SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2025
ORGANIZATION AND MANAGEMENT SERIES NO. 230

MACHINE LEARNING MODEL OF RISK ANALYSIS IN PROJECTS – CASE STUDY

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Purpose: The article presents the research results concerning the development of a machine learning model for risk analysis in project management. Artificial intelligence, especially artificial neural networks (ANNs), could have significant impacts on decision-making processes by improving the identification and assessment, of risks in complex projects. With the enormous amount of projects, the need for more objective, data-driven tools in risk management calls for innovative solutions that reduce human bias and enhance predictive accuracy. The main purpose of the research is to create and validate an Artificial Neural Network (ANN) model capable of assessing and classifying project's level of risk based on historical or expert reviewed data.
Design/methodology/approach: The objectives of the research were achieved by combining literature review and expert consultation to obtain a structured dataset of project risk factors that are compiled and preprocessed through normalization and feature selection, and then used to train the ANN model. The model's performance is evaluated by inputting predetermined data and checking the accuracy by comparing the result from the predetermined data's result.
Findings: It was found that the ANN model achieved high accuracy (84%) which indicates the model generalizes well with synthetic data but real world data would significantly improve the accuracy and quality of the output.
Research limitations/implications: The complications mainly depends on quality and quantity of the data for the ANN model to train on, potential computational complexity and potential overfitting risks in the ANN model.
Practical implications: The model serves as a decision support tool for project managers, enabling an objective and accurate risk evaluation that can also be integrated into project management software's. Such an approach can support decision makers of new projects.
Social implications: The requirements are users with digital skills which are essential for the future engineers and project managers. The study also suggests future integration with project management software, while educational institutions develop IT and digital skills of future engineers but basic data analysis skills are recommended as they would result in a more optimal usage of the model.
Originality/value: The value of the research is applying an ANN machine learning model which is versatile and can be effectively used with multi-dimensional and complex risk data.
Keywords: project management, risk management, machine learning.
Category of the paper: research paper, case study.

1. Introduction

Risk is an inherent element of all human and organizational activities, manifesting in technical, financial, and temporal dimensions of projects. It arises from the environment, stakeholders, and processes, and although it can occasionally yield positive effects, it most often leads to adverse consequences (Toader, 2024; Didraga, 2013). In project management, the ability to anticipate and address risks is a critical determinant of success, particularly in projects characterized by high complexity and innovation. Traditional risk management approaches, while effective to a degree, are frequently limited by their reliance on the subjective judgment of evaluators. Decision-making in such conditions often depends on intuition, which is prone to cognitive biases and predictable errors (Virine, 2009). Therefore qualitative and quantitative risk evaluation, potential impacts and mitigation strategies are essential (Volkan, 2021; Hulten, 2019; Sengar, Chandra, 2024).

In this context, the application of artificial intelligence (AI) especially machine learning (ML) presents a significant ability in identifying the level of project risk using historical data from previous projects as it can detect patterns and deliver accurate evidence based predictions. This supports proactive decision making allowing project managers to address risky projects before they materialize.

The purpose of the research is to develop and validate a machine learning model based on artificial neural network (ANN) for project risk assessment. The model uses synthetic project data of selected key risk factors to classify project into different risk levels, preprocessing of the data, implementation of ANN into the code and evaluating the model through comparison of the result with predetermined project data to determine how accurate the model is.

2. The characteristics of applied risk models including a machine learning approach

Different techniques are used to evaluate and prioritize risk. Depending on how well the risk is known, and if it can be evaluated and prioritized in a timely manner, it may be possible to reduce the possible negative effects or increase the possible positive effects and take advantage of the opportunities. “Quantitative risk analysis tries to assign objective numerical or measurable values” regardless of the components of the risk assessment and to the assessment of potential loss. Conversely, “a qualitative risk analysis is scenario-based” (ISACA, 2021).

The quantitative approach aids in identifying pertinent risk scenarios, providing more comprehensive information for decision-making. Prior to executing key judgments or intricate tasks, quantitative risk analysis offers more objective knowledge and precise statistics compared to qualitative analysis. While quantitative analysis is more objective, it is important to acknowledge that it still involves estimation or inference. Prudent risk managers take additional aspects into account during the decision-making process. While qualitative risk analysis is preferred for its simplicity, quantitative risk analysis may be required. Subsequent to qualitative analysis, quantitative analysis may also be implemented.

