Chapter

Risk Management Techniques

*Hafeth I. Naji, Rouwaida Hussein Ali
and Ehsan Ali Al-Zubaidi*

Abstract

The importance of risk management has been increasing for a lot of construction projects in different industries, and thus risk management department must be established to monitor the risks. The construction industry and its managers are exposed to a high degree of risk that leads to increasing the cost or delay in the projects. Therefore, there must be techniques used to control the risk and determine the best method to respond to it. Artificial intelligence and its techniques will be described includes the principle of and its advantages, types and the techniques that used for the classification that includes, decision tree and K-star, neural network and support vector machine and simulation techniques like system dynamic and also using optimization techniques, Particle swarm, Gravitational Search Algorithm as follows: Classification (decision tree, K-star, neural network, support vector. Machine and).

Keywords: risk, risk management, techniques, classification, neural network

1. Introduction

The concept of risk management includes two parts: the first one is the management, and the meaning of management is planning, organizing, and protecting; while the other part which is risk is the variability of what is expected [1].

Risk management is defined as the process that is able to find the risks and analyze these risks using a suitable method and then put the appropriate response to eliminate those risks or reduce them, thereby increasing the success of the project and the achievement of its goals [2].

Risk management is also defined as the process that enables the analysis and management of risks related to the project and its aim is to reduce the risk that threatens the goal of the project and hence it takes the responsibility of increasing the opportunity for the competition of the project in time, cost, and quality [3]. Risk management techniques are considered to be very important and there are a lot of techniques, especially artificial intelligent techniques.

Artificial intelligence is defined as the process of studying systems which behave in an intelligent manner as an observer to another. AI includes the use of tools depending on the intelligent behavior of human beings and other animals too in order for the complex problems [4].

AI is interested in artifacts intelligent behavior, which includes understanding, thinking, learning, communicating, and working in environments which are complex. In general, the utmost objective of AI is the process of perceiving the development of tools and mechanisms that can behave as humans behave or even better. Another objective of AI can be known which can as comprehension behavior, whether it appears in machines or in humans that mean simulate the human's behaviors. Thus, AI contains both scientific and engineering objectives [5]. Various references discover in the scientific literature that artificial intelligence integrates with project management areas are based on the artificial intelligence, project success estimation, critical success factors identification, project budget Relatedness, project schedule connection planning of the project, and risk identification relatedness [6].

Artificial intelligence include the classification techniques.

2. Classification

Classification, as described in statistics and machine learning, is the identification of a group of categories (subpopulations) to identify a new category, depending on the o training set of data that have the same instance whose classes are already known. For instance, if an email is to be assigned as spam or nonspam or diagnosis of a specific patient by certain disease based on known features of the patient like gender, the symptoms that he has and blood pressure, in another word, can be said that classification is a symbol of pattern recognition [7].

Classification is the process of training the objective function f in which each attribute x is a map to class label y that is already known. Resulting in a group of records which is the training set (training set), I every and each record includes a collection of attributes, in which the class is among one of them [8].

The model classification can be used for the following.

I. Descriptive modeling: the model of classification can work as a caption tool to show the difference between different classes with the same objects.

II. Predictive modeling: in this type of classification model, a label of the class that belongs to unknown data can be predicted [8], as shown in **Figure 1**.

The methods used in classification can be split into two categories as parametric and nonparametric problems. As a matter of fact, the basis of the parametric method is on the assumptions that the population normally distributed and the parameters are assessed to solve the problem [9]. On the other hand, there are no assumptions made about the distributions in the nonparametric methods and hence the distribution is free [10].

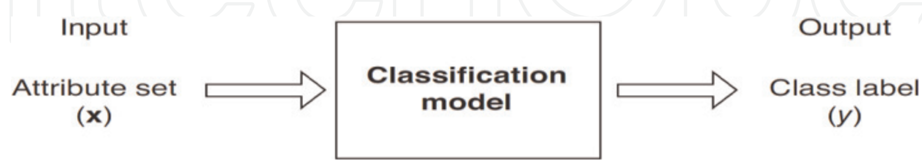

Figure 1.
Process of training the objective function f in which each attribute x is mapped.

3. Classification techniques

The classification techniques are as follows.

3.1 Decision tree

The decision is supported by using a tool like a decision tree by using the graph as a tree or modeling a variety of decisions and their potential effects, which include several examples of the outcomes of a chance event, costs of the resource, and utility [11].

Decision trees are usually used in the research of operations, more specific in analysis of the decision, to assist in the identification of the most of the strategies used to reach a goal, but they are a very popular tool to use in machine learning [11].

The induction of the decision tree is to learn the decision trees from the row of training in the class that is already labeled. A decision tree as can be considered as a flowchart, for instance, tree structure, in which the internal node stands for test on an attribute, and the outcome of this test is represented by the node of the leaf containing a class label [12].

3.2 K-star algorithm

An instance-based classifier called K-star or K*, is a class of the instance in the test step depending on the similar instance in the training step, as found by the function of the similarity. The difference between this algorithm and other instance-based learners is that this one uses a distance based on the entropy function. Classification based on the instance-based learners is made by comparing the instance to database examples that are previously classified. The basic assumption is that instances with similar classifications will be similar too. "Similar instance" and "similar classification" can be defined as follows: the instance-based components are the distance function that identifies the similarity between the two instances, and the classification function assigns how the instance similarities yield a final classification to classify the new instance. The entropic measure is used in K-star algorithm, depending on the likelihood of an instance transforming randomly into another by selecting among all potential transformations. The distance of the instance by using entropy as a meter is very helpful and the distance between the instances is measured with the help of the information theory. The distance between the instances is actually represented by the transformation complexity of one instance into another. It is being accomplished into two parts: first, a limited group of transformations is identified, which will assign one instance into another. Later, one instance (a) is tranformed to another instance (b) with the help of programs in a limited transformations sequence, beginning at (a) and ending at (b). A collection of points that is unbounded is given and a group of transformations that previously defined T is defined; group T has the value of. This t will be assigned as t: I → I. To assign instances with it, σ is used in the T (σ(a) = a). σ ending P, the group of all codes of the prefix from T*. Transformation on I is identified by members of T* and of P uniquely.

For the employment of the classifier for the instance-based of a that employs the distance measure of entropy, there is the necessity of a method to select values for the $x0$ parameters for attributes that are real and s for the attributes that are symbolic, as method employment the values returned by the measure of distance to give a prediction.

For every dimension, the selection of values must be made to the $x0$ parameters (for attributes that are real) and s (for attributes that are symbolic). The distance measure attitude as changes in these parameters is interesting. Function P* that considers the efficient number instances can be calculated using the expression[13]:

$$n0 \le (\sum_b p * \frac{\frac{b}{a}}{\Sigma_b p * (\frac{b}{a})^{\wedge}2)} \le N \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots$$

where N is considered to be the whole number of instances in the training and the instance number is in the training with the distance that considers the smallest from an (in this attribute).

