Fuzzy Clustering Based Approach for Prediction of Level of Severity of Faults in Software Systems

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Abstract—There is lot of work done in prediction of the fault proneness of the software systems. But, it is the severity of the faults that is more important than number of faults existing in the developed system as the major faults matters most for a developer and those major faults needs immediate attention. As, Neural networks, which have been already applied in software engineering applications to build reliability growth models predict the gross change or reusability metrics. In which majority of faults are found in a few of its modules so there is a need to investigate the modules that are affected severely as compared to other modules and proper maintenance need to be done in time especially for the critical applications. In this present work, hybrid fuzzy-Genetic Algorithm and fuzzy clustering based technique to be studied. Fuzzy clustering Based techniques are also discussed for the comparative analysis in order to predict level of impact of faults in NASA's public domain defect dataset. Predicting faults in the software life cycle can be used to improve software process control and achieve high software reliability. The results show that when the best prediction techniques are evaluated.

Index Terms—Neural network, software faults, software metric, fuzzy clustering, decision tree, k-means, software quality.

I. INTRODUCTION

Faults in software systems continue to be a major problem. A software bug is an error, flaw, mistake, failure, or fault in a computer program that prevents it from behaving as intended (e.g., producing an incorrect result). A software fault is a defect that causes software failure in an executable product. In software engineering, the non-conformance of software to its requirements is commonly called a bug. Most bugs arise from mistakes and errors made by people in either a program's source code or its design, and a few are caused by compilers producing incorrect code. Knowing the causes of possible defects as well as identifying general software process areas that may need attention from the initialization of a project could save money, time and work. The possibility of early estimating the potential faultiness of software could help on planning, controlling and executing software development activities. Prediction of fault prone modules in software development process and mostly used the metric based approach with machine learning

techniques to model the fault prediction in the software modules.

Software Metrics

Metrics is defined as “The continuous application of measurement based techniques to the software development process and its products to supply meaningful and timely management information, together with the use of those techniques to improve that process and its products”. Software metrics is all about measurement and these are applicable to all the phases of software development life cycle from initiation to maintenance.

The IEEE Standard Glossary defines metric as a “Quantitative measure of degree to which a system, component or process possess a given attribute. Amount of incoming pulses needed to activate a neuron also change. This behavior allows the NN to learn. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output.

The main aim of this work is to model the impact of faults in function based software modules. The main objectives are described as follows:

- To find the structural code and design attributes of software systems
- Find the best algorithms that can be used to model impact of faults in object oriented i.e. the predict the level of impact of the faults in the software system

This paper is organized as follows: Section two describes the Methodology part of work done, which shows the steps used in order to reach the objectives and carry out the results. In the section three, results of the implementation are discussed. In the last section, on the basis of the discussion various Conclusions are drawn and the future scope for the present work is discussed.

II. PROPOSED METHODOLOGY

The methodology consists of the following steps:

A. Find the Structural Code and Design Attributes

The first step is to find the structural code and design attributes of software systems i.e. software metrics. The real-time defect data sets are taken from the NASA's MDP (Metric Data Program) data repository <http://mdp.ivv.nasa.gov/>. The dataset is related to the safety critical software systems

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being developed by NASA.

B. Collection & Processing of Metric Values

The suitable metrics like product module metrics out of these data sets are considered. The term product is used referring to module level data. The term metrics data applies to any finite numeric values, which describe measured qualities and characteristics of a product. The term product refers to anything to which defect data and metrics data can be associated. In most cases products will be synonymous with code related items such a functions and systems/sub-systems. The description of the module level metrics are shown in Table 1.

C. Analyze and refine metrics the metric values

In the next step table of module levels metrics PC4_product_module_metrics is joined with PC4_defect_product_relations and thereafter again the join operation of the resultant table is performed with PC4_static_defect_data. An Entity-Relationship diagram relates Modules to Defects and Defects to Severity of Defects is shown in figure 1.

