Package Level Test Case Minimization for Bug Prediction using Linear Regression Machine Learning Approach

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DOI: https://doi.org/10.26438/ijcse/v7i6.364370 | Available online at: www.ijcseonline.org

Accepted: 11/Jun/2019, Published: 30/Jun/2019

Abstract— With the growing complexities in Object Oriented (OO) software, the number of bugs present in the software module is increased. In this paper, a technique has been presented for minimization of test cases for the OO systems. The Camel 1.6.1 open source software was used the evaluation of proposed technique. The mathematical model used in the proposed methodology was generated using the open source software WEKA by selecting effective Object Oriented (OO) metrics. Ineffective and effective Object Oriented metrics were recognized by using the techniques based on feature selection to generate test cases that cover fault proneness classes of the software. The defined methodology used only effective metrics for assigning weights to test paths for minimization. The results show the significant improvements.

Keywords: Camel 1.6.1, Test Case Minimization, WEKA

I. INTRODUCTION

Presence of defects in software modules reduces the quality of the software. It is necessary to improve the quality of software by identifying defects and remove them from the software module to deliver reliable software product[1].In testing phase s development team finds the defects present in the software module . It is costly to test the entire software within a limited period of time. As a result, less reliable and defective software is released. It becomes necessary to eliminate software defects within limited time and less cost. Software defect prediction model is one of the solutions to this problem. The use of software defect prediction model is to predict the defects present in the software. To select the minimum number of test cases test case minimization technique is used which are able to reveal more software defects within less time and cost.

The software defect prediction model is skilled by using attributes of the software and fault data according to the previously released software or identical projects. This information is used to calculate whether the software module is defective or not. The effectiveness and performance of software defect prediction model rely on the characteristics of the software attributes that are used to calculate or predict whether defects are present in the software module or not.

A. Organization of this paper

The organization of paper is as follows. In Section II we provide information about the background or related work on software defect prediction using software metrics. In Section III provide details about the methodology used in this paper. In Section IV implementation steps are defined. Section V shows the results. Section VI and section VII shows conclusions and future work respectively.

II. RELATED WORK

In 2016, S. Puranik, P. Deshpande, and K. Chandrasekaran [2] researchers select only the minimum number of software metrics. The researchers proposed an algorithm that predicts the bug proneness index by using marginal R-square values method. The regression testing was perform as mediator step in this given algorithm, it was found that they was different in nature when they compare with the models by using regressions alone.

In 2013, S. Prateek, A. Pasala, and L. M. Aracena [3] performed an analysis to check the effectiveness of the network metrics above code metrics for the prediction of bug. This work was carried out on the 11 datasets from the Open source PROMISE repository [4] by using three different machine learning algorithms. For each project the binary classification model was built to identify the files that contain bugs in different condition. It was seen that the

code metrics was predict better results over the network metrics.

In 2018, A. Singh, R. Bhatia, and A. Singhrova [5] discussed the usage of Object Oriented metrics for fault prediction. The effective metrics was used to determine the quality of the software module. It was concluded that the code metrics needed in minimizing the efforts required in software during the maintenance phase of the software.

In 2018, M. Akour and L. Abuwardih [6] found that a large number of test suite were required to test the software module and different methods were required to reduce the test cases. The study was conduct to deal with the effectiveness of genetic algorithm (GA) in order to reduce the number of test cases. The GA steps were repeated to minimize test suite.

In 2017, D. L. A. L. Gupta and K. Saxena [7] proposed software bug prediction system (SBPS) . The model predicted the bugs present in a class using metrics. The model forecasted the occurrence of bugs in a class during test of the software. They formulate hypotheses corresponding to each metric. The logistic regression classifier gives high accuracy among all classifiers used in this study.

In 2005, R. Ferenc [8] described how to calculate the Chidamber and Kemerer (CK) Object Oriented metrics was used in the detection of fault-proneness of the source code of openly available software systems. The authors check the value obtain against the bugs found in the database containing bugs using machine learning and regression algorithms to confirm convenience of the OO metrics for the prediction of fault-prone classes .

In 2017, A. Boucher [9] presented the hybrid self organizing map (SOM) model using source code metrics to find out the fault prone functions present in software module. The authors used Hybrid SOM model for OO software systems to calculate fault prone code at the class level using OO source code metrics which made it easier to prioritize the efforts of the testing team .