A quantitative risk analysis evaluates high-priority and/or high-impact risks by assigning numerical ratings to facilitate a probabilistic assessment of business-related concerns. Moreover, the application of quantitative risk analysis in project management is constrained by the project's nature, associated risks, and the accessibility of data for such analysis. The objective of a quantitative risk analysis is to convert the likelihood and consequences of a risk into a quantifiable metric.

Qualitative risk analysis is fast but inherently subjective. Conversely, quantitative risk analysis, while optional, is objective and provides more detailed insights, including contingency reserves and go/no-go decisions. However, it is more time-consuming and complex.

The research design of this paper focuses on developing an Artificial Neural Network (ANN) model to assess risk levels in projects using machine learning. The dataset comprises of multiple project risk records with 31 distinct risk factors, where each project is assigned a risk score for every factor. These scores collectively determine whether a project falls into one of five categories: very high risk, high risk, medium risk, low risk, or very low risk.

The first step in the research process involves gathering and preparing the dataset, ensuring that all data points are structured correctly for model training. Since the dataset consists of numerical values, it is necessary to normalize and standardize the data to ensure that risk scores are on a uniform scale, preventing any feature from disproportionately influencing the model. The ANN architecture is composed of an input layer containing 31 neurons, corresponding to the identified risk factors, one or more hidden layers for pattern extraction and an output layer of five neurons corresponding to risk categories (very high, high, medium, low, very low) each hidden layer applies activation functions like ReLU and Sigmoid to capture non-linear relationships between project risk factors. The model learns through adjusting weights and biases to minimize prediction errors.

Next, the data set is partitioned into training and test subsets, with eighty percent allocated for training the ANN and twenty percent reserved for performance evaluation. This split ensures that the model can learn patterns from historical risk scores while still being evaluated on unseen data.

3. The research results based on the elaborated machine learning model of risk analysis in projects

The problem defined is evaluation of risk factors of projects to identify how risky is the project. Ideally, real data would have been used to derive weight of each risk factor and how effective it is for each project to provide good insight on appropriate risk management procedures to avoid or minimize the effect of these factors. However, such data is very difficult to gather.

According to COSO (Committee of Sponsoring Organizations of the Treadway Commission, 2023) there are several types of risks within the context of compliance risk management. Here are the key types of risks used for the model:

- ✓ Organizational risks: Risks arising from structure or governance of the organization which can be leadership issues, strategic alignment or decision making.
- ✓ Operational risks: Risks arising from internal processes, people, and systems, or from external events. These encompass the blunders of processes, breakdowns of systems, or mistakes made by individuals.
- ✓ Financial risks: Risks associated with financial losses like asset depreciation, unpredictable changes in the financial market, and inaccuracies in financial reporting.
- ✓ Strategic risks: Risks which affects an organization's capabilities to accomplish their strategic goals. Such risks include alterations in the business landscape, rivalry, and changes in the economic environment.

After reviewing various sources and gathering inputs from a limited survey of project management expert, the risks in table 1 are recognized to be the most impactful in projects. These risks are used in the AI model as inputs to asses if the project is worth pursuing or not.

Table 1.
The selected risk factors implemented in the elaborated ANN model

Risk factor	Reference	Risk factor	Reference
Organizational level		Inadequate material deliveries in terms of quantity, quality, time, place and cost	Gaschi-Uciecha, A. (2019)
Unclear objectives of project	Shrivastava, S.V., Rathod, U. (2015)	Operational cost overruns	Own study
Product portfolio uncertainty	Chiu, Yu-Jing et al. (2022)	Inadequate adjustment of order fulfillment conditions to the company's capabilities	Gaschi-Uciecha, A. (2019)
Frequent Architectural Changes	Shrivastava, S.V., Rathod, U. (2015)	Unrealistic requirements risk	Borghesi, A., Gaudenzi, B. (2012)
Shortage of employees	Gaschi-Uciecha, A. (2019)	Shortfalls in functionality	Borghesi, A., Gaudenzi, B. (2012)
Regulatory Compliance	Own study	No maturity for a project of a company in the scope of knowledge management	Kozień, E., Kozień, M.S. (2019)
Inefficient manual processes for risk management	GRC 20/20 (2024)	Inefficient Task Execution	Own study

Cont. table 1.

