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Development of VRS Empirical System for Volcanic Rocks

Luís Ribeiro e Sousa[1], Joaquim Tinoco[2], Rita Leal e Sousa*[3], Karim Karam[4] and António Topa Gomes[1]

[1] Construct, School of Engineering, University of Porto, Portugal

[2] ISISE, University of Minho, Guimarães, Portugal

[3] Dept. of Civil, Environ. & Ocean Engineering, Stevens Institute of Technology, Hoboken, USA

[4] Sarooj, Muscat, Oman

* rsousa@stevens.edu (*corresponding author's E-mail)*

Abstract

Preliminary calculation of the geomechanical parameters of rock masses can be carried out using empirical classification systems. These systems consider, between others, the properties like the strength of the rock, density, condition and orientation of discontinuities, groundwater conditions and the stress state. For volcanic rocks, a new empiric system was developed designated VRS (Volcanic Rock System), from the adaptation of the RMR (Rock Mass Rating) system. For the VRS, geotechnical information was collected from samples from several Atlantic Ocean islands that include Madeira and Canarias archipelagos, taking also into consideration data from other different sources. The various rock types are described with particular emphasis on the Madeira Island rock formations and their geomechanical properties. The new empirical system is based on the consideration of six geological-geotechnical parameters to which relative weights are attributed. The final VRS index value, which varies between 0 and 100, is obtained through the algebraic sum of these weights. With this index, it is possible to obtain strength properties, deformability moduli, and description of the rock mass quality, as well as recommendations for excavation and support needs and support loads, using correlations with other geomechanical indices. Some representative correlations were obtained between VRS coefficients and RMR values. Correlations were obtained between deformability rock mass modulus and VRS with an exponential expression and also for each rock type. Finally, Artificial Intelligence techniques were applied to predict volcanic rock masses classes, using different algorithms, like Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Multiple Regression (MR). Considering variables from the VRS and RMR systems, a better performance is achieved using attributes from the VRS; and ANN and MR algorithms present very similar performances that are superior to the SVM.

Keywords: Volcanic rocks, Geomechanical characterization, VRS empirical system, Data Mining (DM).

1. Initial Considerations

Evaluation of the geomechanical parameters of rock masses can be carried out using the empirical classification systems. These systems consider, between others, the properties like the strength of the rock, density, condition and orientation of discontinuities, groundwater conditions and the stress state. To evaluate these properties, a numerical measure is given and, subsequently, a final geomechanical index is obtained by applying a numerical expression associated with the system. The result allows classifying the rock mass in a certain class associated with important information for the design like in some cases construction sequences, support needs and geomechanical parameters.

The purpose of this paper is to analyze the geomechanical behavior of volcanic rock formations, characterize them, and develop an empirical system, as well as to apply Data Mining (DM) techniques in order to develop new models. The empirical systems for volcanic rocks have been designated by VRS (Volcanic Rock System). Geotechnical information was collected from samples from several Atlantic Ocean islands that include Madeira, Azores and Canarias archipelagos, taking into consideration the data from different sources (Miranda et al., 2018). The various rock types are described with particular emphasis on the Madeira Island rock formations and their geomechanical properties.

Artificial Intelligence (AI) techniques are progressing very rapidly since 1956. AI today is labeled as a narrow when it is designed to perform a specific task or labeled general when designed to outperform humans at a very cognitive task (Sousa et al., 2018). The prediction of geotechnical formation behavior in geoengineering is complex because of the uncertainties in characterizing rock masses. In large projects, the real amount of geotechnical data that is generated and collected can be used to reduce uncertainties (Miranda and Sousa, 2012).

Data can hold valuable information such trends and patterns that can be used to improve decision making and optimize processes. Therefore, it is necessary to define standard ways of collecting, organizing and representing data. There are automatic tools from the field of AI and pattern recognition that enable one to analyze and interpret data using DM techniques (Witten et al., 2011, Leskove et al., 2014). DM is an area of computer science that lies at the intersection of statistics, machine learning, data management and databases, pattern recognition, artificial intelligence and other areas.