Value for $x0$ (or so) is being selected by the K* algorithm, $n0$, and N with a number in between is selected and overturn the above expression. The nearest neighbor algorithm will be obtained by choosing $n0$ and weighted instances by choosing N. For convenience, the blending parameter "b" is used to specify the number in which the blending is different for $n0$, b = 0% and for N, b = 100%, with values of intermediate and linearly interpolated [13].

3.3 Neural network

The neural network is an analogous, information that considers distributed processing structure being composed of a processing element (which can have a local memory and implement operations that are considered as localized information processing) interrelated together as connections by using unidirectional signal channels. Each output is rlated to one element that connects with branches ("fans out") into many collaterals as like (everyone has the same signal which is the output signal of the processing element) [14].

3.4 Support vector machine

In COLT-92 by Boser, Guyon and Vapnik introduced support vector machine (SVM). Since that time, it has become popular. This algorithm was theoretically developed from the theory of the statistical learning, and it considers the well-motivated algorithm since the 1960s [15].

Pattern classification consider the main problem that deals with, that means different types of patterns is classified using this algorithm. Now, different sort of pattern exists, i.e., linear and nonlinear. Patterns that are linear can be distinguished easily or are able to be separated in low dimension easily, and on the other hand, the patterns that are nonlinear cannot be distinguish easily or are not able to be separated easily, and thus these patterns sorts require manipulation in order to be easily separated [15].

The SVM main idea is the formation of a hyperplane that is considered an optimal, that is, able to be used for classification, in order to split the linear patterns. The selection of the optimal hyperplane is based on the selection of a hyperplane among the group of hyperplanes for the classification of the patterns in which the hyperplane margin is maximized like the distance between the nearest point of each pattern and the hyperplane. The main goal of SVM is that the margin is maximized in order and the process of the classification is preformed correctly of the given patterns, i.e., when the margin size is larger, the classification of the patterns is more accurate [15, 18]. The hyperplane equation:

$$\text{Hyper plane, } aX + bY = C \ldots\ldots\ldots\ldots\ldots\ldots$$

The pattern that is given by using kernel functions is able to be assigned to higher space of dimension; the function of the kernel is $\Phi(x)$. I.e. $x\ \Phi\ (x)$, the various functions of kernel election are very necessary for the classification using SVM; usually, the functions of the kernel that are used contain RBF, linear sigmoid, and Poly. For example [14].

The Poly Kernel function equation is given as [14]:

$$K(x, y) = <x, y>^{\wedge}p \ldots\ldots\ldots\ldots\ldots\ldots$$

The basic concept of support vector machine is that a group of training sample is given (a) that contains a distributed sample which is considered identical and independent; the sample has xi, in which xi belongs to the Rd, and yi belongs to the

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{−1,1} and they both as {(xi,yi)}N i = 1, and they both refer to the classification input and output. The object is to determine wT.x + b = 0 that consider a hyperplane equation, in which two various samples are being split accurately. Hence, problem-solving with the classification that considers optimal is translated into quadratic programming for problems-solving. The search for a partition hyperplane is to maximize the area of bilateral blank (2/||w||), which means the weight of the margin has to be maximized. It is expressed as [14]:

$$\text{Min } \Phi(w) = \tfrac{1}{2} \| w \| 2 = \tfrac{1}{2} (w, w) \ldots\ldots\ldots\ldots\ldots$$

4. Case study

The main problem with the construction industry that contains a number of risks, and in order to minimize these risks, a model should be used to analyze these risks. A scientific research methodology is adopted which includes three stages:

4.1 Theoretical study

1. A review of the scientific literature and sources (books, magazines, engineering, research), which dealt with all of them.

2. Risk responses concept and strategies in construction projects.

3. Studying cost elements, types, and factors affecting it with the study of the causes of their appearance.

    a. Studying the artificial intelligence techniques and the steps of its procedures and its uses in the construction projects.

    b. Studying the simulation methods and the steps of its procedures and its uses in the construction projects.

4.2 Field study

The field study includes the following:

4.2.1 Open questionnaire

This stage includes conducting many interviews with experts. The interviews include managers and university professors, and other parts of the projects in the following ministries: the Ministry of Higher Education and Scientific Research, the Ministry of Construction and Housing, and the Ministry of Education. These interviews have a very important role in helping the researcher in the later stage, also discussion about the questionnaire which is initially prepared from the literature and previous studies as well as doing some modifications on the form and adding another questions with the help of the experts to make sure of the success of the method and questions presented.

4.2.2 Closed questionnaire

After the interviews with many experts have been finished. The problems of the research were divided into several groups which including the risks that cause to cost overruns, the top risk and their impacts on the projects, the strategies that are used for each risk, the reasons for risk response failure and finally the risks generated from risk response.

4.3 Stage of system building and software design

In the light of the responses received from the questionnaire, the practical study is as follows:

1. Planning of risk.

2. Identification of risk.

3. Analysis of risk using decision tree and K-star machine.

4. Risk response evaluation using neural network and support vector.

In this model, two types of classification were used, descriptive classification by using decision tree and predictive classification by using K-star and as follow:

- Identify the dependent variable.

- Identify the independent variable.

- Implement descriptive classification using a decision tree.

- Implement predictive classification using K-star.

4.4 Identify the independent variable of descriptive classification

The decision tree application is an example of a descriptive classification. This type of classification considers a number of attributes (variable) which affect the variable to be described. This type of classification is important to the variables that have an effect on the target.

This research describes the method of classification by using a decision tree to describe the qualitative analysis of the risks of project cost based on historical data. The data used to develop the classification model were the past data from various engineering works in different ministries. The method that is used to collect data is the direct data gathering from the engineering and the direct interview with the engineers and managers.

Results gained were collected from two parts: first one is the literature survey and the second one is the field of investigation (interview and questionnaire analysis) as mentioned before; 23 variables were considered as the independent variables; these variables are risks and their probabilities are considered too high, high, medium, low, and too low, and the impacts as too high, high, medium, low, too low, which are shown in **Table 1**.

4.5 Dependent variables

Qualitative analysis is considered to be the dependent variable which is too high, high, medium, low, too low, and each individual engineer or manager is used as the basic unit of the observation. Therefore this model is considered to be an attempt to make a model consisting of the independent variables which could describe the qualitative analysis classification.

RISKS
1-Price fluctuation
2-Inflation
3-Unavailability of information
4-Increase in cost due environment constrain
5-Financial difficulty by the contractor
6-financial difficulty by owner
7-Absence of measurement before advance
8-Design team performance
9-Inadequate owner requirement
10-Delay in agreement of design
11-Mismanagement of contract
12-Ambiguity of contract
13-Selection of team management
14-Miss selection of sit
15-Labor production
16-Luck of labor
17-Delay in deliver in equipment
18-Quality control on material
19-Exceptional circumstances and risks
20-Weather
21-Wrong estimation
22-Delay in the completing of the project
23-Increase in the cost of material and equipment

Table 1.
The identified risks.

