CLASSIFICATION OF ENGINEERING STUDENTS' SELF-EFFICACY TOWARDS VISUAL-VERBAL PREFERENCES USING DATA MINING METHODS

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Abstract

The purpose of this research was to build a classification model and to measure the correlation of self-efficacy with visual-verbal preferences using data mining methods. This research used the J48 classifier and linear projection method as an approach to see patterns of data distribution between self-efficacy and visual-verbal preferences. The measurement of the correlation of engineering students' self-efficacy with visual-verbal preferences using the data mining method approach gets the result that self-efficacy does not correlate with visual-verbal preferences. However, engineering students' self-efficacy influences the achievement of initial learning outcomes. Visual-verbal preference is more influenced by students' interest in images so it can be concluded that self-efficacy affects the initial results of learning but does not have a correlation with visual-verbal preferences. The results of the decision tree provide the results that are easily understood and present a correlation between self-efficacy and visual-verbal preferences in a visual form.
Keywords: *self-efficacy, visual-verbal preferences, data mining.*

Introduction

Every student has different levels of self-efficacy because they have different initial abilities and learning experiences. Self-efficacy influences people 's belief to face failure and try harder in achieving success. Success can build a robust belief in the level of confidence. If someone achieves success easily, then he/she are easily discouraged by failure because the level of confidence requires experience to overcome the problems that occur. The experience gained when dealing with problems becomes capital to help improve self-efficacy (Bandura, 1994). Self-efficacy refers to the ability of someone who uses prior experience references to solve problems (Boswell, 2013). Individuals who have high self-efficacy have high confidence to deal with problems, while individuals with low self-efficacy have fears of facing failure (Wu, Tsai, & Wang, 2011). Students try to process information and appraise their self-efficacy from ability and learning experience. The success of students to overcome problems can increase self-efficacy and reduce failure (Schunk, 2003). Self-efficacy is formed from experience, common experiences, social persuasions, and physiological reactions (Jordan, Amato-henderson, Sorby, & Donahue, 2011). Self-efficacy in the engineering field is very important. Bandura (1997) explained that self-efficacy determines the action to be chosen, how much effort is made to solve the problem, how can they survive in failure and realize the level of self-achievement (Bandura, 1997; Marra & Bogue, 2006). Engineering students need quantitative skills to prepare

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themselves to face problems in engineering courses. Self-efficacy contributes to academic performance even though the factors of problem-solving ability and intellectual ability also influence learning outcomes (Aleta, 2016). The factors that influence confidence in success in engineering students are mastery experiences, vicarious experiences, social persuasions, and physiological states. Classroom and curricular practice influence students' engineering to have self-confidence, retention, and success (Hutchison, Follman, & Bodner, 2005). Bandura revealed that engineering self-efficacy was measured using the developed self-efficacy scale (Bandura, 2006). Carberry et al. (2010) showed three findings to measure self-concept in student engineering, namely (1) measurement design considers the factors of self-efficacy, motivation, anxiety, and outcome expectation; (2) self-efficacy depends on the experience of the engineer students; (3) High correlation between self-efficacy with motivation, expertise and outcome expectation (Carberry, Hee-Sun, & Ohland, 2010).

Engineering courses are often associated with things related to configuration, symbols, codes, and topology. Engineering students have process information based on their preferences. When Engineering students have presented a content consisting of images and text, it will try to process which content matches their preferences (Kurniawan, Setyosari, Kamdi, & Ulfa, 2018). If a student who has visual preferences processes information from the content, then the first time he is looking for is image content. If the content displayed is only in the form of text, he will still try to process information even though the content does not match his learning preferences (Peterson, 2016; Plass, Chun, Mayer, & Leutner, 1998). Visualization is essential in learning. Visualization can simplify the information that is difficult to understand (Sudatha, Degeng, & Kamdi, 2018). A student always has different preferences in processing information. Also, students also have self-efficacy in dealing with problems in the information processing process. Someone who has high self-efficacy tends to be able to make more efforts in processing information if the information presented does not match his preferences. Therefore, research is needed, which aims to identify the self-efficacy that a person has seen from the visual-verbal preferences approach.

