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Risk Assessment of railway tunnel segments using machine learning models

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Abstract: Tunnels, as unique structures, have a wide range of applications for different purposes; however, their specificity is accompanied by numerous uncertainties that can generate risks. In Republic of North Macedonia, a significant number of tunnels are planned along the railway of Corridor 8. Across three sections of this railway corridor, 49 tunnels have been designed with varying characteristics influenced by multiple factors. The detailed processing and classification of data for these tunnels provide a substantial database that can be utilized for risk assessment. This research aims to conduct a comprehensive analysis using machine learning models for assessing risks of tunnel segments application, taking into account various project data without predefined risk categories.

Keywords: Tunnel construction, assessment of uncertainties, risk analysis, machine learning

1. Introduction

In the lifecycle of infrastructure projects, risk and uncertainty are inevitable, particularly in complex underground construction. Tunnel projects are highly sensitive to varying geological conditions and unforeseen events, making implementation of effective risk management crucial. This paper addresses risk identification in tunnel construction through a combined methodological approach, integrating traditional techniques with modern data-driven machine learning models.

Tunnel construction along Corridor 8 in North Macedonia, a major pan-European transportation axis, serves as a case study. A total of 49 railway tunnels spanning approximately 25,5 km had been planned across three sections, providing a solid dataset for risk modelling. For all three railway sections, complete project documentation has been prepared at the level of main design, which also include the tunnels. The first two sections are in similar area (2 continuous sections with total length of 57,4 km) in the north-east part of the country, while the third section (with length of 63,2 km) is in different area in the south-west part. Also, one section is under construction, while the other two have not yet started.

2. Data overview

The dataset used comprises detailed information for total of 341 tunnel segments designed, according to the New Austrian Tunneling Method (NATM). The main parameters (numerical values) are grouped into four main categories:

- General-geometric characteristics (segment length, maximum overburden, excavation area);
- Geological-geotechnical characteristics (coefficient for investigative boreholes, deformation module, global strength, RMR, RQD, GSI, UCS, probability of appearance of faults);
- Support characteristics (quantities per one meter for anchors, shotcrete, reinforcement mesh, steel ribs/girders, tunnel face support (shotcrete), pipe roof umbrella, final concrete lining);
- Construction technology characteristics (excavation step length, blasting disturbance, groundwater conditions-coefficient).

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After creating the first models some parameters (tunnel slope and curve radius, volume weight, cohesion and angle of friction) were removed due to their apparent lower importance level, illogical correlation with other parameters and/or overall anomaly exhibited through modeling.

3. Methodology

The general idea for this research was to use machine learning (ML) models to assess the risk level of each segment using the available design data, without previously defining the risk in quantitative or qualitative form as a target variable.

At first, basic statistical and corelation analysis were performed in order to identify the most significant factors and to make distribution of values for each parameter (Fig. 1). Segment length and the maximum overburden have a wide distribution, i.e. there are quite different geometric conditions in these tunnels, which is expected. The geotechnical characteristics have different distribution shapes (normal and asymmetric). Support elements have a variation that can be associated with different geological condition. The construction technology data have specific values that can be grouped.

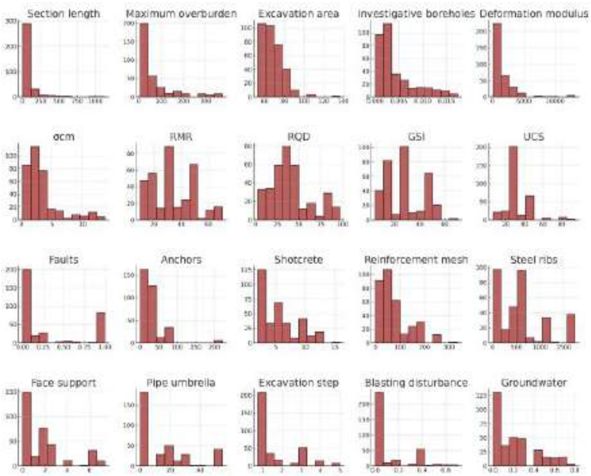

Fig. 1. Histograms of distribution for each parameter.

After a correlation analysis, the correlations between the parameters show similar conditions as for real tunnel states. Here are some of the more important correlations:

- RMR, RQD and GSI are highly correlated, which is expected as they all reflect rock mass quality;
- Deformation modulus has a moderate correlation with RMR and RQD, suggesting that weaker rocks have lower stiffness;
- Fault probability has a negative correlation with RMR and RQD, suggesting that fault zones often have weaker rock mass;
- Anchors, shotcrete and reinforcement mesh have a positive correlation with lower RMR and RQD values, suggesting that more of reinforced support is applied to weaker rocks;
- Steel ribs and pipe umbrella show a strong relationship with critical geological conditions;
- Excavation sequencing is negatively correlated with weak rocks, suggesting that in weaker conditions a shorter excavation advances are applied for increased stability;
- Groundwater has a negative impact on RMR and is associated with increased use of support.

Because this research approach is implemented without predefined target value, the next step was arriving at cluster analysis for determination of groups of tunnel segments with similar characteristics (Fig. 2).

