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RISKS RESPONSE FAILURE IN CONSTRUCTION PROJECTS

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ABSTRACT

This paper aims to identify the risk response failure in a construction project in the periods in the periods between 2006 t0 2013 and identify the techniques that use to predict the failure in the construction projects in the periods of 2014 to 2016 and select the technique with high accuracy. The methodology of the paper includes two part, questionnaire and the use of data mining techniques. The questionnaire was distributed to the owners, the contractor and other parties involved in the project, 41 projects were taken and the questionnaire was distributed to 15 people who workin theproject. The questionnaire includes the strategies for each risk and five measurements were used which are too low, low, medium, high and too high The second stage include the use of data mining techniques which are decision tree, neural network and support vector machine ,the period from 2006-2013 as training set to predict the failure of 2014-2016 projects The program that use is KNIME (pronounced /naɪm/), the Konstanz Information Miner, is data analytics with an open source, reporting and integration platform. All the project face failure in construction projects, at this stage doesn't receive much attention in the projects that lead to the failure. The decision tree shows the highest accuracy and that because it considers the best algorithm in prediction of nominal class. This study is the only one made in identifying the risk response failure in construction projects First, we have identified the risk in the construction project in different periods, the identified the risk response for each risk, finally we determine the risk response failure in construction projects.

Keywords: risk, risk response, decision tree, neural network, support vector machine.

1. INTRODUCTION

Project risk is an uncertain event or condition that, if it occurs, has an effect on at least one project objective. Objectives can include scope, schedule, cost, and quality. A risk may have one or more causes and, if it occurs, it may have one or more impacts. A cause may be a requirement, assumption, constraint, or condition that creates the possibility of negative or positive outcome (1).

Risk management as a method to prevent the risk and make sure not to be repeated through the project and that by study of the causes of each risk to be avoided in the future, also risk management extends to the fundraising to make up for the project for the losses that occur in order not to stop working and production (2)

Risk response in the projects is to rank the elements of the risk by taking an action andrelevant to its level. it's very necessary that risk response has the ability to treat all the type of risk event like the planned risk response, the possible risk response and the estimation of cost for the responding which is consider to be essential (3)

The core of this research that our object lays the aim of this paper is to assess the risk response failure in construction projects and that by using data mining techniques and focuses on the study risks response in the construction projects. We decided, in this paper, to identify the failure by using three techniques which are decision tree, neural network and support vector machine and make a comparison between them. In the end, our work will lead to identifying the risk response failure in the construction projects.

2. LITERATURE REVIEW

Risk response used the collective information in the analysis stage and that to take decision how to improve the possibility to complete the project within time, cost and performance. This stage work on preparing the response for the main risks and appoint the people who are responsible for each response. When its needed risk response may be started in quantitative analysis stage and the repetition may be possible between the analysis and risk response stage (4) risk response is considered to be a very important stage in of risk management because it's finding who well the managers are able to increase opportunities and eliminate threats in projects. To be specific, the risk response plan has the probability to make the conditions which considered being essential for optimal risk identification and evaluation, therefore, risk response action should be designed, classified and rationalized on systematic principle. (5)

The techniques used a decision tree. The decision tree that builds using C4.5 algorithm usuallystartsfrom a set of the training TS, which is a collection of instances or a group of terms included in the database. The set attributes and a class is specified bythe instanceand each attributemay be represented by either discrete or as continuous value. Whilethe unknown is permitted to denote as unspecified values. The class may represent discrete values (6)

Rprop, is a termfor resilient back propagation, is a supervised learning that considers being heuristic learning in artificial neural networks feedforward. This is a first-order optimization algorithm. This algorithm was created by Martin Riedmiller and Heinrich Braun in, the algorithm RBF is considered to be a schemewith alocal

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learning that performs batchlearning in asupervised feed-forward neural network. The main principle of RBF is to remove the harmful impact of weight step due to the partial derivations size. (7)