2. VRS Empirical System to Volcanic Rocks

The VRS empirical system for volcanic rocks is an adaptation of the RMR system and includes a classification developed at São Paulo, for tunnels in basaltic formations (Ojima, 1981, Menezes et al. 2005). The new empirical system is based, like RMR system, on the consideration of six geological and geotechnical parameters to which relative weights are attributed. The final VRS index value, which varies between 0 and 100, is obtained through the algebraic sum of these weights (Miranda et al., 2018). With this index, it is possible to obtain strength properties, deformability moduli, and description of the rock mass quality, as well as recommendations for excavation and support needs and support loads, using correlations with other geomechanical indices.

The following geomechanical parameters were considered: P_1 - UCS; P_2 - rock weathering characteristics; P_3 - intensity of jointing; P_4 - discontinuity conditions; P_5 - presence of water; P_6 - disposition of blocks. Different weights are assigned to each parameter, as illustrated in Fig. 1. In relation to RMR, the properties were identical for P_1, P_4 and P_5, but have different weights. The parameter due to discontinuities orientation P_6, introduced by Bieniawski (1989) as an adjustment of the sum of the remaining five parameters, was difficult to assign a weight, because it depends on groundwater conditions. Instead, it was substituted by another parameter related to the disposition of blocks. This parameter is considered to evaluate block stability. Four situations were considered: blocks of very favorable, favorable, acceptable and not acceptable which refer to the stability of the geotechnical structure. The VRS system considers for P_2 the rock weathering effect which is not considered by the RMR system, while P_3 is related to the joint intensity combining the effects of parameters P_2 (RQD) and P_3 (discontinuity spacing) considered by RMR system. The meaning of different parameters is given in Fig. 1.

A rock mass is classified into six classes. A rock mass designated as class VI has a behavior conditioned by the rock characteristics of deformability and strength, while a formation designated as class I behaves in accordance with the characteristics of the discontinuities. For rock masses with other classes, behavior is determined by the combination of both types of characteristics.

The collected data were organized and structured in a database composed of 108 records with 29 attributes which are described in Table 1 (Miranda et al., 2018). The data were mainly obtained from Madeira Island (76%), with the rest from Canarias Islands (18%) and Mexico (6%). In the database, the deformability modulus of the rock mass (E_{RM}) was derived from the Serafim and Pereira (1983) formula, assuming the restriction of RMR<80. GSI was only calculated for RMR>23 according to the Hoek and Brown criterion (Koek, 2007). The values of cohesion and internal friction angle were obtained through the software RocData (Rocscience, 2015).

Some representative linear correlations were obtained between VRS coefficients and RMR and GSI values as indicated in Figs. 2 and 3, for the most representative rock mass formations (basalt and breccia). Also, correlations between E_{RM} and VRS for basalt and breccia formations are illustrated in Fig. 4.

3. Application of DM techniques to the database

Prediction of geotechnical formation behavior in geoengineering is complex because of the uncertainties associated with the characterization of rock masses. The database can hold valuable information such as trends and patterns that can be used to improve decision making and optimization processes. It is however necessary to define standard ways of collecting, organizing and representing the data. AI tools and pattern recognition techniques enable one to analyze datasets to retrieve information there (Witten et al., 2011, Leskove et al., 2014). DM is an area of computer science that lies at the intersection of statistics, machine learning, data management and databases and pattern recognition. The formal and complete analysis process is called Knowledge Discovery from Databases (KDD) that defines the main procedures for transforming data into knowledge (Cortez, 2010).

