuals of the population will be able to carry over their offspring into the next generation. The next generation is formed by the following activities taking place.

- a) *Reproduction* – reproduction process takes place when two chromosomes exchange a portion of their code to form the new individuals. The crossover points (where the bits of the code will exchange) are selected by random (for a simple version of the algorithm). At the crossover point, the chromosomes exchange the data keeping the original data up to that point.
- b) *Mutations* – this comes in to introduce variation in the next generation which prevents the reaching of local minima. Whereas crossover alters the genes after a randomly selected crossover point between 2 chromosomes, mutation selects on node in the tree of one chromosome and changes the genetic material.

This process repeats itself until there is a perfect solution set reached (optimal fitness level). However, there are occasions when this does not happen. In such cases, the program terminates after a set of iterations. The iterations of the proceeds are also known as generations.

### Example of using Genetic Algorithms in a Web Fault Prediction

Research on Genetic Algorithms being applied is few since this is a relatively new domain. In the following, we show how it can be applied to an online web application, proposed by Marshima M. Rosli et al. [16].

Namely, there is the requirement of three components to build the model of Fault prediction using Genetic Algorithms. They are as follows

- a) Software Metric Extractor
- b) Fault Classes Detection System
- c) Genetic Algorithm Generator

The model can be represented diagrammatically as follows:

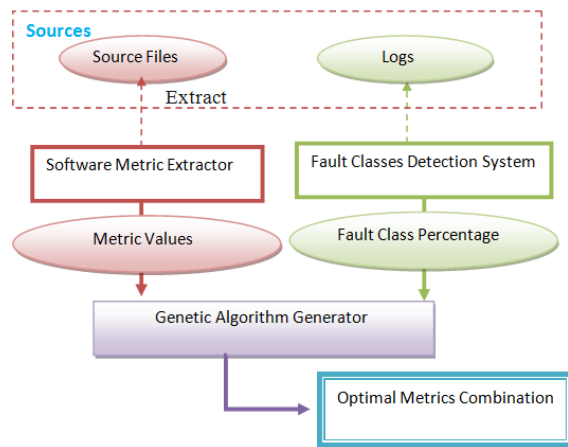


Fig 5 Genetic Algorithm Approach

How this model would work is that the information about metrics would be extracted from source files as well as the logs. Then the optimal metrics can be found by the GAG part of the model which will subsequently use reproductions and mutations to create new generation of populations until the optimal set of metrics are found.

### 3.2.4 Software Defect Prediction Models using Artificial Neural Network

The artificial neural network is based on the human biological system in its architecture and design. It processes information in a way similar to the human brain using an intricate system of interconnected neurons to solve highly complex problems. The artificial neural networks work in a similar fashion and use a trial and error process to construct models of the problem space. Using “guesses” of what the desired output should be, the actual result and the predicted result ( guesses) are compared and if there is a difference, that value is passed on to the network as feedback so that internal adjustments can be made to get a better quality of results in the future. Over a period of time, this process continues as the network is presented with other sets of data until it gives an accurate model of the process.

As told in the introduction, the artificial neural network has a set of elements which perform the computations required on the problem set. In this case, the feed forward as well as the back propagation training algorithm have been used for the purposes of defect prediction. The architecture of the network is such that there are two neurons in the output layer (basically fault and non fault). The output that has the greatest value is selected thereafter. The learning process happens by finding a vector of the

connection weights which lower the error sum squared on the training set. The training of the network happens with the continuous back propagation and the weights are adjusted after each observation which is then fed forward for each of the classes (fault and non fault).

Neha Gautam, Parvinder S. Sandhu, Sunil Khullar [11] recommended to use Multilayer Perceptron and RBF based Neural Network approaches for the identification of the relation between the several qualitative as well as quantitative factor of the modules. These approaches also identify the number of defects existing in the module that will be beneficial for the prediction of defects. The methodology consists of the following steps:

1. Find the Qualitative and Quantitative attributes of software systems
2. Select the suitable metric values as representation of statement
3. Analyze, refine metrics and normalize the metric values and Explore different Neural Network Techniques

### 3.3 Defect Density Prediction Model

Defect density is a measure of the total confirmed defects divided by the size of the software entity being measured. The Number of Known Defects is the count of total defects identified against a particular software entity, during a particular time period. Defect to date since the creation of module, defects found in a program during an inspection, defects to date since the shipment of a release to the customer are examples of most commonly known defects. Size is like a normalizer that permits comparisons between various software entities (i.e., modules, releases, products). Size is normally measured either in Lines of Code or Function Points [21]. Defect density is useful for the comparison of defects in different software components in order to identify high-risk components and associated resources. Moreover, it can also used for comparison among various software products in term of quality.

#### 3.3.1 Constructive Quality Modeling for Defect Density Prediction (COQUALMO)

Sunita Chulani [12] presented Constructive Quality Modeling for Defect Density Prediction (COQUALMO), a quality prediction model. This software model focuses on the prediction of defect density and is hence an estimation model. The COQUALMO model is generally applied to the early phases of the software lifecycle such as the activities of analysis and design. However, this model can also be applied to the later stages of the SDLC helping in refining the defect density estimate when a larger set of

information is available. The COQUALMO model enables project managers to get an estimate with relation to metrics like shipping time as well as the payoffs for investing in quality as well as a better understanding of the interactions involved with respect to quality strategies.

This model comprises of two main phases namely

1. *Defect Introduction Model* – this model deals with the basis that defect can be introduced in any stage of the SDLC and the classification is done based on the origin of the defects. Conceptually, this model can be through of being similar to a tank with specific pipes. These pipes relate to the origin of defects which in this case can be of three types, namely requirements, design and coding. The same has been illustrated in the given model.