4.6 Weka implementation: two techniques were used in this program

4.6.1 Decision tree implementation: Weka program

Waikato Environment for Knowledge Analysis (Weka) is a famous software in machine learning suite; the language used is Java; and University of Waikato, New Zealand developed this program. It is a software that considered as free, and the license of this program is a GNU General Public License. The Weka (said to rhyme similar to Mecca) is considered to be a workbench [16] which includes a group of tools for visualization and algorithms that are used to analyze the data and molding for the predictions; it is easy to access this function by using graphical user interface [15] and the version of Weka 3 that was developed in the early 1997 was used for many different implementation areas, especially for the purpose of education and research.

Several standard data mining tasks are supported by Weka, to be more specific, preprocessing of the data, regression, classification, clustering, visualization, and selection of the feature [17, 19], as shown in **Figure 2**.

The Explorer is in the GUI which is opened and the explorer is pressed on to insert the file that needs to be classified and by pressing the bottom open file to insert the file in the preprocess window which is used to choose and modify the data being acted on. As shown in **Figure 3**.

At this stage, the model was uploaded and full information such as relation means the name of the file, the total number of instances, attributes, type, the missing value, and others is shown in the figure above.

After this stage, a classifier was selected to perform the descriptive analysis as shown in **Figure 4**.

In the section of Classify at the top, there is a Classifier box. This box has a number of text area that provides the name of the classifier that the research work with, and by clicking on the tree bottom, there are several algorithms available under this option, the researcher selects j48 algorithm which one the application and implementations of C4.5 as shown in **Figure 5**.

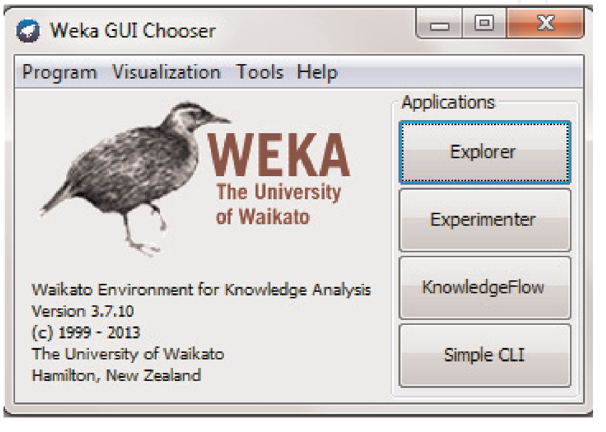

Figure 2.
Graphing component of WEKA 3.7.10 program.

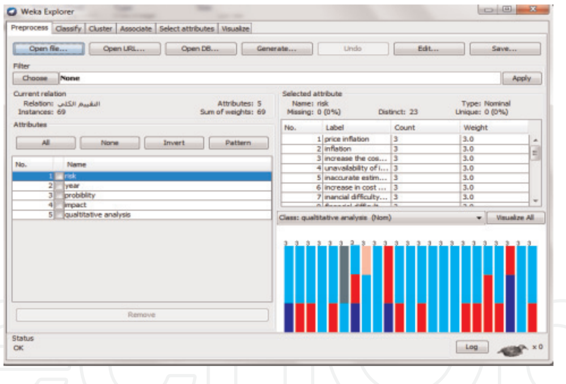

Figure 3.
Displays the preprocess window in the explorer.

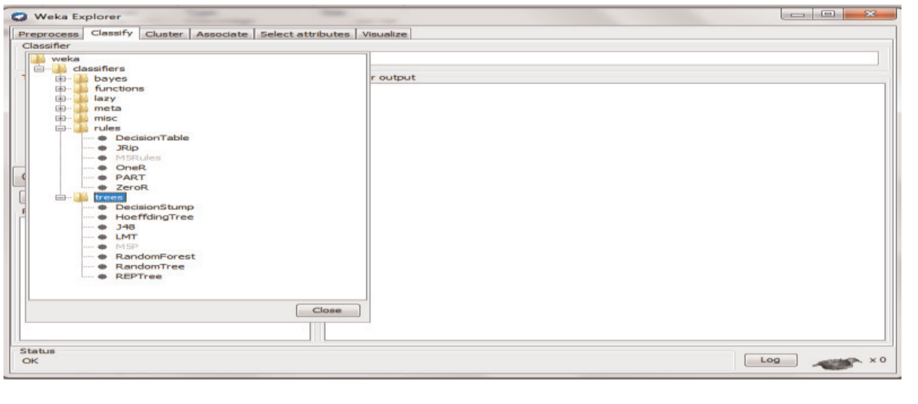

Figure 4.
Displays the process of selecting the classifier.

In this step, the properties of the algorithm are selected. In this model after the trial and error, the confidence factor is 0.25, the debug is false, min NUM obj is 2, NUM Folds are 3, and the unpruned option is true, which give the researcher the best results achieved as shown in **Tables 2** and **3**.

According to the tree, the risk with medium impact has the following probability: medium—13 risks, low—3 risks, and too low and high—there is no medium classification; while the risk with low impact has the following probability: medium there are 7 class low, too low has 1 class, low has 36 class, and high does not have

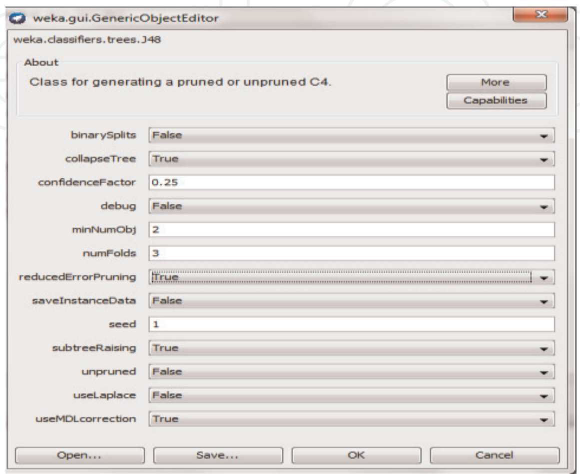

Figure 5.
Displays the process of selecting j48 properties.

Tp rate	Fp rate	Precision	Recall	F-measure	MCC	ROC area	Prc area	Class	Description of the results
1.000	0.031	0.714	1.000	0.833	0.832	0.970	0.638	High	The results show that this class is classified correctly as the Tp is 1 and Fp low and precision acceptable and the recall high, the MCC takes the classification between each two class and Roc area is high which indicates good performance for the high class and Prc is the medium indicator of the model performance
0.867	0.000	1.000	0.867 .	0.929	0.983	0.983	0.957	Medium	The results show that this class is classified kind off correctly as the Tp is 0.867 and Fp is zero and precision acceptable and the recall high, the MCC takes the classification between each two class and Roc area is high which indicate good performance for the medium class and

Tp rate	Fp rate	Precision	Recall	F-measure	MCC	ROC area	Prc area	Class	Description of the results
									Prc is the good indicator of the model performance consider very good
1.000	0.130	0.939	1.000	0.968	0.904	0.978	0.979	Low	The results show that this class is classified correctly as the Tp is 1 and Fp is low and precision high and the recall high, the MCC takes the classification between each two class and Roc area is high which indicates good performance for the low class and Prc is the good indicator of the model performance which considers very good
0.000	0.000	0.000	0.000	0.000	0.000	0.739	0.264	Too low	The results show that this class is classified incorrectly as the Tp is zero and Fp is zero and precision, the recall, the MCC are zero while Roc area is very low which indicates bad performance for the too low class and Prc is the good indicator of the model performance which considers very bad
0.000	0.000	0.000	0.000	0.000	0.000	0.493	0.014	Too high	The results show that this class is classified incorrectly as the Tp is zero and Fp is zero and precision, the recall, the MCC are zero while Roc area is very low which indicates bad performance for the too high class and Prc is the good indicator of the model performance which considers very bad
0.928	0.089	0.895	0.928	0.908	0.861	0.965	0.915		As a total cumulative result, its consider being good classification

Table 2.
The decision tree results in the WEKA program.