Inefficient managerial and organizational system of a company supporting management of a project	Kozień, E., Kozień, M.S. (2019)	**Financial level**	
Timeline mismanagement	Chiu, Yu-Jing et al. (2022)	Raw material/exchange rate/price fluctuation	Shrivastava, S.V., Rathod, U. (2015)
Performance risk	Own study	Customer demand uncertainty cost	Chiu, Yu-Jing et al. (2022)
Operational level		Tax compliance	Kerur, S., Marshall, W. (2012)
Lack of communication between team and the client	Shrivastava, S.V., Rathod, U. (2015)	Sudden changes in technical progress	Kozień, E., Kozień, M.S. (2019)
Lack of communication infrastructure	Shrivastava, S.V., Rathod, U. (2015)	**Strategic level**	
Lack of Documentation	Shrivastava, S.V., Rathod, U. (2015)	Market conditions, standards and practices	Kerur, S., Marshall, W. (2012)
Failure by suppliers to meet technical standards for materials	Gaschi-Uciecha, A. (2019)	Geopolitical conflicts	Kerur, S., Marshall, W. (2012)
Employee turnover risk	Chiu, Yu-Jing et al. (2022)	Lack of availability of components	Borghesi, A., Gaudenzi, B. (2012)
Inappropriate IT system	Gaschi-Uciecha, A. (2019)	Societal disruptions	Own study
Production procedure complexity	Shrivastava, S.V., Rathod, U. (2015)		

Source: own elaboration.

When the model is established, it is trained on a prepared dataset. Artificial neural network (ANN) is used as it can model complex and nonlinear relationships between risk factors. At this point, the algorithm is attempting to learn the patterns and relationships present in the data by adjusting its internal parameters. The quality of training can be influenced by several factors such as size of the dataset, selection of features and hyper parameter tuning. These, if optimized, will certainly help in ensuring that the model is able to generalize new data rather than just learning the training set.

Because a real world dataset did not exist in a big enough quantity for training purposes, a synthetic method was used. For a number of projects, data was created where each project was given scores for 31 predetermined risk factors within a scale of 1 to 100. Those risk factor scores were used as input features for the model, 506 synthetic project data was created for the purpose of training the model. The example of a few risk factors in an input record is given in table 2.

Table 2.
The example of a record as input data to train the model

Raw material/ exchange rate/price fluctuation	Customer demand uncertainty cost	Tax compliance	Sudden changes in technical progress	Market conditions, standards and practices	Geopolitical conflicts	Societal disruptions	Risk level
62	64	69	69	68	79	78	High

Source: own elaboration.

As a standard procedure, the dataset is partitioned into training data which constitutes 80% of the entire data, while the remaining 20% is testing data (Testas, 2023). After dividing the data set into testing and training data, Kappa Measurement can be calculated which shows how good prediction measures for both unseen data is. Folds of cross-validation such as k-fold cross-validation are also employed to improve accuracy in model prediction. Though the synthetic dataset is not real, it is useful for its intended purpose because it has the required amount and diversity of data which would be needed to train machine learning models.

When the model was established, it was trained on the prepared dataset, where the algorithm attempted to learn the relationships in the data by adjusting its internal parameters. To strengthen reliability of evaluation, k-fold cross validation was introduced, thereby reducing the possibility of overfitting.

The ANN architecture consisted of an input layer of 31 neurons (corresponding to the risk factors), one or more hidden layers responsible for extracting complex patterns, and an output layer of 5 neurons representing five risk categories (very high, high, medium, low, very low). The general idea of the artificial neural network (ANN) is given in figure 1. In the hidden layer contains densely connected layers with ReLU activations to help map non-linear relationships, and dropout layers to prevent overfitting. The model is trained with the Adam optimizer and sparse categorical cross entropy loss. This training method is suitable for multiclass problems where the target's labels can be expressed through integers.