Fig. 1 An entity-relationship diagram relates modules to defects and defects to severity of defects

In the figure 1 the MODULE_ID is the unique numeric identifier of the module and DEFECT_ID is the unique numeric identifier of the associated defect. The SEVERITY field in the PC4_static_defect_data table shows the value that quantifies the impact of the defect on the overall environment in the range of 1 to 5. Where, 1 means most severe and 5 being least severe. For example, severity 1 may imply that the defect caused a loss of functionality without a workaround where severity 5 may mean that the impact is superficial and did not cause any major disruptions to the system.

D. Explore Fuzzy Clustering Technique

It is very important to find the suitable algorithm for modeling of software components into different levels of fault severity in software systems. The following fuzzy clustering algorithm is experimented

TABLE I :MODULE LEVEL METRICS

Metric Name	Description
MODULE	Unique numeric identifier of the product.
LOC_BLANK	Number of blank lines in a module.
BRANCH_COUNT	Branch count metrics.
CALL_PAIRS	Number of calls to other functions in a module.
LOC_CODE_AND_COMMENT	Number of lines which contain both code & comment in a module.
LOC_COMMENTS	Number of lines of comments in a module.
CONDITION_COUNT	Number of conditionals in a given module.
CYCLOMATIC_COMPLEXITY	Cyclomatic complexity of a module.
CYCLOMATIC_DENSITY	Ratio of the module's cyclomatic complexity to its length in NCSLOC.
DECISION_COUNT	Number of decision points in a given module.
DECISION_DENSITY	Calculated as: Cond / Decision.
DESIGN_COMPLEXITY	Design complexity of a module.
DESIGN_DENSITY	Design density is calculated as: $iv(G)/v(G)$.
EDGE_COUNT	Number of edges found in a given module.
ERROR_COUNT	Number of defects associated with a module.
ERROR_DENSITY	Number of defects per 1000 lines of code for a module
ESSENTIAL_COMPLEXITY	Essential complexity of a module.
ESSENTIAL_DENSITY	Essential density is calculated as: $(ev(G)-1)/(v(G)-1)$.
LOC_EXECUTABLE	Number of lines of executable code for a module
PARAMETER_COUNT	Number of parameters to a given module.
GLOBAL_DATA_COMPLEXITY	Global Data Complexity quantifies the cyclomatic complexity of a module's structure as it relates to global/parameter data.
GLOBAL_DATA_DENSITY	Global Data density is calculated as: $gdv(G) / v(G)$.
HALSTEAD_CONTENT	Halstead length content of a module.
HALSTEAD_DIFFICULTY	Halstead difficulty metric of a module.
HALSTEAD_EFFORT	Halstead effort metric of a module.
HALSTEAD_ERROR_EST	Halstead error estimate metric.
HALSTEAD_LENGTH	Halstead length metric of a module.
HALSTEAD_LEVEL	Halstead level metric of a module.
HALSTEAD_PROG_TIME	Halstead programming time metric of a module.
HALSTEAD_VOLUME	Halstead volume metric of a module.
MULTIPLE_CONDITION_COUNT	Number of multiple conditions that exist within a module.
NODE_COUNT	Number of nodes found in a given module.
NUM_OPERANDS	The number of operands contained in a module.
NUM_OPERATORS	The number of operators contained in a module.
NUM_UNIQUE_OPERANDS	The number of unique operands contained in a module.
NUM_UNIQUE_OPERATORS	The number of unique operators contained in a module.
NUMBER_OF_LINES	Number of lines in a module.
PATHOLOGICAL_COMPLEXITY	A measure of the degree to which a module contains extremely unstructured constructs.
PERCENT_COMMENTS	Percentage of the code that is comments.
LOC_TOTAL	The total number of lines for a given module.