Risks	Actual	Classified
Price fluctuation	High	High
Inflation	Medium	Medium
Increase the cost of skilled labor	Medium	Medium
Unavailability of information	Low	Low
Inaccurate estimation	Low	Low
The increase in cost due environment	Too low	Low
Financial difficulty by the contractor	Low	Low
Financial difficulty by owner	Low	Low
The absence of measurement before	Low	Low
Delay in time of the project	High	High
Design team performance	Low	Low
Inadequate owner requirement	Low	Low
Delay in agreements of design	Low	Low
The ambiguity of contract	Low	Low
Miss selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Medium	Medium
The decrease in labor	Medium	Medium
Delay in delivery in equipment	Medium	
Quality control on material	Low	Low
Unexpected condition	High	High
Weather	Low	Low
Mismanagement of the contract	Low	Low
Price fluctuation	Low	Low
Inflation	Low	Low
Increase the cost of skilled labor	Low	Low
Unavailability of information	Low	Low
Inaccurate estimation	Low	Low
The increase in cost due environment	Too low	Low
Financial difficulty by the contractor	Medium	Medium
Financial difficulty by owner	Low	Low
The absence of measurement before	Low	Low
Delay in time of the project	Medium	Medium
Design team performance	Medium	Medium
Inadequate owner requirement	Low	Low
Delay in agreements of design	Low	Low
The ambiguity of contract	Low	Low
Selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Low	Low

Risks	Actual	Classified
The decrease in labor	Low	Low
Delay in delivery in equipment	Low	Low
Quality control on material	Medium	High
Unexpected condition	Medium	Medium
Weather	Low	Low
Mismanagement of the contract	Medium	Medium
Price fluctuation	Low	Low
Inflation	Low	Low
Increase the cost of skilled labor	Low	Low
Unavailability of information	Low	Low
Inaccurate estimation	Medium	Medium
The increase in cost due environment	Low	Low
Financial difficulty by the contractor	High	High
Financial difficulty by owner	Too high	Low
The absence of measurement before	Low	Low
Delay in time of the project	Medium	Medium
Design team performance	Low	Low
Inadequate owner requirement	Low	Low
Delay in agreements of design	Medium	Medium
The ambiguity of contract	Low	Low
Selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Low	Low
The decrease in labor	Low	Low
Delay in delivery in equipment	Medium	High
Quality control on material	Low	Low
Unexpected condition	High	High
Weather	Low	Low
Mismanagement of the contract	Low	Low

Table 3.
The classified and the actual data of decision tree the WEKA program.

any class; on the other hand, the risk that has the impact high has class high with two of them are wrongly classified and the risks with impact too low and too high have the class of one too low and one too high, respectively, as shown in **Figure 6**.

4.6.2 K-star implementation: Weka program

As mentioned, Weka is a popular software for machine learning, and this type of algorithm will be used for predictive classification to predict the qualitative analysis of the risks for the periods 2014–2016 depending on the qualitative analysis for the previous periods from 2006 to 2014. The result is shown in **Table 4**.

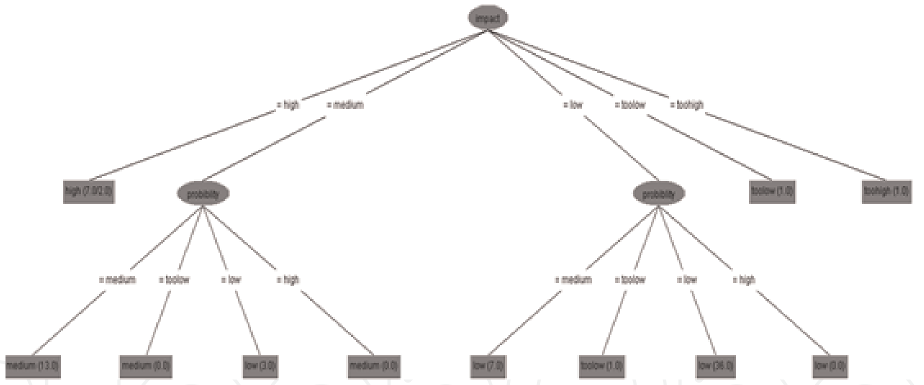

Figure 6.
Displays the tree of j48.

Risks	Actual	Classified
Price fluctuation	High	Medium
Inflation	Medium	Medium
Increase the cost of skilled labor	Medium	Medium
Unavailability of information	Low	Low
Inaccurate estimation	Low	Low
The increase in cost due environment	Too low	Low
Financial difficulty by the contractor	Low	Low
Financial difficulty by owner	Low	Low
The absence of measurement before	Low	Low
Delay in time of the project	High	High
Design team performance	Low	Low
Inadequate owner requirement	Low	Low
Delay in agreements of design	Low	Low
The ambiguity of contract	Low	Low
Miss selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Medium	Medium
The decrease in labor	Medium	Medium
Delay in delivery in equipment	Medium	
Quality control on material	Low	Low
Unexpected condition	High	High
Weather	Low	Low
Mismanagement of the contract	Low	Low
Price fluctuation	Low	Low
Inflation	Low	Low
Increase the cost of skilled labor	Low	Low
Unavailability of information	Low	Low
Inaccurate estimation	Low	Low
The increase in cost due environment	Too low	Low
Financial difficulty by the contractor	Medium	Medium

Risks	Actual	Classified
Financial difficulty by owner	Low	Low
The absence of measurement before	Low	Low
Delay in time of the project	Medium	Medium
Design team performance	Medium	Medium
Inadequate owner requirement	Low	Low
Delay in agreements of design	Low	Low
The ambiguity of contract	Low	Low
Selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Low	Low
The decrease in labor	Low	Low
Delay in delivery in equipment	Low	Low
Quality control on material	Medium	High
Unexpected condition	Medium	Medium
Weather	Low	Low
Mismanagement of the contract	Medium	Medium
Price fluctuation	Low	Low
Inflation	Low	Low
Increase the cost of skilled labor	Low	Low
Unavailability of information	Low	Low
Inaccurate estimation	Medium	Medium
The increase in cost due environment	Low	Low
Financial difficulty by the contractor	High	Medium
Financial difficulty by owner	Too high	Too low
The absence of measurement before	Low	Low
Delay in time of the project	Medium	Medium
Design team performance	Low	Low
Inadequate owner requirement	Low	Low
Delay in agreements of design	Medium	High
The ambiguity of contract	Low	Low
Selection of team management	Low	Low
Miss election of sit	Low	Low
Labor production	Low	Low
The decrease in labor	Low	Low
Delay in delivery in equipment	Medium	Medium
Quality control on material	Low	Low
Unexpected condition	High	Medium
Weather	Low	Low
Mismanagement of the contract	Low	Low

Table 4.
The classified and the actual data of K-star in the WEKA program.