Problem of Research

Data mining methods aim to determine the classification model by determining data classes and grouping examples based on similarity attributes. Previous research measured correlation using descriptive statistical methods, such as in the research of measuring cognitive style visualizer correlations to the achievement of learning outcomes in design modeling and performance (Pektaş, 2013). In the research Pektaş (2013) used the analysis of variance analysis (ANOVA) to determine whether cognitive style has any effect on design modelling and performance. However, descriptive statistics method is not optimal for drawing correlations in the form of data visualization so that the tendency of one variable/class cannot be seen. Therefore, the measurement of correlation of self-efficacy to visual-verbal preferences with data mining methods is needed as an alternative method besides descriptive statistical methods. This research was tried to build a classification model for experimental data that has been collected. This research discusses the analytical method for measuring the correlation of engineering students' self-efficacy if it is associated with visual-verbal preferences.

Research Focus

The focus of this research was: (1) building a data mining classification model, and (2) measuring the correlation of engineering students' self-efficacy and visual-verbal preferences using data mining methods.

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Research Methodology

General Background

This study used experimental research with data mining methods for educational data. Data mining in this research is a classification technique assisted by WEKA data mining software (Abernethy, 2010; Witten, Frank, Hall, & Pal, 2017) and Orange data mining (Demšar et al., 2013). Data mining classification in this research uses decision tree-J48 (WEKA) and Linear Projection (Orange) classification techniques. WEKA data mining provides various methods for classifying (Kabakchiev et al., 2017). This research used Decision Tree-J48 to do classification. Decision tree-J48 is the implementation of the C4.5 algorithm in WEKA data mining. The C4.5 algorithm has a method for breaking nodes into several nodes based on the similarity of attribute data. Linear projections provide an overview of the linearity correlation between engineering students' self-efficacy and visual-verbal preferences displayed in graphical form.

Sample

Participants in this research were 250 engineering students, with details of 72 female participants and 178 male participants, as shown in Table 1.

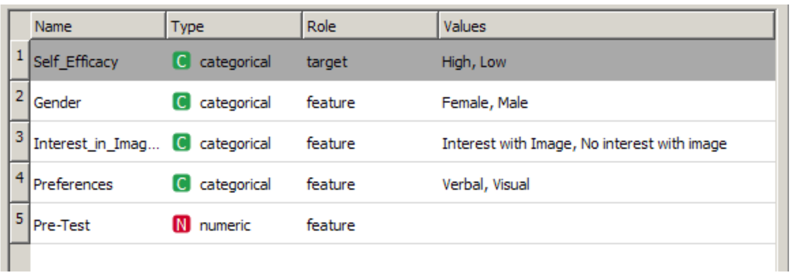
Table 1. Distribution of participant.

Self-Efficacy	Preferences		
	Verbal	Visual	Total
High Self-efficacy			
Female	4	28	32
Male	26	47	73
Low Self-efficacy			
Female	12	28	40
Male	28	77	105

Figure 1 shows the preferences and attributes of self-efficacy for each gender, where participants who had high self-efficacy consisted of 32 female and 73 male. Participants who had low self-efficacy included 40 female and 105 male. Preference has two attributes, namely visual and verbal, while self-efficacy has two attributes, namely high and low. The measurement of the self-efficacy scale uses the self-efficacy instrument developed by Bandura (2006), where students who obtain value on means from the measurement results are grouped into groups of students with high self-efficacy, while students who obtain the value under means from the measurement results grouped into groups of students with low self-efficacy.

Instrument and Procedures

Participants in this research were given several tests aimed at measuring the preferences of visual-verbal, self-efficacy, and pre-tests. Test results were processed using data mining methods, namely decision trees, and linear projection classifications. Visual-verbal preference was measured using a visual-verbal questionnaire (VVQ) developed by Richarson (1977) which contained the VVQ category (Richardson, 1977) and Kirby (1988) that developed question item of VVQ (Kirby, Moore, & Schofield, 1988).   While the self-efficacy measurement used a self-efficacy questionnaire (Bandura, 2006). Meanwhile, the analysis of the pre-test results in this research has used the questions given in the Cisco Networking Academy Program, Chapter 1 to measure the initial value of the pre-test (Cisco Systems, 2003). Data mining process data classified into five classes, each of which is self-efficacy, gender, interest in images, preferences, and pre-test results, can be seen in Figure 1.