As a result, the derivations sign is only considered to determine weight update direction .to accomplish this, for every weight Wij have its own its individual update - value Δij(t), which only find the weight- update size. (8)

$$\Delta_{ij}^{(t)} = \begin{cases} \eta^{+} \cdot \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial \Psi}{\partial w_{ij}}^{(t-1)} \cdot \frac{\partial \Psi}{\partial w_{ij}}^{(t)} > 0 \\ \eta^{-} \cdot \Delta_{ij}^{(t-1)} & , \text{ if } \frac{\partial \Psi}{\partial w_{ij}}^{(t-1)} \cdot \frac{\partial \Psi}{\partial w_{ij}}^{(t)} < 0 \\ \Delta_{ij}^{(t-1)} & , \textit{ else} \end{cases} \tag{1}$$

in COLT-92 by Boser, Guyon & Vapnik introduced Support vector machine SVM. Since that time it became popular. This algorithm was theoretically developed from the Theory of the Statistical Learning and it considerswell-motivated algorithm since the 60s Classification of pattern regard the main problem that dealswith, that means different types of patterns is classified using this algorithm. (9)

Risk response strategies includerisk avoidance which is about searching forthe substitutions solution in the project, a lot of risks can be discarded. To avoid the risks some changes are desired in the project and that by implementing advanced strategies instead of replacing them with new ones, in spite of the new ones save more money (10)

Risks acceptance is the strategy that used to accept the effect of risk. Risks that can classify with low efficiency and repeat during the project can be efficiently managed by accepting the responsibility of the project by the owner. There are two kinds of risk acceptance, i.e. passive acceptance and active acceptance (11)

"Risk mitigation planning is the process of developing options and actions to enhance opportunities and reduce threats to project objectives. Risk mitigation implementation is the process of executing risk mitigation actions. Risk mitigation progress monitoring includes tracking identified risks, identifying new risks, and evaluating risk process effectiveness throughout the project"(1)

"Risk transfer requires shifting some or all of the negative impact of the threat, alongwith ownership of the response, to a third party. Transferring the risk simply gives another party the responsibility for its management - it does not eliminate it. Transferring liabilities for risk is most effective in dealing with financial risk exposure "(1)

2.1 Issues and research interests

Identifying the risk response failure in a construction project is done for following reasons:

- There is weakness in the decisions taken by Beneficiaries regarding risk response and this leads to the generation of risks
- As a result, risk response hasbecome themain concern in the paper.
- There is need to increase the awareness and interest in the phase of risk response due to the size of construction projects and its complexity
- Moreover, assessment of risks response in construction projects ensures a better performance evaluation and this by keeping a focus on the owner and contractor satisfactions.

3. SAMPLE AND METHODS

3.1 Methodology

The methodology of the paper includes two parts, questionnaire and the use of data mining techniques. The questionnaire was distributed to the owners, the contractor and other parties involved in the project, 41 projects were taken and the questionnaire was distributed to 15 people who workin theproject. The questionnaire includes the strategies for each risk and five measurements were used which are too low, low, medium, high and too high, the risk of the project are shown in the table below and its distributed on three periods 2006-2007, 2008-2013 as shown in the Appendix Aand 2014-2016, for each period different risk appeared for the measurement of risk response Likert scale used which range from one to five as shown in the table and the risk response strategies was denoted by the table

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Table-1. Shows the risk for each period.

Year	Risk
2006-2007	1- Price fluctuations 2- inflation 3- Increase in the cost of skilled labor 4- The delay in completing the project 5- labor productivity 6- Changes in the purchase costs or delay in the delivery of equipment and machinery 7- lack of site workers 8- Exceptional circumstances and risks 9- Wrong estimation
2008-2013	1- Financial difficulty by the contractor 2- The delay in completing the project 3- Design team performance 4- The quality control on the material and expertise in execution 5- Miss management of the contract 6- Exceptional circumstances and risks 7- Wrong estimation
2014-2016	1- Financial difficulty by the contractor 2- The delay in completing the project 3- Design team performance 4- Wrong estimations 5- Financial difficulty by owner and delay in making the decisions 6- Changes in the purchase costs or delay in the delivery of equipment and machinery 7- Exceptional circumstances and risks

Table-2. Show Norms and standards for risk response.

scale	Numerical
Very high	5
high	4
medium	3
low	2
Very low	1

Table-3. Shows the symbols of risk response.

scale	Numerical
Avoidance	1
acceptance	2
transfer	3
Mitigate	4

The second stage includes the use of data mining techniques which are decision tree, neural network and support vector machine, the period from 2006-2013 as training set to predict the failure of 2014-2016 projects