In 2014, S. K. Mohapatra [10] proposed a approach for test case reduction using genetic algorithm with different length of chromosome to decrease test suit by finding representative set of test cases that fulfilled the testing criteria.

In 2017, S. Ali, Y. Li, T. Yue, and M. Zhang,[11] proposed multi-objective uncertainty-wise test case minimization approach. The approach focused on to choose a minimum

number of test cases for execution by maximizing effectiveness e.g. coverage, limited cost, execution time.

In 2013, A. S. A. Ansari, P. K. K. Devadkar, and P. Gharpure, [12] defines a test suite method which was a effective technique that achieve significant reduction in the test suite and also ensure product quality of the software. It reduced the time and cost of regression testing and also reduces the cost of maintenance activity and effort.

In 2018, O. Banias [13] proposed a dynamic programming algorithm that was apply in software testing domain, generally in the selection of the test cases. The authors defines specific problem present in software testing that is running a subset of test suite from the complete set of test suite and the aim is to maximize the probability of finding potential defects present.

In 2014, K. Choudhary [14] proposed a multi objective optimization that deals with the disagreeing objectives. A multi-objective problem was used to find the solution for all disagreeing objectives. The authors focused on the automatic test data generation. One of the objectives was uniform distribution and another was to maximize the code. The approach covered non-dominance property to maintain sub-population of best fitness value.

In 2016, C. Technology, R. Khan, M. Amjad, and A. K. Srivastava [15] proposed path based testing approach covering all du-paths for a given program. The GA was used for automatic test suite generation and optimization purposed against the accepted a set of inputs and checked for the path coverage.

In 2013, S. Sun, X. Hou, C. Gao, and L. Sun [16] combined test case selection with test case prioritization. The reason of test case selection was to check modified impact of programs and dependencies between the programs. Test cases which were selected during the selection phase were ordered for the prioritization of the test cases.

In 2017,Vandana, Ajmer sigh [17] proposed a multi objective optimization technique for minimizing test cases. The authors finds that the use of meta heuristic algorithms with the optimization can reduce the number of redundant test cases and increase in the accuracy of automated testing.

In 2015, V. Gupta [18] proposed a quantitative research and develop a prediction models which uses bug indicators as models input and performed on open source projects namely Ant and Camel. In the research, the results verified that there was considerable correlation exist between the size metrics or bug indicators metrics such as DIT, WMC, CBO, LOC and bugs. The DIT metric took control in achieving better

impact than other bugs predicting metrics such as WMC, CBO and LOC.

In 2018,Rajvir Singh, Anita Singhrova and Rajesh Bhatia [19] proposed an optimized test case generation (TCG) approach. The effective OO metrics were selected and study carried out for the ant-1.7 software. The multivariate linear regression approach was used for generating mathematical model and for giving weights to test paths.

In 2019, Rajvir Singh, Rajesh Bhatia and Anita Singhrova

[20] proposed demand based TCG method that selects the

This present paper is proposes the minimization of test cases at package level and analysis the applicability of proposed

within the budget limitations.

at package level and analyses the applicability of proposed methodology. In the existing techniques, the test suite were generate at the class level.

test scenarios as per contextual demand in terms of

percentage. The optimized test cases were selected to fit

III. PROPOSED METHODOLOGY

The diagram of proposed methodology for the prediction of bugs is shown in Figure 1 given below.



Figure 1 Block diagram of proposed methodology for test case minimization

vii.

Select of the effective object-oriented metrics for bug prediction of the classes of *Camel-1.6.1* open source software using WEKA machine learning tool as proposed by Singh et al. [19]. Then after selecting effective metrics the below steps were followed.

The followed steps are:

- i. Generate the mathematical model of the selected metrics using WEKA tool.
- ii. Input the source file of software under test i.e *Camel* 1.6.1.
- iii. Generate package dependency graph (PDG) by selecting the java files using code-pro analytic plugin for java eclipse.
- iv. Calculate the weights of the package by adding the weights of the classes present in the packages that covered by the individual test paths.
- v. Generate all paths applying breadth first search (BFS) on PDG.

vi. Assign weights to each of the test path using below proposed equation (1):

$$Weight(TPk) = \sum_{i=1}^{n} (Wp_i)$$
(1)

Where, Wp_n is the weight of ith package covered by the test path and i = 1, 2, 3, ..., n. where n is the total number of packages covered by kth test path. Weight (TP_k) is the weight of kth test path and k = 1, 2, 3, ... m. m is the total number of test paths.