	Name	Type	Role	Values
1	Self_Efficacy	C categorical	target	High, Low
2	Gender	C categorical	feature	Female, Male
3	Interest_in_Imag...	C categorical	feature	Interest with Image, No interest with image
4	Preferences	C categorical	feature	Verbal, Visual
5	Pre-Test	N numeric	feature	

Figure 1. Class of data.

Self-efficacy has two attributes, namely “high” and “low,” gender has two attributes, namely “male” and “female,” image interest has two attributes, namely “interested” and “not interested,” preference has two attributes, namely “verbal” and “visual.

Data Analysis

The classification phase in data mining consists of three stages, namely (1) experimental data; (2) modelling; (3) evaluation (Demšar et al., 2013). Experimental data were presented data in five classes and their attributes. Experimental testing data use 10-fold cross validation because this test is effective for limited data (Kabakchiev et al., 2017). The classification developed in this research can be seen in Figure 2.

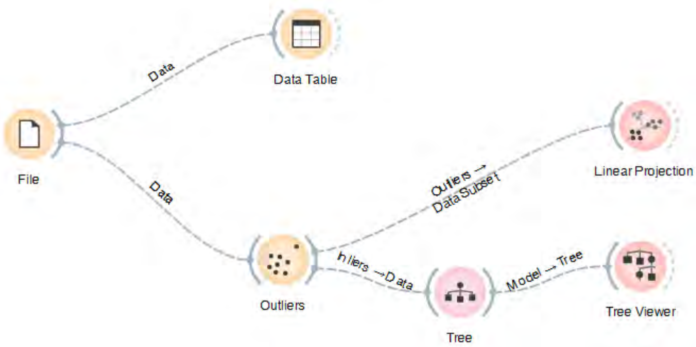


Figure 2. Classification model.

When the classification algorithm functions, data were distributed in two data sets consisting of training data and test data. The algorithm runs ten times and produces a classification model, as shown in Figure 3.

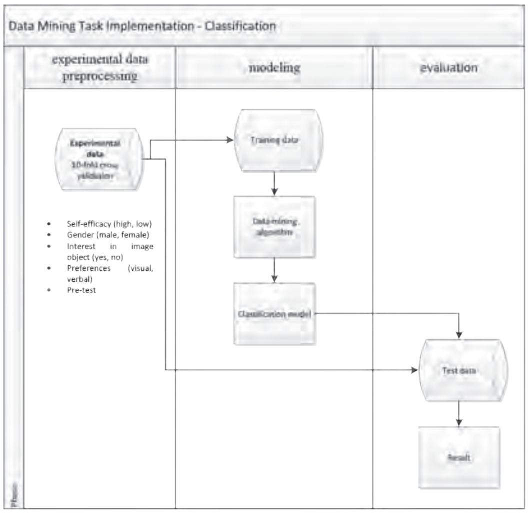


Figure 3. Data mining task implementation-classification.

The model classification in Figure 2 shows the class of data grouped based on the similarity of attributes to form a decision tree model. Outliner data were processed by the linear projection method. This method displays linear projections from classes labelled data. The projection in question is to generalize graphical projections and consider the effect of projections on geographical objects (Orange Data Mining, 2015). Rules classify attributes and attributes by making algorithm models in decision making. The algorithm for building a decision tree model can be seen in Figure 4.

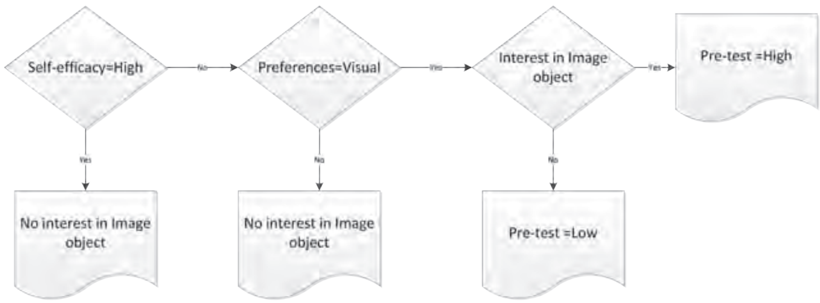


Figure 4. Model of a decision tree classifier.