The program that uses is KNIME (pronounced /naɪm/), the Konstanz Information Miner, is data analytics with an open source, reporting and integration platform. Various components can be integrated using KNIME in data mining and machine learning by using the concept of data pipelining modular. A graphical user interface permits assembly of nodes for the preprocessing of data (ETL: Extraction, Transformation, Loading), for data analysis, modeling, and visualization. Since 2006, pharmaceutical research was the area of KNIME,however, it can use in different areas like CRM customer data analysis, financial data analysis and business intelligence (12)

4. RESULT AND DISCUSSIONS

All the projects face some kind of risk response failures it range from medium to low

Using the program, risk response failure in construction project were analyzed using the following techniques neural network this technique was used as part of the model to predict risk response failure.

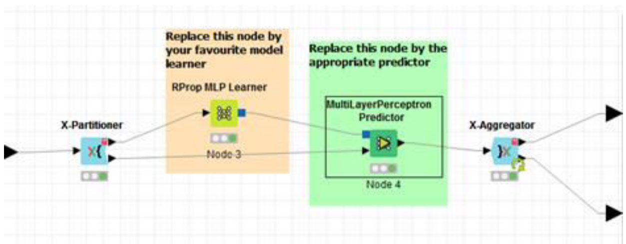

Figure-1. Shows the neural network workflow This workflow represents the neural network model.

X-partitioner: This node in consider cross validation loop beginning. When this loop ends there must be X-Aggregator to so the results will be collected from

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every iteration. All nodes that layamong these two nodes are implemented as many times as iterations should be performed.
RProp MLP Learner: execution of the RProp algorithm for multilayer feed forward networks right-click it and select "Configure" from the menu. The max number of iteration was selected 100 and by try and error the number of the hidden layers was 1 and hidden neuron were 10

X-aggregator: This node should be the end of a cross validation loop and must come after an X-Partitioned node. the result from a predictor node is collected, compares predicted class and real class for all the iteration.

Decision tree

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

The following parameter used: Quality measure: To select the quality measure according to which the split is calculated. Available is the "Gini Index" and the "Gain Ratio".

In this model, gain ratio was selected

Pruning method: tree size is reduced by using Pruning and avoids over fitting that increases the generalization performance, and thus, the quality of prediction (for predictions, use the "Decision Tree Predictor" node). Available is the "Minimal Description Length" (MDL) pruning or it can also be switched off
The MDL was selected

Support vector machine

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

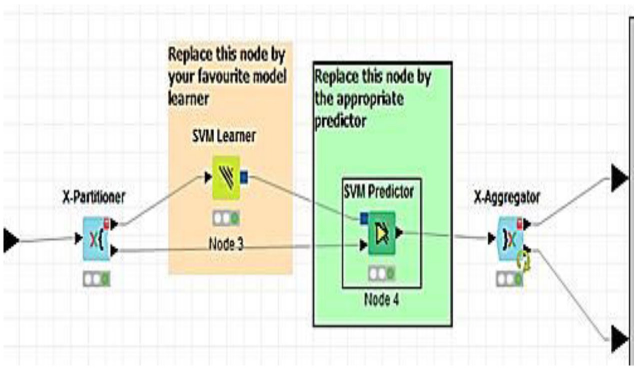

Figure-2. Shows the support vector machine workflow.

Kernel type: There are a different number of kernels to select from. Every kernel has its own parameters, which show in the configuration dialog just under the kernel.

Polynomial kernel was select

Then all the three model were combined to form a model that Compare among these three different techniques and chose it for predictions

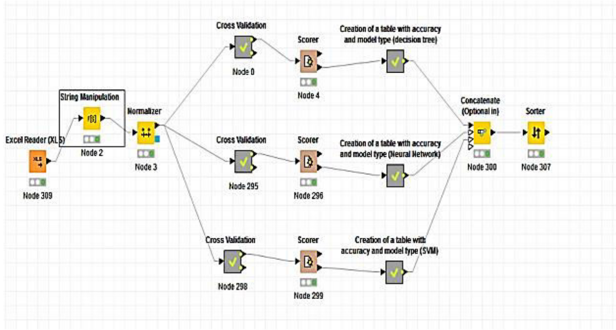

Figure-3. Shows the workflow of the whole techniques.