- Sort the test paths in decreasing weight values assigned and select the test paths with higher weight values covering 50% of highest weight value.
- viii. Generate final test cases corresponds to selected test paths.

The class level CK Object Oriented metrics has been considered for the fault proneness of classes which in turn have been used to calculate weights of packages. The Metrics data was collect from the publicly available and open access repository known as promise repository [4].*Camel1.6.1* have been used for evaluation of proposed methodology.



Figure 2 Package Dependency Graph of Camel1.6.1 Module

TC8

TC9

TC10

The implementation	of the	proposed	methodology	depicte
in Fig1 is as under:				

Step1. Select effective Object Oriented metrics finding bugs. The OO metrics namely *wmc*, *rfc*, *lcom*, *ce*, *npm*, *loc*, *bug* have been selected and were used for generating mathematical model using Weka tool. The screen shot of generated mathematical model is shown in Figure. 3.

Step2. Generate PDG of the software module *camel1.6.1* using code-pro analytic in eclipse neon for testers as shown in Figure 2.

From the package dependency graph (PDG) in Figure 2, the test cases were generated using BFS method. The test cases generated are given in Table1below:

Table1. All Test Cases					
Test Case ID	Test Case				
TC1	1,6				
TC2	1,5				
TC3	1,4				
TC4	2,1				
TC5	2,1,4				
TC6	2,1,5				
TC7	2,1,6				

Step3. Select test paths using equation (2) generated by using open source software tool known as WEKA. The selection of the test cases based on the value of weight assigned to each test cases. Weights are assigned to each test cases by using linear regression model "(2)" i.e. the values of the weight that are calculated by using model generated in WEKA for *Camel1.6.1* open source software module.

3.5

4.5

4,1,6

Bug = 0.1758 * wmc - 0.0206 * rfc - 0.0008 * lcom - 0.0932 * npm + 0.0018 * loc - 0.0524(2)

The mathematical model represented in Figure. 3, the value of root relative squared error (R2) is 136.6585%.

The table 2 shows the value of weight assigned to the test cases based on mathematical model generated by WEKA represented by equation "(1)" and "(2)". The tests paths are sorted in decreasing order of the weights are shown in Table

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3. The sorted test path help in selecting the optimum test paths.

Step4. The package level test cases have been generating resultant to the selection of test path. In this case study of *camel1.6.1*, Table 4 represents the selected test paths which are selected on the basis of weights value assigned to each

test path. Test case are selected whose value is greater than 50% of highest weight value because of the limited time and less cost requirements.

Table5 represent the selected test cases and their packages detail and table 6 shows the bug revealed by all selected test cases.

0 Weka Explorer Preprocess Classify Cluster Associate Select attributes Visualize Classifier Choose LinearRegression -S 0 -R 1.0E-8 -num-decimal-places 4 Test options Classifier output Use training set Supplied test set Set. Linear Regression Model Cross-validation Folds 10 bug = 50 Percentage split % 0.1758 * wmc + More options... -0.0206 * rfc + -0.0008 * 1com + -0.0932 * npm + 0.0018 * loc + (Num) bua -0.0524 Start Stop Time taken to build model: 0.01 seconds Result list (right-click for options) === Evaluation on test split === 06:15:02 - functions.LinearRegression Time taken to test model on test split: 0.01 seconds 06:20:39 - functions.LinearRegression = Summary ==== 0.0908 Correlation coefficient Mean absolute error 0.8454 2.4724 Root mean squared error 102.7983 % Relative absolute error 136.6585 % Root relative squared error Total Number of Instances 482 Figure 3 Mathematical model All the test cases are generated by using the breadth first search(BFS) are shown in these figures given below: path from src 1 to dst 4 are 14 path from src 1 to dst 6 are 16 Process exited after 0.03073 seconds with return value 0 Press any key to continue . . . Process exited after 0.07755 seconds with return value (Press any key to continue . . . path from src 2 to dst 1 are 21 path from src 1 to dst 5 are 15 Process exited after 0.07779 seconds with return value 0 Press any key to continue . . . Process exited after 0.06059 seconds with return value Press any key to continue . . .

