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Software Defect Prediction Using AWEIG+ADACOST Bayesian Algorithm for Handling High Dimensional Data and Class Imbalanced Problem

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Abstract : The most important part in software engineering is a software defect prediction. Software defect prediction is defined as a software prediction process from errors, failures, and system errors. Machine learning methods are used by researchers to predict software defects including estimation, association, classification, clustering, and datasets analysis. Datasets of NASA Metrics Data Program (NASA MDP) is one of the metric software that researchers use to predict software defects. NASA MDP datasets contain class imbalanced and high dimensional data, so they will affect the classification evaluation results to be low. In this research, data with class imbalanced will be solved by the AdaCost method and high dimensional data will be handled with the Average Weight Information Gain (AWEIG) method, while the classification method that will be used is the Naïve Bayes algorithm. The proposed method is named AWEIG + AdaCost Bayesian. In this experiment, the AWEIG + AdaCost Bayesian algorithm is compared to the Naïve Bayes algorithm. The results showed the mean of Area Under the Curve (AUC) algorithm AWEIG + AdaCost Bayesian yields better than just a Naïve Bayes algorithm with respectively mean of AUC values are 0.752 and 0.696.

1. Introduction

1.1. Research Background

The most important part in software engineering is a software defect prediction [1]. Software defect prediction is defined as a software prediction process from errors, failures, and system errors [2]. Users will be harmed in terms of time and cost if they have built a defective software. In one year the costs incurred due to software defects reached $ 60 billion [3].

Machine learning methods are used by researchers to predict software defects [4] including estimation, association, classification, clustering, and datasets analysis. Of these methods, the classification method is widely used by researchers [5]. The types of classification methods used are Decision Tree [6][7][8], Neural Network [9][10], Naïve Bayes [11][12], and K-Nearest Neighbor [13]. Software metric is data that can be used to detect software that has software defects [14] based on coupling, inheritance, cohesion, complexity, dan size [15]. Datasets of NASA Metrics Data Program (NASA MDP) is one of the metric software that researchers use to predict software defects [16][6]. NASA MDP datasets have been used around 62 researches on the topic of predicting software defects [17]. In NASA MDP datasets, the software that has been measured defect grouped into the class of defect-prone, while software that has no defects goes inside into non-defect prone.

NASA MDP datasets contain class imbalanced [18] and high dimensional data [19], so it will affect the classification evaluation results to be low. Data with class imbalanced is defined by the amount of data in certain classes more than other classes. Amount of data in class non-defect prone on the NASA MDP dataset more than the amount of data in the class defect-prone. Whereas high

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dimensional data is interpreted as NASA MDP datasets have very many attributes.

Several methods that have been used by previous researchers to handle data with class imbalanced are divided into 3 methods, that is data level method, algorithm level method, and ensemble method. [20][21]. In the data level method, data with class imbalanced will be balanced based on data distribution [22], the algorithm level method will be modified to the classification algorithm to strengthen learning in minority classes [23]. The ensemble method is a combination of data level methods and algorithm level methods [21].

Undersampling and oversampling methods are used by researchers to handle data with class imbalanced on data level methods. The majority class in the undersampling method will be deleted and balanced by a number of data on minority classes [24]. While the oversampling method will replace the data by making new data on the minority class so that the amount is equal with the data in the majority class [25].

Fuzzy SVM (FSVM) used to handle data containing data with class imbalanced [26] at the algorithm level method. FSVM apply membership value of Fuzzy. The membership value will be high in the sampling data that does not contain noise or outlier. While the data contains noise or outlier cause membership value will be of low value.

AdaCost algorithm included in the ensemble method. In the AdaCost algorithm, weighting strategies are used to increase the sample weight and decrease the weight of the error sample correctly classified until the distribution of weighted samples between misclassified samples and samples is correctly classified even at each iteration (looping).

High dimensional data on NASA MDP datasets are equipped with stream completion features. Feature selection method is divided into three techniques, that is filter, wrapper, and hybrid [27]. Filter techniques use relevance between attributes based on the intrinsic nature of the data [28], Wrapper techniques choose attributes based on classifier performance evaluations [29], while hybrid techniques combine filter techniques and wrapper techniques. Filter techniques are faster to use compared to wrapper and hybrid techniques, other than that filter techniques increase better and easier to implement than wrapper and hybrid techniques [30].