The decision tree model in this research predicted the possibility of a class formed by the attributes possessed by the instance. The class was the status owned by the instance. The Class is often referred to as conclusions from data. Attributes were information that a class has. The decision tree model can be seen as follows:

If self-efficacy=’high’ then interest in image object=’no’
Else if preferences=’ visual.’
If self-efficacy=’high’ and preferences=’ visual ‘then interest in the image object
Else if pre-test=’high’

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Research Results

The number of instances in this research was 250 data instances. Each instance has a class, namely self-efficacy, gender, interest in the object image, and preference. This research uses data mining methods with classification techniques to identify classes, attributes, and examples. Research data can be seen, as shown in Figure 5.

	Self_Efficacy	Gender	est_in_Image_0	Preferences	Pre-Test
1	High	Male	Interest with Ima...	Visual	77
2	High	Male	No interest with I...	Visual	77
3	High	Male	Interest with Ima...	Visual	80
4	High	Male	Interest with Ima...	Visual	85
5	High	Male	Interest with Ima...	Visual	75
6	High	Male	Interest with Ima...	Verbal	90
7	High	Male	No interest with I...	Verbal	80
8	Low	Male	Interest with Ima...	Verbal	65
9	Low	Male	No interest with I...	Visual	60
10	Low	Male	No interest with I...	Visual	70
11	High	Male	Interest with Ima...	Visual	80
12	Low	Male	No interest with I...	Visual	77
13	Low	Male	Interest with Ima...	Visual	65
14	Low	Male	No interest with I...	Verbal	85
15	Low	Male	Interest with Ima...	Visual	75
16	High	Male	Interest with Ima...	Visual	90
17	Low	Male	Interest with Ima...	Visual	80
18	Low	Female	Interest with Ima...	Visual	75
19	Low	Female	Interest with Ima...	Visual	80
20	High	Male	Interest with Ima...	Visual	65
21	Low	Male	No interest with I...	Verbal	65
22	Low	Male	No interest with I...	Visual	65
23	Low	Male	Interest with Ima...	Visual	75
24	Low	Male	No interest with I...	Visual	80
25	High	Female	No interest with I...	Visual	80
26	High	Male	Interest with Ima...	Visual	65
27	Low	Male	Interest with Ima...	Visual	77
28	Low	Male	No interest with I...	Visual	80
29	Low	Male	No interest with I...	Visual	65
30	High	Female	No interest with I...	Visual	80
31	High	Male	Interest with Ima...	Verbal	80
32	Low	Female	No interest with I...	Visual	80
33	Low	Female	Interest with Ima...	Visual	75
34	Low	Male	No interest with I...	Visual	77
35	Low	Female	Interest with Ima...	Visual	80
36	High	Female	Interest with Ima...	Visual	80
37	High	Female	Interest with Ima...	Visual	85
38	Low	Male	No interest with I...	Verbal	65
39	Low	Female	No interest with I...	Verbal	80
40	Low	Male	Interest with Ima...	Visual	75
41	High	Female	Interest with Ima...	Visual	77
42	High	Male	Interest with Ima...	Verbal	90
43	Low	Female	Interest with Ima...	Visual	80
44	Low	Male	No interest with I...	Verbal	70
45	Low	Male	Interest with Ima...	Verbal	70
46	Low	Male	No interest with I...	Visual	80

Figure 5. Instance data of the research.

Figure 5 shows an example of data in each class with each pre-test value. The Class has 105 high-value attributes, while the class that had a “low” attribute has an instance of 145. The distribution of self-efficacy can be seen in Figure 6.