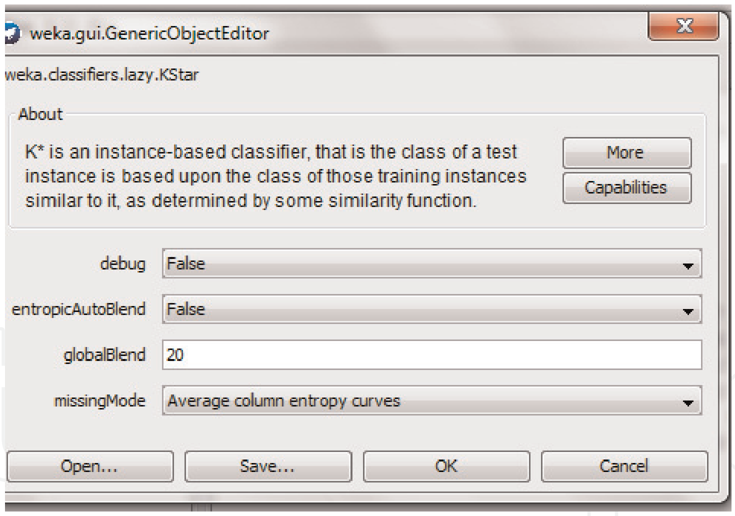

Figure 7.
Displays the process of selecting K-star properties.

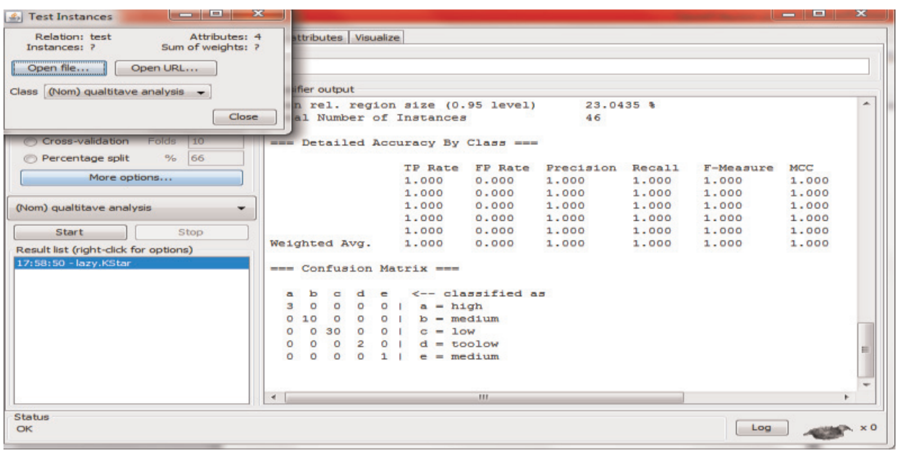

Figure 8.
Displays the process of uploading the test file.

Correctly classified instances	91.304%	This is considered being good classification accuracy
Incorrectly classified instances	8.6975	There is no classification error
Kappa statistic	81.85%	Consider being good value as compared to the realistic

Table 5.
The correctly and incorrectly classified instance using cross validation in K-star.

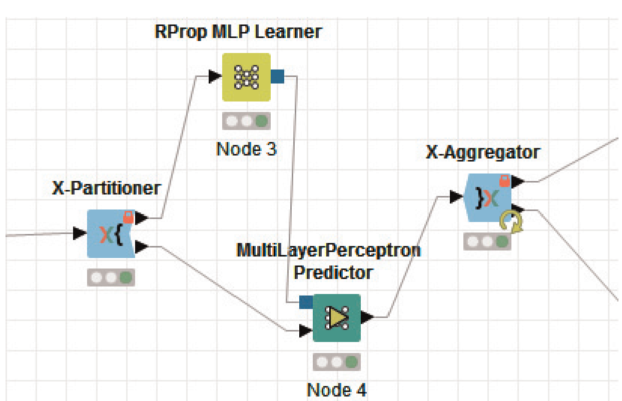

Figure 9.
Display neural network model.

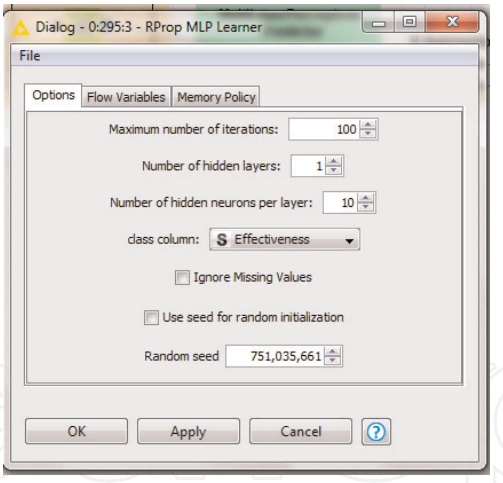

Figure 10.
Display configure menu.

Thus the probability for each instance is calculated in the category of the qualitative analysis, and the highest probability is taken for the classification of the new instance.

The process of opening the program and loading the file is mentioned earlier; the next step is choosing the properties of the algorithm as shown in **Figure 7**.

The global blending was taken as 20 after several trial and error; it was found to be the best result, the entropy autoblending which means entropy base blending in this case, it does not use for better accuracy.

The training data set has good accuracy, this high accuracy because the algorithm uses an entropy distance and use the whole data as training data**.** As shown in **Figure 8**.

After this step, the testing data set is uploading to perform the prediction classification.

In order to make a comparison between the two techniques, the whole data are used in cross-validation to make a comparison. As shown in **Table 5**.

4.6.3 KNIME implementation

Using the program, risk response failure in construction project was analyzed using the following techniques.

4.6.3.1 Neural network

This technique was used as part of the model to describe the risk response failure.

This workflow represents the neural network model right-click it and select "Configure" from the menu, as shown in **Figure 9**.

The max number of iterations was selected 100 and by trial and error the number of the hidden layers was 1 and hidden neuron were 10, as shown in **Figure 10**.

The results are shown in **Tables 6** and 7.

4.6.3.2 Support vector machine

This technique was used as part of the model to predict risk response failure. As shown in **Figures 11** and **12**.