One of filter technique for selecting relevant attributes in NASA MDP datasets is Average Weight Information Gain (AWEIG) method [31]. Each attribute in the NASA MDP dataset is weighted by Weight Information Gain (WIG) algorithm, then the average value is calculated. The selected attribute is an attribute with a weight value above the average value.

In this study data with class imbalanced will be solved by AdaCost method and high-dimensional data will be handled with Average Weight Information Gain (AWEIG) method. While the classification method that will be used is Naïve Bayes algorithm [17], Naïve Bayes algorithm produce the best evaluation results for prediction of software defects compared to other classification algorithms like C4.5, Decision Tree, Logistic Regression, dan Neural Network. The proposed method is named AWEIG+AdaCost Bayesian.

1.2. Research Background

Based on research background and research problems, the research question is how to improve the evaluation results on application of AWEIG+AdaCost Bayesian methods to handle data with class imbalanced and high dimensional data on prediction of software defects.

1.3. Research Background

The purpose of this research is to develop an AdaCost method for resolving data with class imbalanced and AWEIG method to resolve high dimensional data with Naïve Bayes classifier algorithm for prediction of software defects.

2. Literature Review

2.1. Naïve Bayes Algorithm

Naïve Bayes is one of the most efficient and effective inductive learning algorithms for machine learning and data mining. The simplest form of Bayesian network. Naïve Bayes is one of machine learning method that uses probability methods. The probability of membership can be predicted by classifiers and processes based on the Bayes theorem. Bayesian classifiers have also shown high accuracy and speed when applied to large databases. The equation of Naïve Bayes algorithm written as follows:

$$P(H \mid X) = \frac{P(X \mid H)P(H)}{P(X)} \tag{1}$$

where :

P(H|X) = probability of hypothesis H based on conditions X

P(X|H) = probability of hypothesis X based on conditions H

P(H) = probability of hypothesis H

2.2. AdaCost Algorithm

AdaCost algorithm is a cost-sensitive boosting method to handle misclassification [32] where AdaCost is a variant of AdaBoost algorithm. AdaCost achieve cost sensitivity by weight manipulation of AdaBoost parameter. The weighting strategy is used to increase the sample weight and decrease the weight of the sample error correctly classified until the distribution of weighted samples between misclassified samples and samples is correctly classified even at each iteration (looping).

The equation of AdaCost algorithm written as follows:

$$F(x)=\sum_{t=1}^{T}\alpha_t h_t(x) \qquad (2)$$

where:

$h_t(x)$ = basic or weak classifier

α_t = level of learning

$F(x)$ = results, in the form of final classifiers or strong classifiers

2.3. Weight Information Gain Algorithm

Weight Information Gain (WIG) is a method of weighting each of the most common variables of evaluation attributes [33]. To calculate information gain, first step are understand another rule called entropy. In the field of Information Theory, often uses entropy as a parameter to measure heterogeneity (diversity) of a collection of data samples. If the collection of sample data is increasingly heterogeneous, then the entropy value gets bigger. Mathematically, entropy is formulated as follows:

$$entropy=\sum_i^c - p_i \log_2 p_i \qquad (2)$$

where c is the number of values in the target attribute (number of classes). While stating the number of samples for class of i.

After getting the entropy value for a collection of data samples, the effectiveness of an attribute can be measured. This measure of effectiveness is called information gain. Mathematically, the information gain of an attribute A is written as follows:

$$Gain(S,A)=Entropy(S)-\sum_{v\in Value(A)}\frac{|S_V|}{|S|}Entropy(S_V) \qquad (2)$$

where A is an attribute and V represents a possible value for attribute A, Value(A) Value (A) is the set of possible values for attribute A is the number of samples for value v, |S| total of data, and entropy(Sv) is entropy for samples that have a value of v.