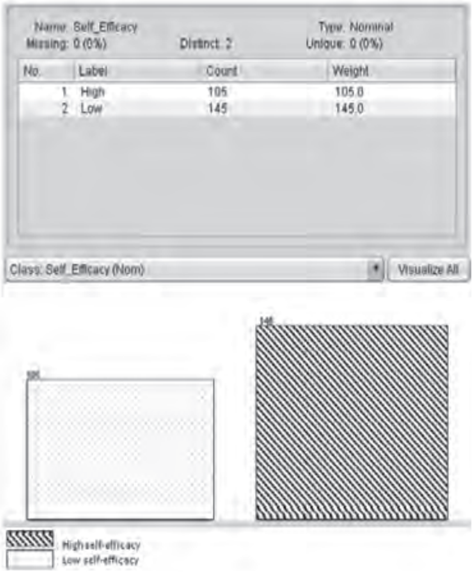

Figure 6. Class of self-efficacy.

The Class “gender” had a distribution of ‘male’ attributes consisting of 178 instances and ‘female’ consisting of 72 instances. The distribution of the class “gender” can be seen in Figure 7.

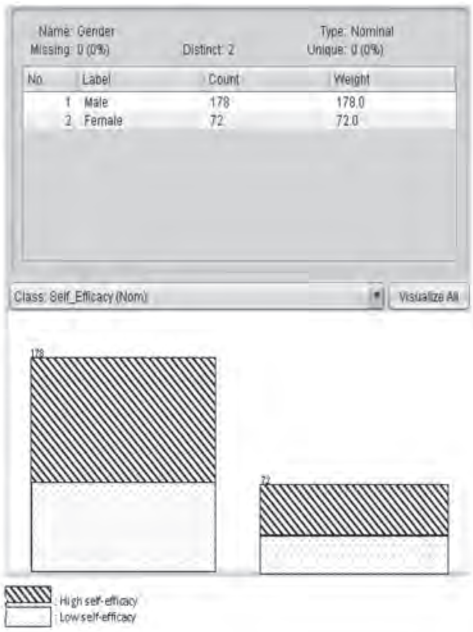

Figure 7. Class of gender.

Class “interest in the image” had a distribution of attributes ‘yes’ consisting of 145 instances and ‘no’ consisting of 105 instances. The distribution of the class “interest in the image” can be seen in Figure 8.

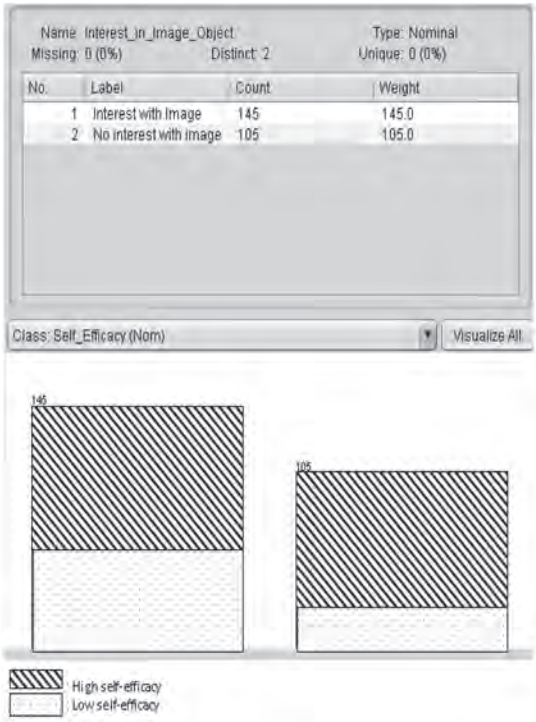

Figure 8. Class of interest in the image.

Figure 9 shows that class "preferences" had a distribution of 'visual' attributes as many as 180 instances, while 'verbal' attributes have as many as 70 instances.