Volcanic Rock Mass classification and weights						
P_1	UCS (weight)	R_1 (15)	R_2 (9)	R_3 (6)	R_4 (3)	R_5 (1)
P_2	Rock weathering (weight)	A_1 (20)	A_2 (12)	A_3 (4)		
P_3	Joint frequency (weight)	F_1 (25)	F_2 (20)	F_3 (15)	F_4 (10)	F_5 (5)
P_4	Joint surface conditions (weight)	B_1 (30)	B_2 (25)	B_3 (17)	B_4 (10)	B_5 (0)
P_5	Presence of water (weight)	C_1 (10)	C_2 (7)	C_3 (4)	C_4 (0)	
P_6	Block position (weight)	D_1 (0)	D_2 (-2)	D_3 (-5)	D_4 (-10)	

Uniaxial Strength (P_1)				
R_1 (>120 MPa)	R_2 (60-120 MPa)	R_3 (30-60 MPa)	R_4 (15-30 MPa)	R_5 (<15 MPa)

Rock Weathering (P_2)		
A_1 – Sound or practically sound	A_2 – Moderately weathered	A_3 – Highly or extremely weathered

Joint Frequency (P_3)				
F_1 – One or less per m	F_2 – 2-4 m	F_3 – 5-10 m	F_4 – 11-15 m	F_5 – 15 or more per m

Joint Surface Conditions (P_4)				
B_1 - Very rough discontinuities; closed; hard walls	B_2 – Slight rough discontinuities; separation <1mm; hard wall.	B_3 – Slight rough discontinuities; separation >1mm; soft walls.	B_4 – Separation >5mm discon-tinueties with slickensided walls or 1-5mm thick gouge.	B_5 – Discon-tinuities with soft gouge; separation >5mm discontinuous.

Presence of Water (P_5)			
C_1 - Dry or damp	C_2 - Dripping	C_3 - Flowing	C_4 - Inflow >0.1l/mm

Block Position (P_6)			
D_1 - Very favorable to stability	D_2 - Favorable to stability	D_3 - Acceptable to stability	D_4 - Not acceptable to stability

Fig. 1. VRS volcanic rock mass classification.

Table 1. Name and description of the attributes in the database

P_1, P_2, P_3, P_4, P_5, P_6	VRS weights related to: UCS of the intact rock, rock weathering, joint frequency, joint surface conditions, presence of water, and block position, respectively.
VRS and class	Volcanic rock system value and classification of VRS system.
P_1’, P_2’, P_3’, P_4’, P_5’, P_6’	RMR weights related to: UCS of the intact rock, RQD, joint spacing, joint conditions, groundwater conditions and joint orientation, respectively.
RMR and class	Rock Mass Rating proposed by Bieniawski (1989) and classification based on RMR value.
Type of rock	1-compact basalt; 2-fractured basalt; 3-compact breccia; 4-desegregated breccia; 5-compact tuff; 6-desegregated tuff; 7-pyroclastic; 8-trachitics.
Depth (m)	Depth of the sample.
E(GPa),UCS(MPa),W	Deformability modulus, UCS and weathering of the rock, respectively
E_{MR}(GPa),c(MPa),φ(°)	Deformability modulus, cohesion and internal friction angle of the rock mass, respectively.
m_i,m_b,s, GSI	Rock material constant, rock mass constants, and Geological Strength Index by Hoek (2007), respectively.