2.4. Average Weight Information Gain Algorithm

Weight Information Gain (WIG) algorithm used only to weight each variable or attribute. As for attribute selection is used Average Weight Information Gain (AWEIG). After the attributes are known for each weight, then the average value of each weighting attribute is calculated (Equation 5). The attribute chosen is the attribute that has a weight above the average value of the weight ($A_N > AVG$).

$$AVG=\frac{A_1+A_2+A_3+...+A_N}{N} \qquad (2)$$

where:

AVG = Average Weight Information Gain

A_N = attribute weight to-N

N = data to-N

3. Proposed Methods

The NASA MDP dataset that is used for software defect prediction contains data with class imbalanced and high dimensional data. AdaCost method proposed for handling data with class imbalanced AWEIG method proposed for handling high dimensional data, then used Naïve Bayes algorithm as a classifier. The proposed method is named AWEIG+AdaCost Bayesian. Figure 1 show AWEIG+AdaCost Bayesian methods. Steps of AWEIG+AdaCost Bayesian methods are as follows:

1. Select one of the NASA MDP datasets containing data with class imbalanced and high dimensional data.
2. The NASA MDP dataset is divided into two parts using the stratified sample method, 70% as training data and 30% as testing data.
3. Calculate the weight of each attribute in the training data with Weight Information Gain method.
4. Calculate the average attribute weight,.
5. Select an attribute with a weight value above the average value of the attribute weight. If the attribute weight is smaller than the average weight value, then the attribute is deleted, whereas if the attribute weight is greater than the average weight value, then the attribute is used as a new dataset.
6. A new dataset that has been selected features
7. Model training using data testing using AdaCost based on Naïve Bayes algorithm.
8. Perform an evaluation by calculating the value of AUC.

The dataset used in this research is the NASA MDP dataset. NASA MDP datasets are used by researchers on the topic of predicting software defects. The dataset used are CM1, KC3, PC1, PC2, PC3, PC4, and PC5. NASA MDP Repository data specifications and attributes are shown on Table 1. The specifications of the NASA dataset attributes are divided into 4 parts, that are LOC count, halstead attribute, McCabe attribute, and miscellaneous attribute. LOC count is the number of lines of code and comments from the program. Halsted attribute is the operand calculation 32 and the operator in the program. McCabe Attribut is cyclomatic complexity in the program.

4. Experimental Result

Experiments carried out using Microsfot Excel for Office 365, SPSS 16.0, and Rapidminer version 7.2.001. The computer specifications used in this study can be seen in Table 2.

In this research, AWEIG+AdaCost Bayesian algorithm will be compared with Naïve Bayes standard algorithm (NB). Measurement of classification evaluation results used is Area Under the Curve (AUC). AUC chosen because of clear statistical interpretation. Measurement of probability in fault-prone class given a higher rating compared non-fault-prone class [33]. In addition AUC has the potential to significantly increase convergence throughout empirical experiments in the prediction of software defects [34], because it separates predictive performance from operating conditions and represents the general size of the prediction.