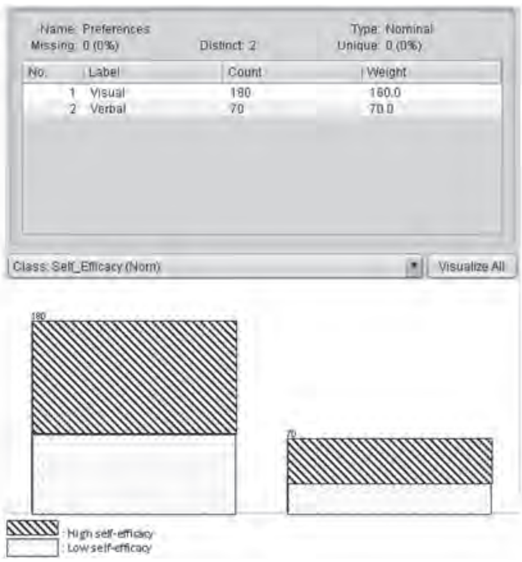

Figure 9. Class of preferences.

Participants involved in this research then followed the pre-test to test the initial ability level. The minimum value obtained by participants was 60, and the maximum value obtained is 95, where the mean value is 76.288, and the standard deviation is 8.184, as shown in Figure 10.

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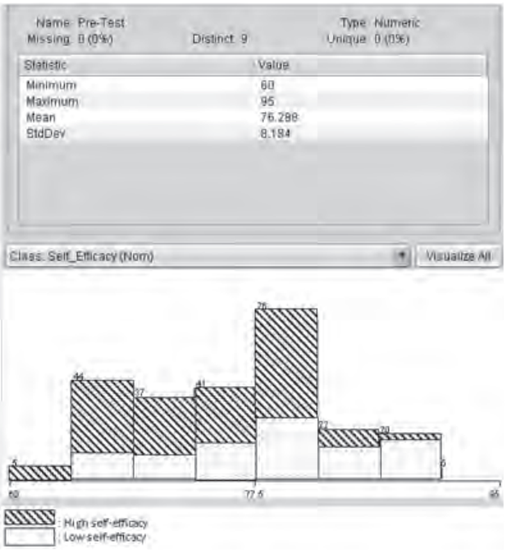

Figure 10. Means of pre-test.

J48 Classifier Analysis

The J48 classifier is a data mining method that implements a C4.5 algorithm to build a decision tree model. The decision tree model is created to form a classification model (Bhuvaneswari, Prabaharan, & Subramaniyaswamy, 2015). The level of accuracy obtained in this research is 66%, and the mean absolute error (MAE) is 0.3855. MAE serves to measure the accuracy of predictions by averaging errors (the absolute value of errors). The analysis process in this section uses WEKA data mining to form a classification model. The classification process in WEKA data mining produces a confusion matrix. The confusion matrix is a method for measuring classification performance. The classification system performance describes how well the system classifies data. The confusion matrix can see the results of 2 lines. The first line, “41 64” shows that there are (41 + 64) instances class self-efficacy ‘high‘ and all right are classified as self-efficacy ‘high.‘ In the second line, “21 124” shows that there are (21 + 124) instances class self-efficacy ‘low‘ and all are classified as self-efficacy ‘low,‘ as in Figure 11.

```
J48 pruned tree
------------------

Pre-Test <= 85
|   Interest_in_Image_Object = Interest with Image
|   |   Pre-Test <= 80: Low (108.0/47.0)
|   |   Pre-Test > 80: High (16.0/3.0)
|   Interest_in_Image_Object = No interest with image: Low (101.0/21.0)
Pre-Test > 85: High (25.0/1.0)

Number of Leaves  :     4

Size of the tree :      7


Time taken to build model: 0.07 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         165               66      %
Incorrectly Classified Instances        85               34      %
Kappa statistic                          0.2604
Mean absolute error                      0.3855
Root mean squared error                  0.4489
Relative absolute error                 79.1021 %
Root relative squared error             90.9317 %
Total Number of Instances              250

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.390    0.145    0.661      0.390    0.491      0.281    0.706     0.663     High
                 0.855    0.610    0.660      0.855    0.745      0.281    0.706     0.727     Low
Weighted Avg.    0.660    0.414    0.660      0.660    0.638      0.281    0.706     0.700

=== Confusion Matrix ===

   a   b   <-- classified as
  41  64 |   a = High
  21 124 |   b = Low
```

Figure 11. Confusion matrix.