International Journal of Computer Sciences and Engineering		Vol. 7(6), Jun 2019, E-ISSN: 2347-2693			
path from src 2 to dst 4 are 2 1 4		 Total number of faults that is covered by the chosen test cases = 31. The Fault Exposition Potential (FEP) of the chosen 			
		test cases =	80%.	11	
Process exited after 0.09561 seconds with return valu	e	Execution	time reduce	d by 50%.	
Press any key to continue		Hence, it can be concluded that the proposed methodology is			
path from src 2 to dst 5 are 2 1 5	effectiv	ve methodo	ology in tern	ns of FEP.	
	Test Case-ID			Weight Value	
	TC1			4.7438	
Process exited after 0.03099 seconds with return value	TC2			4.4612	
Press any key to continue	TC3			10.0074	
	TC4			10.6780	
path from src 2 to dst 6 are	- 1C5 TC6			10.3882	
216	TC7			10.8420	
	TC8			12.2246	
Process exited after 0.02176 seconds with return value	<u>TC8</u>			5 8742	
Press any key to continue	TC10			10.5540	
path from src 3 to dst 5 are		T (C	Table3. Orde	ered Test Cases	
3 5		Test Cas	e-ID	Weight Value	
		TC5		16.3882	
	TC7			12.2246	
Process exited after 0.09629 seconds with return value 0				10.8420	
Press any key to continue	1C4		1	10.5540	
	TC3			10.0074	
path from src 4 to dst 1 are	TC9			5 8742	
4 1	TC1			4.7438	
	TC2			4.4612	
Process exited after 0.01836 seconds with return value 0 Press any key to continue		TC8		1.4982	
path from src 4 to dst 5 are		Table4. Selec		ted Test Cases	
113		TC4		2 1	
	TC5			2.1.4	
Process exited after 0.07608 seconds with return value 0	TC6			2.1.5	
Press any key to continue	TC7			2,1,6	
	TC10			4,1,6	
path from src 4 to dst 6 are	Table5 Final test apparented				
Ή L D	Table5. Final t		Package L	o cases generated	
	Case-ID	Case	1 acrage Le	even rest Cases	
Process exited after 0.03499 seconds with return value 0 Press any key to continue	T4 2,1 Org.apache.camel.manageme Org.apache.camel.model Org.apache.camel.model		e.camel.management \rightarrow		
	T5 2,1,4 Org.ap		Org.apache	g.apache.camel.management \rightarrow	
			Org.apache	e.camel.model \rightarrow	
V. Results and Discussion	T (215	Org.apache	e.camel.model.dataformat	
The analysis of the results that are obtained by using	5 10	2,1,5	Org.apache	e.camel.management \rightarrow	
proposed methodology is discussed below:			Org.apache	camel language constant	
 Total faults avposed if all the test areas were avecuted 	T7	2.1.6	Org.anache	e.camel.management \rightarrow	
= 39		_,_,0	Org.apache	e.camel.model \rightarrow	
	Org.apache.camel.modify.config				

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T10	4,1,6	Org.apache.camel.model.dataformat \rightarrow		
		Org.apache.camel.model \rightarrow		
		Org.apache.camel.modify.config		

Table6. Bug covered by selected Test Cases

Test Case ID	Test Case	Bug Revealed
T5	2,1,4	31
T4	2,1	23
T6	2,1,5	23
T7	2,1,6	23
T10	4,1,6	12

VI. CONCLUSION

The proposed methodology firstly selected the effective Object Oriented metrics for bug prediction using WEKA tool. The PDG was generated using code-pro for *camel-1.6.1* open source software module. Using BFS test paths were generated. The model is generated using WEKA for the *camel-1.6.1* dataset available at promise repository. Weights values were assigned to each of the generated test case. The final test suite has been generated resultant to selected test paths only which saved time and effort of testing. To fit within the limited time the test cases have been minimized whose FEP = 80% and execution time reduced by 50%. This showed that the proposed methodology is an effective methodology.

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