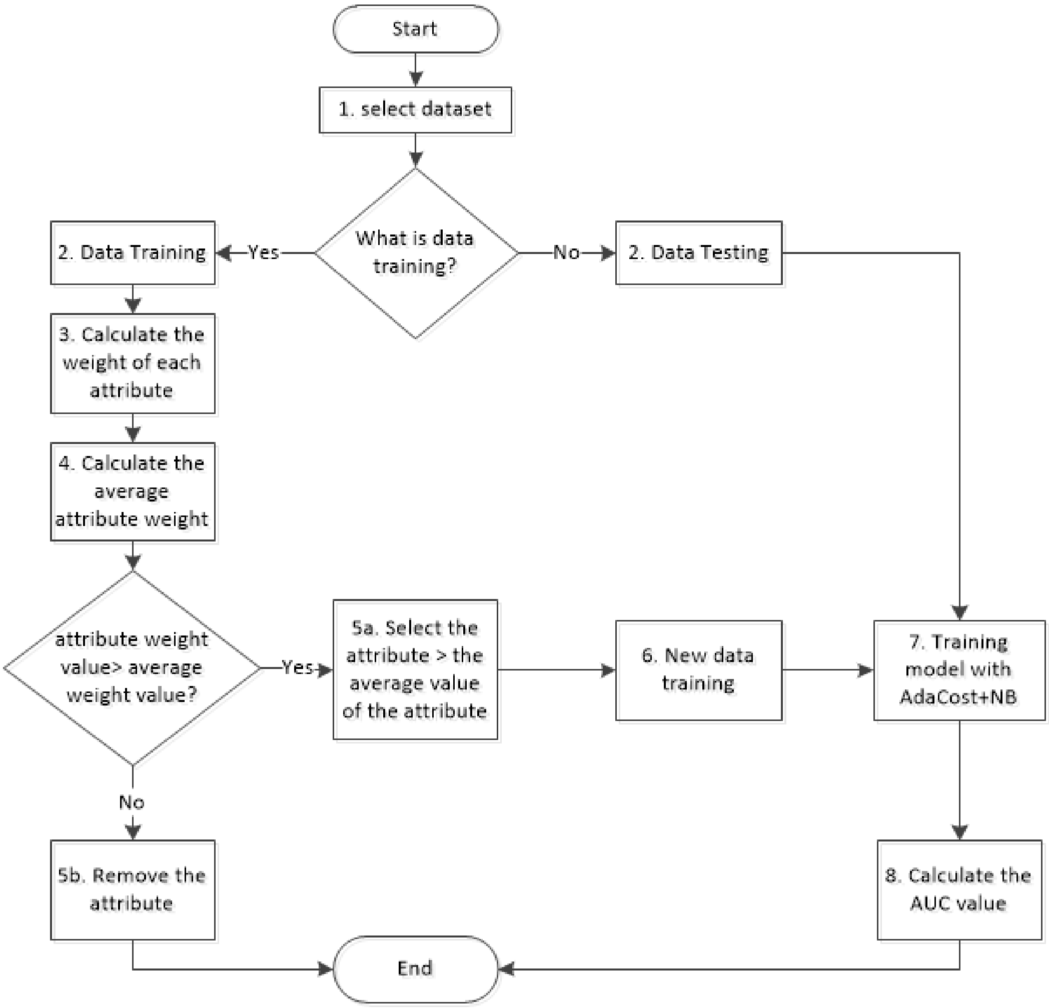

Start
1. select dataset
What is data training?
Yes
No
2. Data Training
2. Data Testing
3. Calculate the weight of each attribute
4. Calculate the average attribute weight
attribute weight value> average weight value?
Yes
No
5a. Select the attribute > the average value of the attribute
6. New data training
7. Training model with AdaCost+NB
5b. Remove the attribute
8. Calculate the AUC value
End

Fig 1. Proposed Methods (AWEIG+AdaCost Bayesian)

Table 1. NASA MDP Dataset Specifications and Descriptions

Datasets	Number of Attributes	Number of Records	Defects (%)	Systems	Language
CM1	38	327	12,84	Spacecraft instrument	C
KC3	40	194	18,56	Field data storage management	JAVA
PC1	38	679	8,10	Satellite flight software	C
PC2	37	722	2,22	Behavior control simulator	C
PC3	38	1.053	12,35	Satellite flight software	C
PC4	38	1.270	13,86	Satellite flight software	C
PC5	39	1.694	27,04	Improved cockpit system security	C++

Table 2. Computer Specifications Used

Processor	Intel® Core ™ i5-6200 CPU @ 2.30GHz 2.40GHz
Memory	4 GB
Hardisk	1 TB
Operating System	Windows 10 Pro 64-bit
Tools	Microsfot Excel for Office 365, SPSS 16.0, dan Rapidminer versi 7.2.001

Paired T-Test used to find out if there are significant differences in calculations of AUC between two models. In Paired T-Test set value α as big as 0,05, if value of p-value bigger than value α then there is no significant difference between models. Whereas if the value p-value smaller than value α then there are significant differences between models.