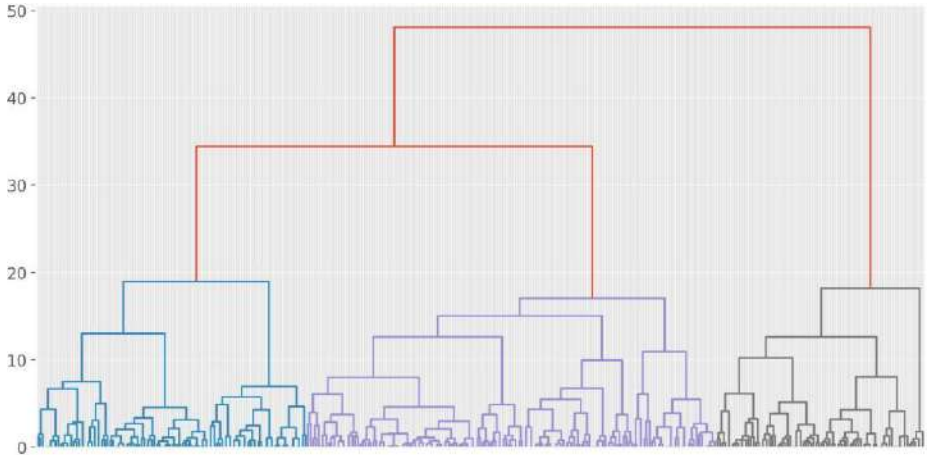

Fig. 2. Dendrogram of tunnel segments with similar characteristics (the horizontal axis represents the segments and the vertical axis is the Euclidean distance)

According to the cluster analysis, three clusters or risk categories are assessed. Some of the main characteristics with their average values for the clusters are:

- Category (cluster) 1 – High risk
  - Low values for RMR (17,1), RQD (29,3) and GSI (12,6) – very weak rock mass.
  - High probability of faults (0,99).
  - High use of anchors (54,4 m/m), shotcrete (9,99 m³/m), reinforced mash (123,9 m²/m) and steel ribs (1269,8 kg/m).
  - Highest use of pipe roof umbrella (32,2 m/m) for protection.
  - Very short excavation step (0,81 m).
  - Significant presence of groundwater (0,42).

- Category (cluster) 2 – Medium risk
  - Medium values for RMR (31,0), RQD (32,7) and GSI (25,1).
  - Low probability of faults (0,09).
  - Moderate use of anchors (26,3 m/m), shotcrete (5,08 m³/m), reinforced mash (60,2 m²/m) and steel ribs (593,3 kg/m).
  - Occasional use of pipe roof umbrella (13,7 m/m).
  - Longer excavation step (1,09 m) compared to category 1.
  - Moderate presence of groundwater (0,17).

- Category (cluster) 3 – Low risk
  - RMR (52,6), RQD (56,8) and GSI (44,8) – better rock mass compared to previous categories.
  - Very low probability of faults (0,03).
  - Low or no usage of anchors (15,0 m/m), shotcrete (3,16 m³/m), reinforced mash (56,4 m²/m) and steel ribs (42,3 kg/m).
  - Longer excavation step (2,95 m).
  - Small presence of groundwater (0,09).

With such defined clusters, 3 models were developed using machine learning technique which based on the input data (numerical values of the characteristics) can predict the target variable in this case risk category.

3.1. ML models for prediction of risk categories

The first ML model is based on the so-called Random Forest Classifier, which is perhaps one of the most popular machine learning algorithms used for classification tasks. It consists of multiple decision trees that are similar to fault and event trees with different subsets of the data. Each of the trees gives its own prediction, and most often the predicted class becomes the final result. To build the model, a set of training and prediction data (80-20%) was first created, and then with the resulting model, a prediction was made for all sections. The dependences of the influence factors are most balanced in this model (Fig. 3).

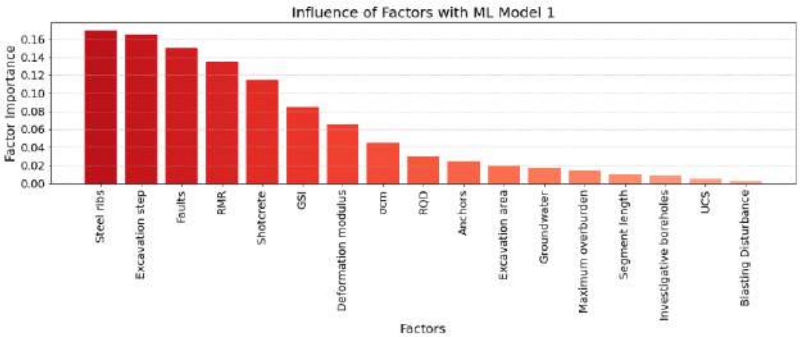

Fig. 3. Dependences of the influence factors with the first ML model.

The results in this model indicate that geological conditions are the most influential factor group in determining the risk category of tunnel segments, contributing over 50% of the total importance (Fig 4). These conditions drive subsequent decisions, such as support measures and excavation advances. This supports the observation that weak or faulted rock masses typically require heavier support and more controlled excavation (excavation in phases with smaller areas).