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
1, 2006	Price fluctuation	Medium	Avoidance	3.33	Medium
1, 2006	Inflation	Medium	Avoidance	2.60	Low
1, 2006	Delay in completing of the project	High	Acceptance	3.07	Medium
1, 2006	Labor productivity	Medium	Acceptance	2.87	Medium
1, 2006	Exceptional circumstance and risks	High	Acceptance	1.85	Low
1, 2006	Wrong estimation	High	Avoidance	3.33	Medium
			Acceptance	2.51	Low
2, 2006	Price fluctuation	Medium	Avoidance	3.40	Medium
2, 2006	Delay in completing of the project	High	Acceptance	1.80	Low
2, 2006	Change in cost of equipment	Medium	Avoidance	2.87	Medium
2, 2006	Luck of the labor	Medium	Avoidance	2.90	Medium
2, 2006	Exceptional circumstance and risks	High	Acceptance	3.10	Medium
3, 2006	Delay in completing of the project	High	Avoidance	3.33	Medium
3, 2006	Labor productivity	Medium	Acceptance	3.13	Medium
3, 2006	Exceptional circumstance and risks	High	Acceptance	1.95	Low
3, 2006	Wrong estimation	High	Avoidance	2.67	Medium
4, 2006	Increase in the cost of skilled labor	Medium	Avoidance	3.07	Medium
4, 2006	Delay in completing of the project	High	Acceptance	2.60	Low
4, 2006	Change in cost of equipment	Medium	Avoidance	3.20	Medium
4, 2006	Luck of the labor	Medium	Avoidance	3	Medium
4, 2006	Exceptional circumstance and risks	High	Acceptance	2.80	Medium
5, 2006	Price fluctuation	Medium	Avoidance	3.20	Medium
5, 2006	Increase in the cost of skilled labor	Medium	Avoidance	2.60	Low
5, 2006	Delay in completing of the project	High	Acceptance	3.20	Medium
5, 2006	Luck of the labor	Medium	Avoidance	3.13	Medium
5, 2006	Exceptional circumstance and risks	High	Acceptance	1.85	Low
6, 2006	Delay in completing of the project	High	Acceptance	3.07	Medium
6, 2006	Change in cost of equipment	Medium	Avoidance	3.40	Medium
6, 2006	Luck of the labor	Medium	Avoidance	2.67	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
6, 2006	Exceptional circumstance and risks	High	Acceptance	3.40	Medium
7, 2006	Price fluctuation	Medium	Avoidance	2.80	Medium
7, 2006	Increase in the cost of skilled labor	Medium	Acceptance	2.90	Medium
7, 2006	Delay in completing of the project	High	Acceptance	2.87	Medium
7, 2006	Luck of the labor	Medium	Avoidance	2.67	Medium
7, 2006	Exceptional circumstance and risks	High	Acceptance	2.60	Low
8, 2006	Price fluctuation	Medium	Avoidance	3.33	Medium
8, 2006	Increase in the cost of skilled labor	Medium	Avoidance	3.17	Medium
8, 2006	Delay in completing of the project	High	Acceptance	2.80	Medium
8, 2006	Luck of the labor	Medium	Avoidance	2.90	Medium
8, 2006	Exceptional circumstance and risks	High	Acceptance	1.90	Low
9, 2006	Increase in the cost of skilled labor	Medium	Avoidance	2.87	Medium
9, 2006	Delay in completing of the project	High	Acceptance	3.13	Medium
9, 2006	Change in cost of equipment	Medium	Avoidance	3.33	Medium
9, 2006	Luck of the labor	Medium	Avoidance	3.04	Medium
9, 2006	Exceptional circumstance and risks	High	Acceptance	3.40	Medium
10, 2006	Price fluctuation	Medium	Avoidance	2.67	Medium
10, 2006	Increase in the cost of skilled labor	Medium	Avoidance	2.77	Medium
10, 2006	Delay in completing of the project	High	Acceptance	3.27	Medium
10, 2006	Luck of the labor	Medium	Avoidance	3	Medium
10, 2006	Exceptional circumstance and risks	High	Acceptance	1.81	Low
11, 2006	Delay in completing of the project	High	Acceptance	3.3	Medium
11, 2006	Exceptional circumstance and risks	High	Acceptance	2.90	Medium
12, 2008	Finical difficulty by the contractor	Medium	Acceptance	3.13	Medium
12, 2008	Delay in completing of the project	Medium	Acceptance	2.67	Medium
12, 2008	Quality control of the material	Medium	Avoidance	3.17	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
12, 2008	Mismanagement of the contract	Medium	Avoidance	2.90	Medium
12, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.85	Medium
12, 2008	Wrong estimation	Medium	Acceptance	3.33	Medium
13, 2008	Finical difficulty by the contractor	Medium	Avoidance	2.60	Medium
13, 2008	Delay in completing of the project	Medium	Acceptance	2.04	Low
13, 2008	Quality control of the material	Medium	Acceptance	2.80	Medium
13, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.90	Medium
14, 2008	Finical difficulty by the contractor	Medium	Avoidance	2.67	Medium
14, 2008	Quality control of the material	Medium	Avoidance	3.10	Medium
14, 2008	Wrong estimation	Medium	Acceptance	3.33	Medium
15, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.13	Medium
15, 2008	Delay in completing of the project	Medium	Acceptance	2.95	Medium
15, 2008	Quality control of the material	Medium	Acceptance	1.81	Low
15, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.07	Medium
16, 2008	Finical difficulty by the contractor	Medium	Medium	2.21	Low
16, 2008	Delay in completing of the project	Medium	Avoidance	3.20	Medium
16, 2008	Design team performance	Medium	Acceptance	3	Medium
16, 2008	Quality control of the material	Medium	Mitigate	2.90	Medium
16, 2008	Mismanagement of the contract	Medium	Acceptance	3.22	Medium
16, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.67	Medium
16, 2008	Wrong estimation	Medium	Acceptance	3.23	Medium
17, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.17	Medium
17, 2008	Delay in completing of the project	Medium	Acceptance	2.85	Medium
17, 2008	Design team performance	Medium	Mitigate	3.17	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
17, 2008	Quality control of the material	Medium	Avoidance	2.22	Low
17, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.67	Medium
17, 2008	Wrong estimation	Medium	Acceptance	1.81	Low
18, 2008	Finical difficulty by the contractor	Medium	Avoidance	2.90	Medium
18, 2008	Delay in completing of the project	Medium	Acceptance	2.80	Medium
18, 2008	Quality control of the material	Medium	Acceptance	2.87	Medium
18, 2008	Mismanagement of the contract	Medium	Avoidance	2.67	Medium
18, 2008	Wrong estimation	Medium	Acceptance	2.60	Medium
19, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.33	Medium
19, 2008	Delay in completing of the project	Medium	Acceptance	2.67	Medium
19, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.07	Medium
20, 2008	Finical difficulty by the contractor	Medium	Avoidance	2.33	Low
20, 2008	Delay in completing of the project	High	Acceptance	2.85	Medium
20, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.03	Medium
20, 2008	Wrong estimation	Medium	Acceptance	2.80	Medium
21, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.40	Medium
21, 2008	Delay in completing of the project	Medium	Acceptance	2.80	Medium
21, 2008	Quality control of the material	Medium	Avoidance	2.90	Medium
21, 2008	Mismanagement of the contract	Medium	Avoidance	2.67	Medium
21, 2008	Wrong estimation	Medium	Acceptance	3.13	Medium
22, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.07	Medium
22, 2008	Delay in completing of the project	Medium	Acceptance	3.13	Medium
22, 2008	Design team performance	Medium	Mitigate	2.95	Medium
22, 2008	Quality control of the material	Medium	Avoidance	2.67	Medium
22, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.07	Medium
22, 2008	Wrong estimation	Medium	Acceptance	3.40	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
23, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.21	Medium
23, 2008	Delay in completing of the project	Medium	Acceptance	2.07	Low
23, 2008	Design team performance	Medium	Acceptance	2.80	Medium
23, 2008	Quality control of the material	Medium	Avoidance	3.21	Medium
23, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.67	Medium
23, 2008	Wrong estimation	Medium	Acceptance	3.20	Medium
24, 2008	Finical difficulty by the contractor	Medium	Avoidance	3.13	Medium
24, 2008	Delay in completing of the project	Medium	Acceptance	2.85	Medium
24, 2008	Quality control of the material	Medium	Avoidance	3.13	Medium
24, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.40	Medium
24, 2008	Wrong estimation	Medium	Acceptance	2.67	Medium
25, 2008	Delay in completing of the project	Medium	Acceptance	3.07	Medium
25, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.90	Medium
25, 2008	Wrong estimation	Medium	Acceptance	2.80	Medium
26, 2008	Delay in completing of the project	Medium	Acceptance	2.67	Medium
26, 2008	Design team performance	Medium	Acceptance	2.70	Low
26, 2008	Quality control of the material	Medium	Avoidance	2.55	Medium
26, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.33	Medium
26, 2008	Wrong estimation	Medium	Acceptance	3.17	Medium
27, 2008	Finical difficulty by the contractor	Medium	Avoidance	2.80	Medium
27, 2008	Delay in completing of the project	Medium	Acceptance	3.40	Medium
27, 2008	Quality control of the material	Medium	Avoidance	3.17	Medium
27, 2008	Exceptional circumstance and risks	Medium	Acceptance	2.87	Medium
27, 2008	Wrong estimation	Medium	Acceptance	3.13	Medium
28, 2008	Delay in completing of the project	Medium	Acceptance	2.33	Low
28, 2008	Quality control of the material	Medium	Avoidance	3.04	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
28, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.21	Medium
28, 2008	Wrong estimation	High	Acceptance	2.73	Medium
29, 2008	Delay in completing of the project	Medium	Acceptance	2.77	Medium
29, 2008	Quality control of the material	Medium	Avoidance	3.27	Medium
29, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.03	Medium
29, 2008	Wrong estimation	Medium	Acceptance	2.81	Medium
30, 2008	Delay in completing of the project	Medium	Acceptance	3.03	Medium
30, 2008	Quality control of the material	Medium	Avoidance	2.90	Medium
30, 2008	Exceptional circumstance and risks	Medium	Acceptance	3.33	Medium
30, 2008	Wrong estimation	Medium	Acceptance	2.33	Low
31, 2008	Delay in completing of the project	High	Acceptance	2.07	Low
31, 2008	Wrong estimation	Medium	Acceptance	2.87	Medium
32, 2008	Finical difficulty by the contractor	Medium	Avoidance	1.81	Low
32, 2008	Delay in completing of the project	High	Acceptance	3.33	Medium
32, 2008	Wrong estimation	Medium	Acceptance	2.60	Medium
33, 2014	Finical difficulty by the contractor	High	Avoidance	3.33	Medium
33, 2014	Finical difficulty by the owner	High	Avoidance	2.80	Medium
33, 2014	Delay in completing of the project	High	Avoidance	2.87	Medium
33, 2014	Change in cost of equipment	Medium	Acceptance	2.90	Medium
33, 2014	Exceptional circumstance and risks	High	Acceptance	2.10	Low
34, 2014	Wrong estimation	Medium	Avoidance	3.33	Medium
34, 2014	Finical difficulty by the contractor	Medium	Avoidance	2.13	Low
34, 2014	Finical difficulty by the owner	High	Acceptance	2.95	Medium
34, 2014	Delay in completing of the project	High	Avoidance	3.07	Medium
34, 2014	Change in cost of equipment	Medium	Acceptance	3.13	Medium
34, 2014	Exceptional circumstance and risks	High	Avoidance	2.60	Medium