Measurement results AUC in this experiment can be seen in Table 3 dan Figure 2. Measurement results of AUC recorded based on the results of an experiment in the dataset of CM1, KC3, PC1, PC2, PC3, PC4, dan PC5. Average value of AUC on AWEIG+AdaCost Bayesian algorithm better than Naïve Bayes algorithm, with an average value of AUC each is 0,752 and 0,696. The result of Paired T-Test also shows value of p-value is 0,04 (p-value smaller than value α), so it can be concluded that there are significant differences between AWEIG+AdaCost Bayesian algorithm dan Naïve Bayes algorithm. Result of Paired T-Test in this experiment can be seen in Figure 3.

Table 3. Measurement Results of AUC on AWEIG+AdaCost Bayesian algorithm and Naïve Bayes

No	Dataset	AWEIG+AdaCost Bayesian	Naïve Bayes
1	CM1	**0,800**	0,743
2	KC3	**0,653**	0,646
3	PC1	**0,738**	0,588
4	PC2	**0,715**	0,587
5	PC3	**0,774**	0,759
6	PC4	**0,835**	0,817
7	PC5	**0,749**	0,731

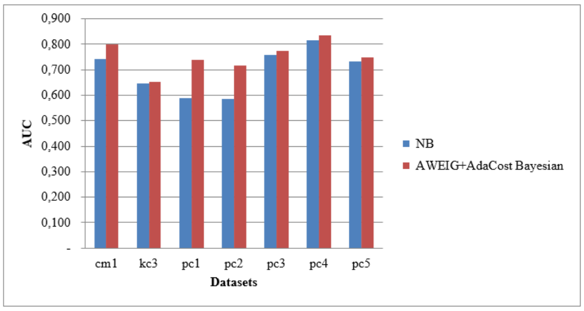
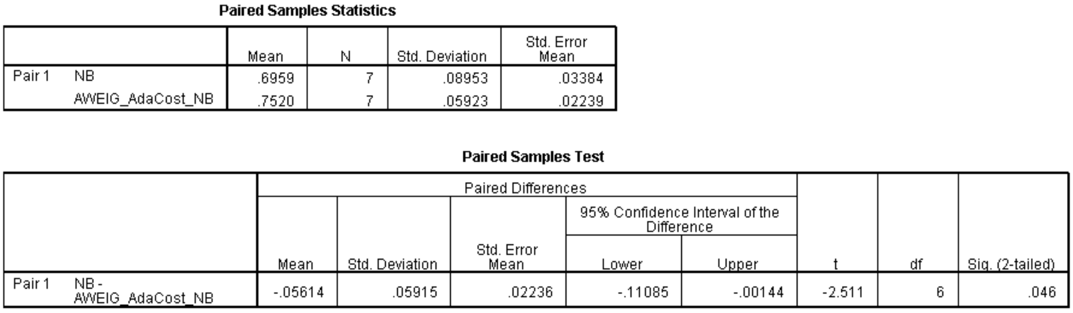


Fig 2. Measurement Diagram AUC on AWEIG+AdaCost Bayesian algorithm and Naïve Bayes



Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	NB	.6959	7	.08953	.03384
	AWEIG_AdaCost_NB	.7520	7	.05923	.02239

Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	NB - AWEIG_AdaCost_NB	-.05614	.05915	.02236	-.11085	-.00144	-2.511	6	.046

Fig 3. Result of Paired T-Test on AWEIG+AdaCost Bayesian algorithm and Naïve Bayes

5. Conlusion

The results showed that AWEIG+AdaCost Bayesian algorithm better than Naïve Bayes algorithm with an average value of AUC are 0,752 and 0,696. Paired T-Test between AWEIG+AdaCost Bayesian algorithm and Naïve Bayes algorithm there are significant differences due to value of p-value (0,04) smaller than α (0,05) value. This research has contributed to the software defect prediction that is handling the problem of high dimensional data and data with class imbalanced. High dimension data is resolved by attribute weighting and attribute selection. The attribute selected is an attribute with a weight value greater than the average value of the attribute weight so that it can handle high dimensional data. While class imbalanced is solved by applying AdaCost method based on Naïve Bayes algorithm.

However, there are several methods that can be done in future research to get better results. The method used for selecting attributes in this study uses filter techniques, so that for future research can be applied wrapper techniques or hybrid techniques. For handling the class imbalanced, can be used another ensemble methods to get better evaluation result.

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