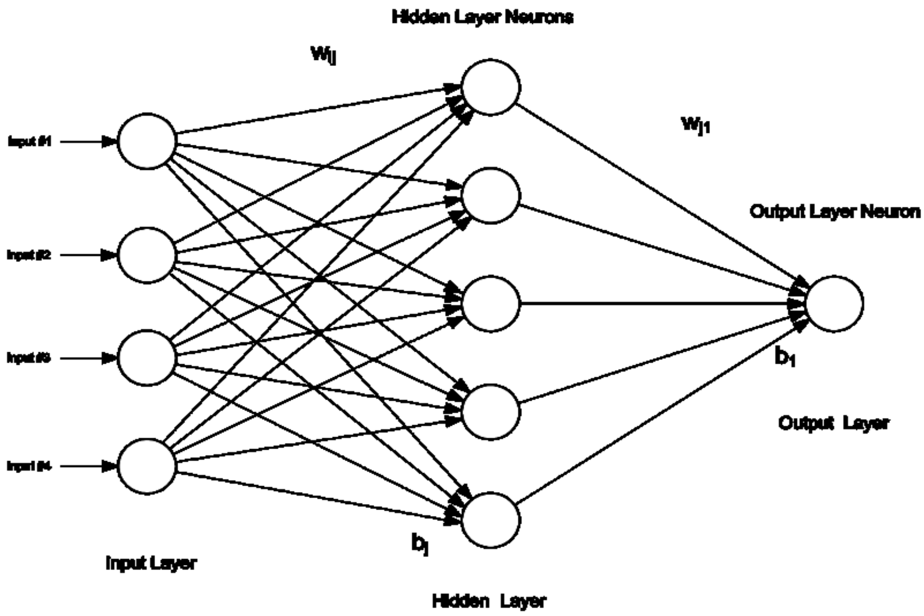

Figure 1. A typical artificial neural network (ANN).

Source: own elaboration.

The model tries to prevent overfitting by implementing early stopping, which monitors the validation loss and automatically stops training when there’s no further improvement. After training, the model is saved to disk so that it can be reused without the need to retrain.

3.1. Code implementation

In fig. 2 the code representing the achitecture and main hyperparametres of ANN was given.

```
model = Sequential()
model.add(Dense(100, activation='relu', input_shape = (n_cols,)))
model.add(Dense(100, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(100, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(5, activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Figure 2. The code representing ANN.

Source: own elaboration.

The neural network model is created using a Sequential API, which enables a straightforward implementation where layers are connected in a sequential order. The first layer of the network is a dense layer consisting of 100 neurons with a ReLU activation function.

This command creates a new instance of a sequential model, which is an ordered linear arrangement of its components. In sequential models, layers are organized in series, so that the output from a certain layer directly becomes input for the next layer. These layers are referred as 'dense' because each node or neuron is connected to all nodes in previous layers. By using dense connections, the layer can capture high level features from data represented by all input variables.

Dense (fully connected) layer with 100 neurons is added. The parameter input_shape=(n_cols,) specifies that each input sample is expected to have a number of features equal to n_cols, where n_cols is the number of columns in the input data which is 31 in this case. The activation function used here is ReLU (Rectified Linear Unit), which transforms the input to the layer by outputting the maximum between 0 and the input value. ReLU introduces non-linearity to the model, enabling it to learn complex patterns in the data while being computationally efficient and helping to mitigate the vanishing gradient problem.

Dropout is a regularization technique used to prevent overfitting by randomly deactivating a fraction of neurons during each training update. In this case, 0.2 means that 20% of the neurons in the preceding layer will be dropped (i.e., their outputs set to zero) during training. This forces the network to develop redundant representations, which enhances its ability to generalize to unseen data.

A third dense layer with 100 neurons and ReLU activation is added, further deepening the network. The additional layer provides more capacity for the model to capture intricate relationships between the input features and the target variable.

Another Dropout layer is introduced with the same 20% dropout rate. Stacking dropout layers in deeper networks is common practice to continuously control overfitting as the network's complexity increases.

The final dense layer consists of 5 neurons, each corresponding to one of the 5 risk categories to be predicted. The activation function applied here is Softmax, which converts the raw outputs (logits) from the layer into a probability distribution over the 5 classes. The softmax function is defined as:

$$\mathrm{softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{5} e^{z_j}} \tag{1}$$

where z_i is the input to the i-th neuron. This transformation ensures that the sum of the probabilities across all classes is equal to 1, making it ideal for multiclass classification problems.

3.2. Results of the elaborated model

The ANN achieved strong performance as it reached an accuracy of 0.84, which indicates that it produced correct prediction 84% of cases. Beyond accuracy the model demonstrated balanced outcomes. The exemplary result of the model' output is given in figure 3.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 108ms/step
previous value = High                --> predictive value = High
previous value = Very High           --> predictive value = High
previous value = Very Low            --> predictive value = Very Low
previous value = High                --> predictive value = Very Low
previous value = Very High           --> predictive value = High
previous value = Medium              --> predictive value = Very Low
previous value = High                --> predictive value = Very High
previous value = Low                 --> predictive value = Low
previous value = Low                 --> predictive value = Low
previous value = Very Low            --> predictive value = Low
```

Figure 3. The results of the elaborated ANN model.