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Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
35, 2014	Finical difficulty by the contractor	Medium	Avoidance	2.20	Low
35, 2014	Finical difficulty by the owner	High	Acceptance	3	Medium
35, 2014	Delay in completing of the project	High	Avoidance	2.90	Medium
35, 2014	Change in cost of equipment	Medium	Acceptance	2.20	Low
35, 2014	Exceptional circumstance and risks	High	Avoidance	2.33	Low
36, 2014	Finical difficulty by the contractor	Medium	Avoidance	3.20	Medium
36, 2014	Finical difficulty by the owner	High	Acceptance	2.13	Low
36, 2014	Delay in completing of the project	High	Acceptance	2.85	Medium
36, 2014	Exceptional circumstance and risks	High	Acceptance	2.07	Low
37, 2014	Wrong estimation	Medium	Avoidance	2.61	Medium
37, 2014	Finical difficulty by the contractor	Medium	Avoidance	2.67	Medium
37, 2014	Finical difficulty by the owner	High	Acceptance	2.60	Medium
37, 2014	Delay in completing of the project	High	Acceptance	2.77	Medium
37, 2014	Exceptional circumstance and risks	High	Acceptance	2.80	Medium
38, 2014	Wrong estimation	Medium	Acceptance	1.87	Low
38, 2014	Finical difficulty by the contractor	Medium	Avoidance	2.67	Medium
38, 2014	Finical difficulty by the owner	High	Avoidance	2.60	Medium
38, 2014	Delay in completing of the project	High	Acceptance	3.13	Medium
38, 2014	Exceptional circumstance and risks	High	Acceptance	3.17	Medium
39, 2014	Finical difficulty by the contractor	High	Avoidance	2.90	Medium
39, 2014	Finical difficulty by the owner	High	Avoidance	2.80	Medium
39, 2014	Delay in completing of the project	High	Acceptance	2.90	Medium
39, 2014	Exceptional circumstance and risks	High	Acceptance	2.87	Medium
40, 2014	Finical difficulty by the owner	High	Avoidance	3.07	Medium
40, 2014	Delay in completing of the project	High	Acceptance	3.33	Medium

Project and year	Risks	Qualitative analyses	Risk response	Effectiveness	Effectiveness linguistic
40, 2014	Change in cost of equipment	Medium	Avoidance	2.04	Low
40, 2014	Exceptional circumstance and risks	High	Acceptance	3.40	Medium
41, 2014	Finical difficulty by the contractor	Medium	Avoidance	2.07	Low
41, 2014	Finical difficulty by the owner	High	Avoidance	2.77	Medium
41, 2014	Delay in completing of the project	Medium	Acceptance	2.27	Low
41, 2014	Exceptional circumstance and risks	High	Acceptance	3	Medium

Table 6.
The results of the risk response effectiveness in the 41 projects.