Data visualization Analysis

The research used data visualization with a decision tree and a linear projection approach to obtain a classification model. Linear projection is a machine learning method that refers to the number of populations from an instance. The linear projection method presents information about statistical correlations, about the linearity of specific aggregate values. Learning preferences of students have a relationship with student interest in images, while the level of self-efficacy does not correlate with the visual-verbal preferences, as shown in Figure 12.

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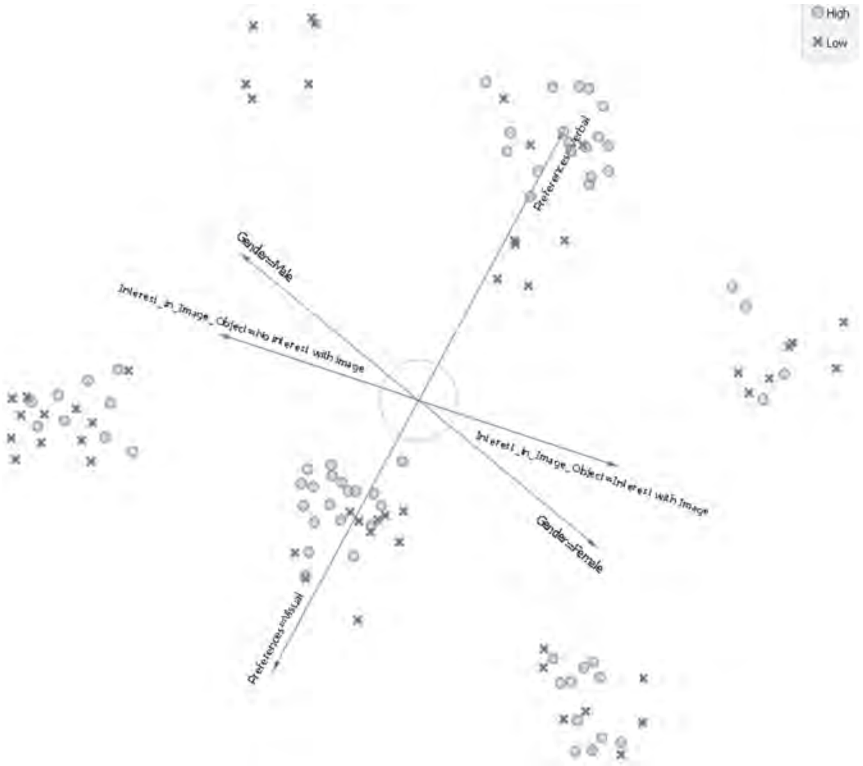

Figure 12. Linear projection of data visualization obtained for the data class.

Figure 12 shows that male students have more interest in images when compared to female students. The result is reinforced by the results that show that male students who have visual preferences have more numbers compared to female students. Grouping in the decision tree is divided based on the value of achievement on the results of the pre-test, consisting of two groups, namely students with a value of> 85 and students with a value of ≤ 85. Students who have pre-test> 85 have high self-efficacy. Whereas in students who have the results of pre-test ≤ 85 are distinguished based on the students' interest in the image, as shown in Figure 13.

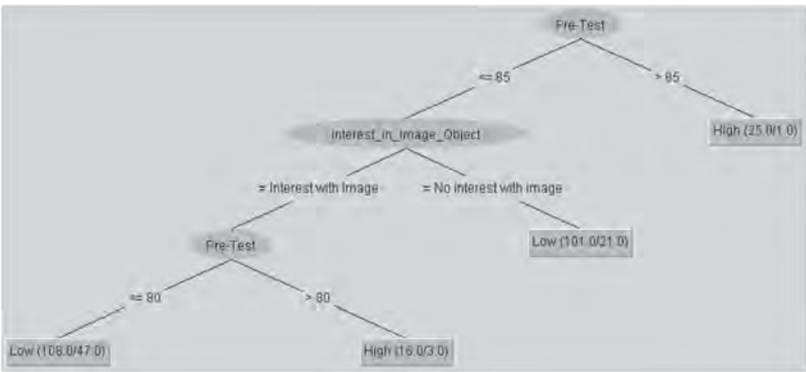

Figure 13. The Decision tree of correlation learning outcomes with the results of the pre-test and self-efficacy.