As you can infer, the defects can be of different types. Critical defects would require the most attention since they could case the system to crash or cause serious damage. The High level would be responsible for loss of system’s critical functions without any measures for a workaround. Medium level is similar to the high level with the only difference being that a workaround solution will exist in this case.

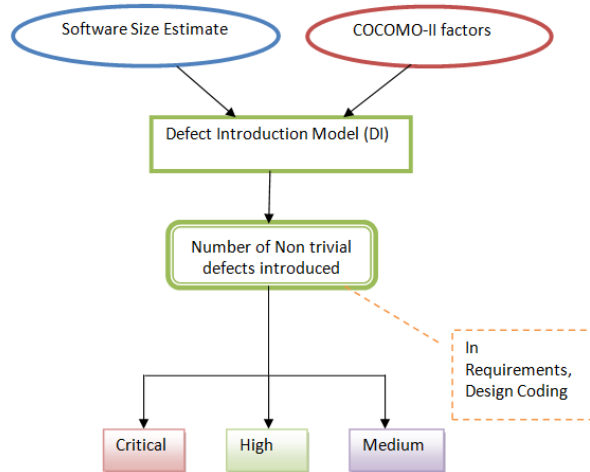


Fig. 6 COQUALMO

2. *Defect Removal Model* - similar to the Defect Introduction model, the DR model estimates the defects in requirements, design and coding which are introduced into the product or system under development. This model aims to estimate the

removed defects. Classification of the defect removal activities falls into 3 techniques namely :

- Very low
- Low
- Nominal
- High
- Very high
- Extra high

The “very low” level is the least effective defect removal method and the extra high is the most effective defect removal method.

### 3.3.2 Defect Prediction Model based on Six Sigma Metrics

Muhammad Dhiauddin Mohamed Suffian and Suhaimi Ibrahim [12] suggested Six Sigma approach, which is a structured and systematic way to construct the mathematical model for prediction of functional defects in system testing. It focuses on those software projects that follow V-Model software development process. Six Sigma methodology provides analysis of key factors in phases earlier to testing phase that have explicit effect in the detection of defect in system testing. This prediction model is organized in to five phases; Define, Measure, Analyze, Design and Verify phases. These phases exhibit the progression and relationship between the outputs of each phase towards building the model.

- *Define phase:* It involves creating project definition and collecting primary requirements of the project.
- *Measure phase:* It uses Measurement System Analysis (MSA) to validate the repetition and reproduction of defects.
- *Analyze phase:* During this phase, data collected earlier, is used to run regression analysis.
- *Design phase:* In this phase, additional refinement is carried out in the previous equation. The predictors used earlier have been revised in order to select only logical predictors. It is done by filtering metrics that include only legitimate data. It produces logical connection with functional defects. Fresh data set are used to generate new regression equation.
- *Verify phase:* In this final phase, reliability of the prediction model is evaluated using statistical method.

Capability flow-up and scorecard are performed to ensure customer requirements are fulfilled.

The Design for Six Sigma (DfSS) methodology also provides a Control plan that guides on subsequent action when the genuine functional defects discovered do not occur within the range of prediction interval. The Six Sigma method of building defect prediction models is a good fit of software defect prediction. The processes and methodologies proposed in Six Sigma provide ample opportunities to formulate a clear outline of issues to be addressed, the data collection as well as measurement along with model generation, construction and validation. Equations formulated by the model give a good idea on what could be the possible factors which contribute to defects.

#### 4. Conclusions

Prediction is the task of predicting continuous or ordered values for given input. However, as we have seen, some classification techniques such as Bayesian belief networks, neural network and genetic algorithms can be adapted for prediction. Training a classifier or predictor is not enough; we would like an estimate of how accurately the classifier can predict the deviating behavior of future defects, that is, future defect data on which the classifier has not been trained. We have observed various methods to construct more than one classifier (or predictor) and now we want to estimate their accuracy. We can use Predictor error measures in techniques for accuracy estimation, such as the holdout, random sub sampling, k-fold cross-validation, and bootstrap methods.

Software defect prediction is the process of tracing defective components in software prior to the start of testing phase. Occurrence of defects is inevitable, but we should try to limit these defects to minimum count. Defect prediction leads to reduced development time, cost, reduced rework effort, increased customer satisfaction and more reliable software. Therefore, defect prediction practices are important to achieve software quality and to learn from past mistakes. Size or complexity measures are simple regression models, which normally assume simple relationship between defects and program complexity. These models are not subjected to the controlled statistical testing required to set up a causal relationship. Fenton and Neil advocate that these models fall short to take account of all the causal or explanatory variables necessitated in order to construct the models generalizable. They presented probabilistic model based on Bayesian belief networks to overcome this problem.

Furthermore, we have presented the use of various machine learning techniques for the software fault prediction problem. The unfussiness, ease in model calibration, user acceptance and prediction accuracy of these quality estimation techniques demonstrate its practical and applicative magnetism. These modeling systems can be used to achieve timely fault predictions for software components presently under development, providing valuable insights into their quality. The software quality assurance team can then utilize the predictions to use available resources for obtaining cost effective reliability enhancements.

There are number of software defect prediction models available but in our study we have arrived on this conclusion that these models heavily depends on the nature ,volume of the defect data and accuracy of classifier and predictors. Most of the researches were carried out with the help of NASA defect data sets. We would like to express gratitude to the NASA MDP organization for making their defect data sets publicly available.

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