Risk response	Actual effectiveness	Predication effectiveness
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Low
Avoidance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Low
Acceptance	Low	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium

Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Low	Low
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium

Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Mitigate	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Mitigate	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Low
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Low
Acceptance	Medium	Low
Avoidance	Medium	Medium
Acceptance	Medium	Low
Mitigate	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Low
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium

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Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Low	Medium
Mitigate	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Low
Acceptance	Medium	Low
Avoidance	Medium	Low
Avoidance	Low	Low
Acceptance	Medium	Medium

Table 7.
Show the actual effectiveness and the predication effectiveness of risk response using neural network results.

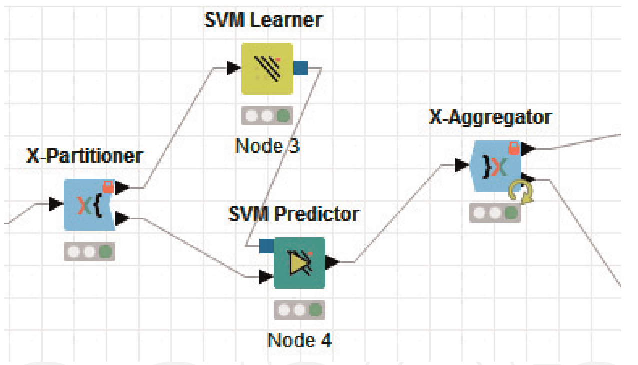

Figure 11.
Display support vector machine model.

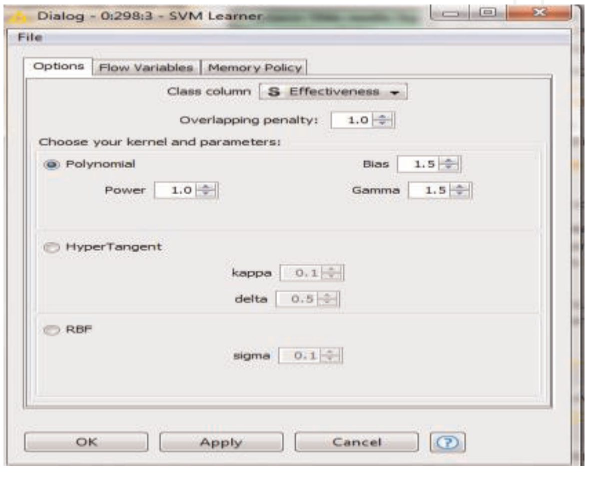

Figure 12.
Display support vector machine learner menu.

Class	True post	False post	True neg	False neg	Recall	Precision	sensitivity	Specify	f-mean	Accuracy	Description
Medium	123	23	0	0	1	0.842	1	0.0	0.941		The results show data classified correctly and the result perform well
Low	0	0	123	23	0.0	0.0	0	1	0		The results show that this class is not classified correctly as there is a lot of error in the low class and the Precision, and also the f measure is less that indicate the reason to lower the classification accuracy
Overall										84.2	

Table 8.
Support vector machine results.

When clicking on the SVM learner node the following window appears. The results are shown in **Tables 8** and **9**.

Risk response	Actual effectiveness	Predication effectiveness
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium

Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Mitigate	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium

Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Low	Medium
Mitigate	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Mitigate	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Low	Medium
Mitigate	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium

Risk response	Actual effectiveness	Predication effectiveness
Acceptance	Low	Medium
Acceptance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Acceptance	Medium	Medium
Avoidance	Medium	Medium
Avoidance	Low	Medium
Acceptance	Medium	Medium

Table 9.
Show the actual effectiveness and the predication effectiveness of risk response using support vector machine results.

5. Conclusions

1. The result from the statistical analysis results in a period of (2006–2007) show that the risks that have the highest qualitative analysis are the same that resulting from the classification result by using j48 algorithm

2. The result from the statistical analysis results in the period of (2014–2016) show that the risks that have the highest qualitative analysis are the same that resulting from the classification result by using j48 algorithm except for one

risk which is the quality control on the material and expertise in execution and that leads to an error.

3. The result from the statistical analysis results in the period of (2014–2016) show that the risks that have the highest qualitative analysis are same that resulting from the classification result by using j48 algorithm except for two risks which are financial difficulty by owner and Changes in the purchase costs or delay in the delivery of equipment and machinery and that leads to an error.

4. Different risks were found due to the different condition of these periods, however, some risks were the same as the delay in completing the project, exceptional circumstances, and the wrong estimation existed in every period

5. The decision tree is a successful quality technique in risk analysis

The result from the statistical analysis results in a period of 2014–2016 showed that the risks that have the highest qualitative analysis are same that resulting from the classification result by using K-star algorithm except for one risk which is financial difficulty by owner.

Second: Risk response identification

- In the periods of (2006–2007) the method that used for risk response selection was historical information for similar previous projects has the mean of 4.03 that means often this method used for selection.

- In the periods of (2008–2013) the method that used for risk response selection was historical information for similar previous projects has the mean of 3.73 that means often this method used for selection.

- In the periods of (2014–2016) the method that used for risk response selection was historical information for similar previous projects has the mean of 3.80 that mean often this method used for selection.

- The existing methods and tools for selecting a risk response are based on historical information for similar previous projects, m.aking them easily affected by anxiety, uncertainty.

- Three techniques to identify risk response failure.

    a. The decision tree shows the high accuracy and that because it considers the best algorithm in prediction of nominal class

    b. The neural network shows the lower accuracy as the nature of the algorithm tends more to the numerical class.

    c. The support vector machine show good results close to the decision tree

- The most important reasons that risk response fails in the period of (2006–2007) were The difficulty of implementing a risk-response plan correctly for internal factors (terrorism and sabotage), Multiple decision sources for selecting a response strategy, Inadequate strategy with high risk and The inability to introduce sophisticated management methods to respond to risks.

- The most important reasons that risk response fails in the period of (2008–2013) were Changes in the cost criteria that have been estimated at the planning stage of the project to the implementation stage, Inadequate strategy with high risk and The inability to introduce sophisticated management methods to respond to risks.

- The most important reasons that risk response fails in the period of (2014–2016) are negligence of supervisors in the follow-up to the risk response plan, lack of funds for training and continuous development of the risk response team, inadequate strategy with high risk, delay in the disbursement of financial dues by the responsible party, the difficulty of implementing a risk-response plan correctly for internal factors (terrorism and sabotage) and The inability to introduce sophisticated management methods to respond to risks.

- The period of (2014) shows many reasons that led to risk response failure in construction projects due to the condition of the country.

Author details

Hafeth I. Naji[1], Rouwaida Hussein Ali[2]* and Ehsan Ali Al-Zubaidi[3]

1 Civil Engineering Department, University of Diyala, Diayla, Iraq

2 Civil Engineering Department, University of Baghdad, Diayla, Iraq

3 Department of Computer and Internet, Faculty of Physical Planning, University of Kufa, Kufa, Iraq

*Address all correspondence to: rowedahhussien@gmail.com

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