Source: own elaboration.

The results as predictions of the model are as follows:

1. High accuracy: The high accuracy (84%) is reflected in the frequent matches between previous and predicted values. For example, the model consistently predicts "High" and "Low" values accurately, showing it has learned the patterns for these categories effectively.
2. Misclassifications: The mismatched predictions (e.g., Very High → High, Medium → Very Low) suggest that the model struggles with fine-grained differentiation between adjacent risk categories (e.g., "Very High" and "High"). This could stem from overlapping features between these categories or limited training data for specific risk levels.
3. Overall Effectiveness: Achieving 84% accuracy indicates that the model generalizes well to unseen data but still leaves room for improvement. Strategies like gathering more balanced data, refining hyperparameters, or using more complex architectures could address the misclassifications.

4. Discussion of the results

The problem, undertaken within the research, concerning the assessment of risk level in projects is of significant importance in a dynamic and complex reality of today's world. The quantitative approach in the form of a machine learning model could improve managers' decisions. The complications mainly depends on quality and quantity of the data for the ANN model to train on, potential computational complexity and potential overfitting risks in the ANN model. The value of the research is applying an ANN machine learning model which is versatile and can be effectively used with multi-dimensional and complex risk data.

The results of the research generated the following recommendations:

1. Enhancing data-driven risk analysis: Organizations should integrate machine learning models for risk analysis to reduce reliance on subjective assessments by project managers.
2. Improving risk prediction models: Incorporate diverse datasets and real-time data analytics to enhance the accuracy and adaptability of AI-based risk prediction models.
3. Standardizing risk evaluation metrics: Establish universal benchmarks for risk probability and impact assessment to facilitate consistent evaluations across industries.
4. Encouraging proactive risk management: Shift from reactive risk mitigation strategies to proactive risk identification through predictive modelling.
5. Strengthening IT risk management: Given the increasing digitalization of projects, a dedicated risk framework for cybersecurity, data protection, and system reliability is essential.
6. Implementing AI in risk assessment: Automating risk identification, categorization, and response planning can improve efficiency and minimize human errors.
7. Enhancing collaboration between AI and human expertise: Machine learning models should complement human decision-making, allowing for a balanced approach in risk management.
8. Continuous training for project managers: Organizations should train project managers in AI-driven risk analysis tools and methodologies to maximize effectiveness.
9. Regularly updating risk models: AI-based risk models should be updated frequently with new data and evolving industry risks to ensure their continued relevance.
10. Encouraging further research on hybrid risk management approaches: Combining traditional qualitative assessments with AI-driven quantitative methods can improve overall risk evaluation processes.

5. Conclusions

The undertaken research on the development of a machine learning model for project risk assessment leads to the following conclusions:

1. The development of the 31 risk factors across organizational, operational, financial and strategic level process shows that project risks are not isolated reinforcing the need to use a holistic approach in risk management, also demonstrates that different qualitative risks can be standardized and transformed into quantitative inputs for consistent analysis.
2. The artificial neural network (ANN) model developed in this study successfully classified projects into five risk levels (very high, high, medium, low, very low) with an accuracy of 84%. This confirms the feasibility of using machine learning for effective project management.
3. Pre-processing steps, including feature selection, normalization and outlier removal proved essential for improving model efficient and accuracy. Reliable risk assessment depends strongly on the quality and structure of available data.
4. The findings of this research suggest that AI-based models significantly enhance risk identification, evaluation, and response strategies. Machine learning models, particularly artificial neural networks (ANNs), provide a robust mechanism for processing risk-related data, identifying correlations, and predicting the probability of adverse events occurring.
5. AI can facilitate real-time risk monitoring, allowing project managers to continuously adjust risk mitigation plans as new variables emerge. However, while AI can predict potential risks with remarkable accuracy, its effectiveness is contingent on high-quality data inputs, proper model training, and ongoing refinement.

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