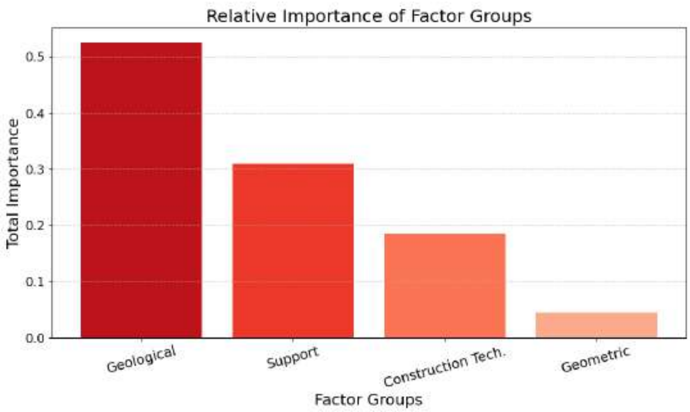

Fig. 4. Feature importance analysis by factor groups with the first ML model.

The second ML model is also a very popular and powerful machine learning algorithm, which is an improved version of Gradient Boosting and is called XGBoost. It is known for its speed, efficiency and high accuracy, and is similar to the first model because it also uses learning trees. The difference is that this model builds the trees one by one, where each new tree improves the previous one, i.e. corrects the error. This model has the most logical dependences for the influence of the factors, but they are not so balanced as the first model.

The last ML model is logistic regression. This is a basic and, in some cases, efficient classification model in machine learning. This model provides more illogical dependencies for the influence of the factors compared to the first two models. A combination with linear regression, i.e. a hybrid model, was also made, but still the model does not improve with respect to the influence of the factors.

Table 1. Prediction of the models according to number of predicted segments.

Model	**Category 1 High Risk**	**Category 2 Medium Risk**	**Category 3 Low Risk**
Cluster analysis	80 (23%)	157 (46%)	104 (31%)
ML model 1	81 (24%)	156 (45%)	104 (31%)
ML model 2	74 (22%)	127 (38%)	140 (40%)
ML model 3	78 (22%)	158 (46%)	105 (31%)

All three ML models have the ability to make prediction of the risk category (Table 1), but with different influences of the factors (data). The first two models have generally good logic for the dependences, where the main dominant factors are: faults, RMR, steel ribs, excavation step, shotcrete, anchors, GSI and global strength. They can be used for different kinds of tunnels segments even with reduced amount of data. The third model although it gives solid prediction, makes dependences that are not very much applicable in real scenarios so its use is limited. ML models can be also compared according to their accuracy MAE (Mean Absolute Error), RMSE (Root Mean Squared Error) and R^2 (Coefficient of determination) as shown in Table 2, where the first model has the best results.

Table 2. Assessment of the accuracy of the models.

Model	**MAE**	**RMSE**	**R^2**
ML model 1	0,0145	0,1204	0,9697
ML model 2	0,0435	0,2085	0,9420
ML model 3	0,0435	0,2085	0,9091

4. Discussion

ML models can outperform classical approaches in terms of scalability, predictive accuracy, and ability to capture complex interactions. Clustering reveals that segments can be assessed in 3 main risk categories according to their parameters. The number of categories can be expanded using the same or different available data and also manual (expert opinion) modifications can be done for assessing the risk categories. The presented models can make predictions of the main risk categories, but the all have different dependences of the influence of factors. Correction of the influence of factors can be made with elimination of some parameters, including more data (if available), making changes in the model (optimising) or changing the model itself. The third model for example even with modification did not improve, giving him usability in more basic or preliminary analysis.

5. Conclusion

This research demonstrates the practical value of applying machine learning techniques for risk assessment in tunnel construction, particularly in the context of the railway tunnels planned along Corridor 8 in North Macedonia. The study focused on evaluating 341 tunnel segments without predefined risk categories, utilizing detailed project design data encompassing geometric, geotechnical, support, and construction technology characteristics.

By applying clustering and supervised ML models such as Random Forest, XGBoost, and Logistic Regression, three distinct risk categories were successfully identified and predicted. Among the tested models, the first one showed the best performance in terms of accuracy and logical correlation between input parameters and risk classification. Key influencing factors such as fault probability, rock mass quality indicators (RMR, RQD, GSI), groundwater conditions, and support measures (anchors, shotcrete, steel ribs) were consistently identified as dominant risk contributors.

The results confirm that ML models can outperform traditional methods by offering scalable, data-driven solutions for automated risk classification and prediction. Furthermore, they provide insights that can assist engineers, planners, and decision-makers in designing more resilient and cost-effective tunnel support systems, while reducing uncertainties during construction.

Future work should focus on expanding the models to include cost and time dimensions, integrating expert judgment, and adapting them to other tunneling environments and construction techniques to enhance generalizability and robustness. Models can be modified to predict a certain numeric value (such as probability of occurrence) to one or multiple risks related to different hazards. The numerical approach can also be used as a backward analysis where risks have already occurred, to determinate the influence of the input parameters and their dependences.

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