Fuzzy clustering:-

Clustering can be a very effective technique to identify natural groupings in data from a large data set, thereby allowing concise representation of relationships embedded in the data. In our study, clustering allows us to group software modules into faulty and non-faulty categories hence allowing for easier understandability. The purpose of clustering is to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. Fuzzy Logic Toolbox command line function fcm starts with an initial guess for the cluster centers, which are intended to mark the mean location of each cluster. Main Steps of fuzzy clustering algorithm:-

Step 1: Calculate the input data to be clusters.

$$X_{ij} \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m$$

n is the number of data

m is the type of data

Step 2: Set the variables value:

$$i - r_j, j = 1, 2, \dots, m$$

$$ii - \eta_{quash \ factor}$$

$$iii - \varepsilon * acceptance \ ratio$$

$$iv - \varepsilon_{reject \ ratio}$$

$$v - X_{j, \min}$$

$$vi - X_{j, \max}$$

Step 3: Set the normal data value based on $X_{j, \min}$ dan $X_{j, \max}$ use with the following model:

Step 4: Set the potential of each data point by the formula:

$$X_{ij}^{norm} = \frac{X_{ij} - X_{j, \min}}{X_{j, \max} - X_{j, \min}}, \quad i = 1, 2, \dots, n; \quad j = 1, 2, \dots, m$$

$$a = 1, \text{ revise } a = n$$

Step 5: Set the highest potential value of data:

$$M = \max_i [p_i] \quad i = 1, 2, \dots, n$$

$$h = i, \text{ so that } D_i = M$$

Step 6: Set cluster centre and update the potential value that correspond to another data:

$$i - Cnt = []$$

$$ii - V_j = X_{hj}, \quad j = 1, 2, \dots, m$$

$$iii - C = 0 \text{ (number of clusters)}$$

$$iv - Cnd = 1$$

$$v - z = m$$

$$vi - Do \ Cnd \neq 0 \text{ and } Z \neq 0$$

Step 7: Put the real data:

$$Cnt_{ij} = Cnt_{ij} * (X_{j, \max} - X_{j, \min}) + X_{j, \min}$$

Step 8: Set the cluster sigma:

$$\sigma_j = \frac{r_j (X_{j, \max} - X_{j, \min})}{\sqrt{8}}$$

Comparison of Algorithms

The comparisons are made on the basis of the more accuracy and least value of MAE and RMSE error values. Accuracy value of the prediction model is the major criteria used for comparison. The mean absolute error is chosen as the standard error. The technique having lower value of mean absolute error is chosen as the best fault prediction technique.

• Mean absolute error

Mean absolute error, MAE is the average of the difference between predicted and actual value in all test cases; it is the average prediction error [13]. The formula for calculating MAE is given in equation 7.

$$\frac{|a_1 - c_1| + |a_2 - c_2| + \dots + |a_n - c_n|}{n} \quad (1)$$

Assuming that the actual output is a, expected output is c.

• Root mean-squared error

RMSE is frequently used measure of differences between values predicted by a model or estimator and the values actually observed from the thing being modeled or estimated [13]. It is just the square root of the mean square error as shown in equation 8.

$$\sqrt{\frac{(a_1 - c_1)^2 + (a_2 - c_2)^2 + \dots + (a_n - c_n)^2}{n}} \quad (2)$$

The mean-squared error is one of the most commonly used measures of success for numeric prediction. This value is computed by taking the average of the squared differences between each computed value and its corresponding correct value. The root mean-squared error is simply the square root of the mean-squared-error. The root mean-squared error gives the error value the same dimensionality as the actual and predicted values.

Fuzzy logic is an effective paradigm to handle imprecision. It can be used to take fuzzy or imprecise observations for inputs and yet arrive at crisp and precise values for outputs. Also, the Fuzzy Inference System (FIS) is a simple and commonsensical way to build systems without using complex analytical equations.

Here, fuzzy logic will be employed to capture the broad categories identified during clustering into a Fuzzy Inference System (FIS). The FIS will then act as a model that will reflect the relationship between the different input parameters.