Figure 13 shows that interest in images can affect the results of pre-test (> 80) if students have high self-efficacy. So, it can be concluded that high self-efficacy directly affects the achievement of the pre-test results, on the other hand, the interest in images and visual-verbal preferences do not influence the achievement of the results of the pre-test. Students who have visual preferences with interest in images can get good pre-test results if there is a high self-efficacy factor.

Discussion

This research showed that participants who have a low level of self-efficacy are 58%, and participants who have a high level of self-efficacy are 42%. However, the results of the research showed that there is a correlation between the level of efficacy of visual-verbal preferences, as indicated by the variation of the results obtained, as shown in Figure 14.

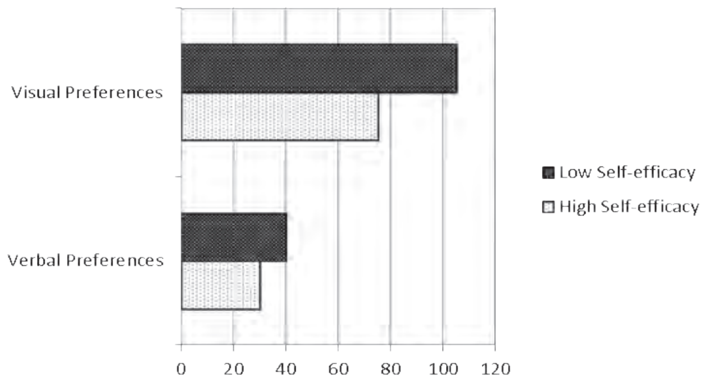

Figure 14. Overall accuracy of classifiers.

The decision tree method can present a correlation and classification model based on the similarity of attributes of data instances. It is consistent with previous research that shows that this method can help establish a classification model for experimental data (Kabakchiev et al., 2017). The classification model classifies data instances with their respective attributes (Demšar et al., 2013; Singh, Naveen, & Samota, 2013). The decision tree method in this study can predict groups in each example where each sample is grouped according to the associated agreement (results see Figure 13). It agrees with Apte and Weiss (1997), which state that classifications in data mining are used to predict problems and group problems based on the objectives to be used (Apte & Weiss, 1997). Decision tree involves the use of training sets to build problem prediction models and classify input data (Singh et al., 2013). The classification model was developed based on predictive algorithms by classifying populations into branches consisting of root nodes, internal nodes, and leaf nodes (Yan-yan Song & Ying Lu, 2015).

An additional alternative method that can be used is the linear projection method. Linear projection can display statistical projection information and describe the tendency of one class to another class. The implementation of data mining methods, such as decision tree-classification, and linear projection, are beneficial for measuring correlations between classes and attributes of experimental data.

This research found that self-efficacy affected the results of the pre-test which agreed with what was revealed by Abosede and Adesanya, who revealed that self-efficacy influences performance and problem-solving abilities (Abosede & Adesanya, 2017). Other studies also found results that engineering self-efficacy had a significant correlation with academic achievement (Aleta, 2016).

Conclusions

Classification techniques in data mining methods designed to classify data instances aim to build a classification model for experimental data. Classification forms a decision tree to group data instances based on attribute attributes. The class results of the class form the model according to the prediction of the problem presented. This research involved engineering self-efficacy towards visual-verbal preferences about the results of the pre-test. There is a need for analysis of experimental results such as self-efficacy towards the tendency toward visual-verbal. This research proposes an alternative method to measure the correlation of self-efficacy with a visual-verbal preferences approach called the J48 classifier technique and linear projection.

J48 classifier is an algorithm used to construct a decision tree with a statistical classifier, while a linear projection presents information about the correlation of linearity to several measured variables. The measurement results show that self-efficacy correlates with the results of visual-verbal preferences. The proposed method can also be applied to the measurement of correlation with more classes and large data instances in the database. This research found that data mining methods, especially decision trees, were able to be used in analysing correlations between several variables. The decision tree method can be used as an alternative method besides the statistical method in measuring the correlation between variables. Further research is expected to develop other data mining methods specifically for processing educational data.

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