The normalization method that selected is Min-max normalization the responsibility of this intriguing technique is achieving linear transformation on actual data set and for maintaining the correlation between them.

$$x' = (x_{max} - x_{min}) \times \frac{(x_i - x_{min})}{(x_{max} - x_{min})} + x_{min} \quad (2)$$

Cross validation: is meta node that provides a skeleton of nodes necessary for cross validation

Scorer: Compares two columns by their attribute value pairs and display the confusion matrix, i.e. how many rows of which attribute and their classification match

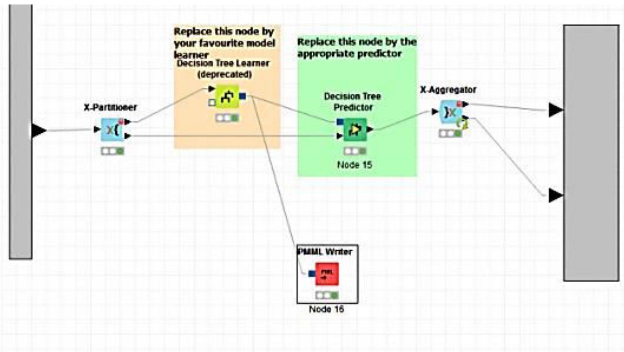

Figure-4. Shows the decision tree workflow.

Table-4. The decision tree results.

class	True post	False post	True neg	False neg	Recall	Precision	sensitivity	Specify	f-mean	Accuracy	Description
Medium	122	20	2	1	.992	.899	.92	.13	.921		The results show that this class isn't classified correctly as there is some error in the medium class and the Precision, but consider as acceptable and the result indicates good classification
low	3	1	122	20	.13	.75	.13	.92	.22		The results show that this class isn't classified correctly as there is some 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										85.6	

Table-5. The neural network results.

class	True post	False post	True neg	False neg	Recall	Precision	sensitivity	Specify	f-mean	Accuracy	Description
Medium	117	22	1	6	.951	.842	.951	.043	.893		The results show that this class isn't classified correctly and show less performance than the last as there is some error in the medium class and the Precision, but consider as acceptable
low	1	6	117	22	.043	.143	.043	.951	.067		The results show that this class isn't classified correctly as there is some 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										80.8	

Table-6. The support vector machine results.

class	True post	False post	True neg	False neg	Recall	Precision	sensitivity	Specify	f-mean	Accuracy	Description
Medium	123	23	0	0	1	.842	1	.0	.941		The results show data classified correctly and the result perform well
low	0	0	123	23	.0	.0	0	1	0		The results show that this class isn't 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-7. The comparison between techniques.

Techniques	Accuracy
Decision tree	85.6
Support vector machine	84.2
Neural network	80.8

decision tree show the best classification that return to the fact that the performance of this techniques regard the best in the nominal classification, there for this technique was used in the research to identify the risk response failure in construction projects in the period from 2006 to 2013 and the depending on the results to predict the failure of the construction projects in the period of 2014 t0 2016.

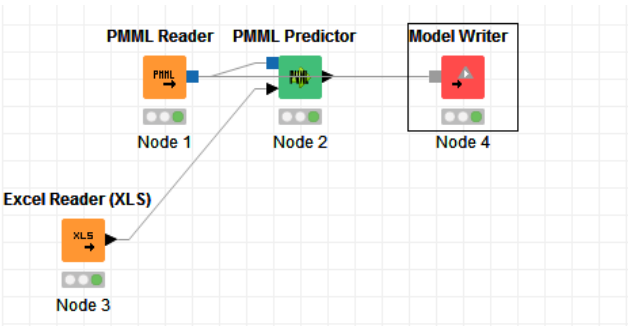

Figure-5. Shows the workflow of prediction using decision tree.

5. CONCLUSIONS

As the results, it can conclude the following:

- All the project face failure in construction projects, at this stage doesn't receive much attention in the projects that lead to the failure.
- The decision tree shows the highest accuracy and that because it considers the best algorithm in prediction of nominal class
- The neural network shows the lower accuracy as the nature of the algorithm tend more to the numerical class
- The support vector machine show good results close to the decision tree

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