III. RESULTS AND DISCUSSION

The real-time defect data set used is taken from the NASA's MDP (Metric Data Program) data repository, the details of that dataset contains 178 modules of C Programming language with different values of software fault severity labeled present as 1, 2 and 3. The severity level 4 and 5 are not present in the PC4 dataset. So, the level 1 represents the highest severity, level 2 represents the medium and level 3 represents the minor fault that can be overlooked to save time. Details of the type of

faults existing in different number of modules of the Dataset are shown in bar chart of figure 1 and numeric values are tabulated in table 2.

Fig. 2. Graphical representation of different Severity of Faults in Modules

TABLE II: DETAILS OF THE DIFFERENT SEVERITY OF FAULTS IN MODULES

Severity Level	Count of Modules
1	58
2	40
3	80

The algorithms are evaluated on the basis of the following criteria:

The developed software computes the mean absolute error, root mean squared error, relative absolute error and root relative squared error. However, the most commonly reported error is the mean absolute error and root mean squared error. The root mean squared error is more sensitive to outliers in the data than the mean absolute error. In order to minimize the effect of outliers, mean absolute error is chosen as the standard error. The prediction technique having least value of mean absolute error is chosen as the best prediction technique.

Mean absolute error, MAE is the average of the difference between predicted and actual value in all test cases. The root mean-squared error i.e. RMSE is simply the square root of the mean-squared-error. The root mean-squared error gives the error value as the same dimensionality as the actual and predicted values.

The mean-squared error is one of the most commonly used measures of success for numeric prediction. This value is computed by taking the average of the squared differences between each computed value and its corresponding correct value. The MAE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be larger or equal to the MAE.

The greater difference between them, the greater the variance in the individual errors in the sample. If root mean squared error is equal to mean absolute error, then all the errors are of the same magnitude. Both root mean squared error and mean absolute error can range from 0 to ∞ .

MAE and RMSE are negatively-oriented scores and lower values are better. So, algorithm with least value of mean absolute error is considered as the best algorithm. The training phase performance of the Batch Gradient without momentum, Batch Gradient with momentum, Variable Learning Rate

without momentum, Variable Learning Rate with momentum and Resilient Backpropagation is shown in figure 3-7 respectively.

Fig. 3. Training Performance of Batch Gradient Descent

Fig. 4. Training performance of batch gradient descent with momentum

Fig. 5. Training performance of variable learning rate without momentum algorithm

Fig. 6. Training performance of variable learning rate with momentum algorithm

Fig. 7. Training performance of resilient back propagation

In the present work the five Neural Network based algorithms experimented in Matlab 7.4 and after the training each trained network is tested with testing dataset of 15 values derived from the PC4 dataset. The overall testing performance of the different algorithms is shown in table 3. The results reveal that the fuzzy clustering algorithm have outperformed all other algorithm under study with 0.2982, 0.4200 and 100% as MAE, RMSE and Accuracy values respectively.

TABLE III: PERFORMANCE RESULTS OF DIFFERENT RESILIENT BACK PROPAGATION AND FUZZY CLUSTERING ALGORITHMS

Sr. No.	Algorithm	MAE	RMSE	Accuracy %
1	Fuzzy clustering	0.2982	0.4200	100

IV. CONCLUSION

According to [17], on comparing the classes of WEKA's machine learning algorithms, it is observed that fuzzy clustering algorithm is best prediction techniques as compared with other classes of machine learning algorithms in modeling of severity of faults in software systems. In [19] resilient backpropagation based technique was also introduced. The purposed fuzzy clustering based technique on the basis of testing data with 100, 0.2982 and 0.4200 as Accuracy, Mean Absolute Error and Root Mean Square Error values.

It is therefore, concluded the model is implemented and the best algorithm for modeling of the function based software modules into different level of severity of impact of the fault is found to be fuzzy clustering technique. It is the best prediction technique as compare to the other machine learning technique. it gives more accurate result as compare to the other machine learning techniques. Hence, the proposed algorithm can be used to identify modules that have major faults and require immediate attention.

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