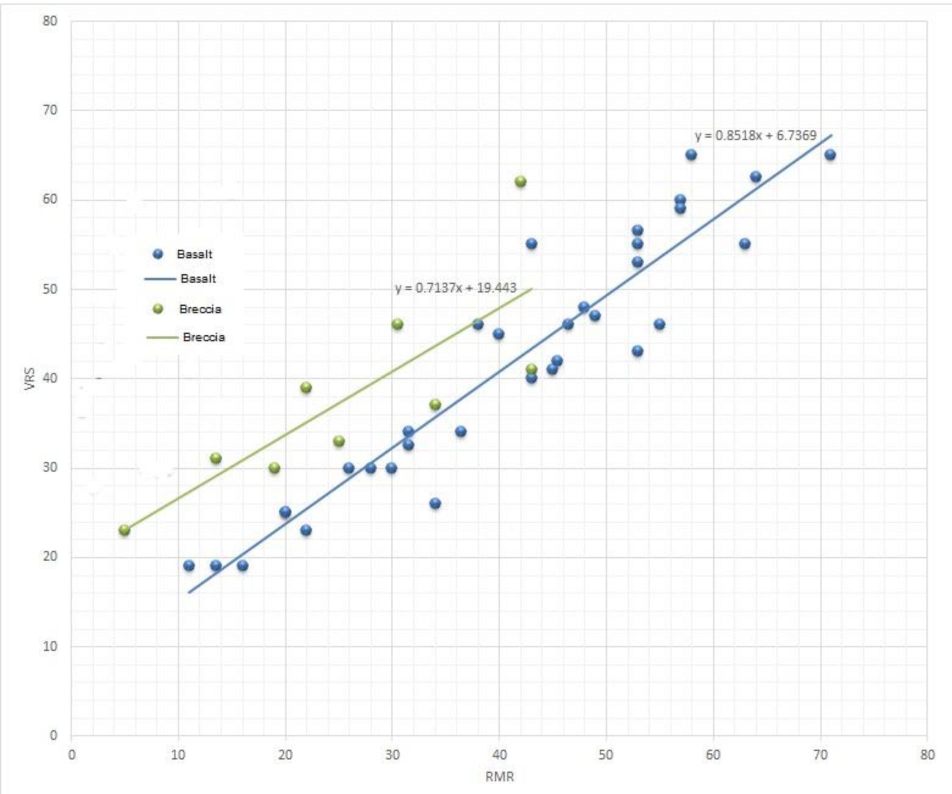


Fig. 2. Correlations between VRS and RMR coefficients for basalt and breccia formations.

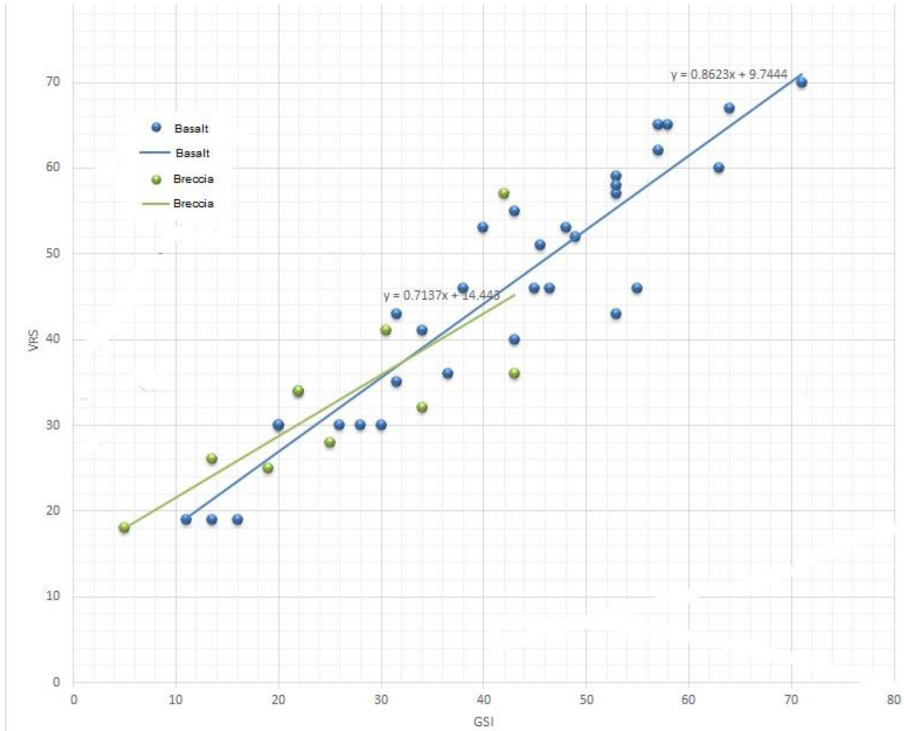


Fig. 3. Correlations between VRS and GSI coefficients for basalt and breccia formations.

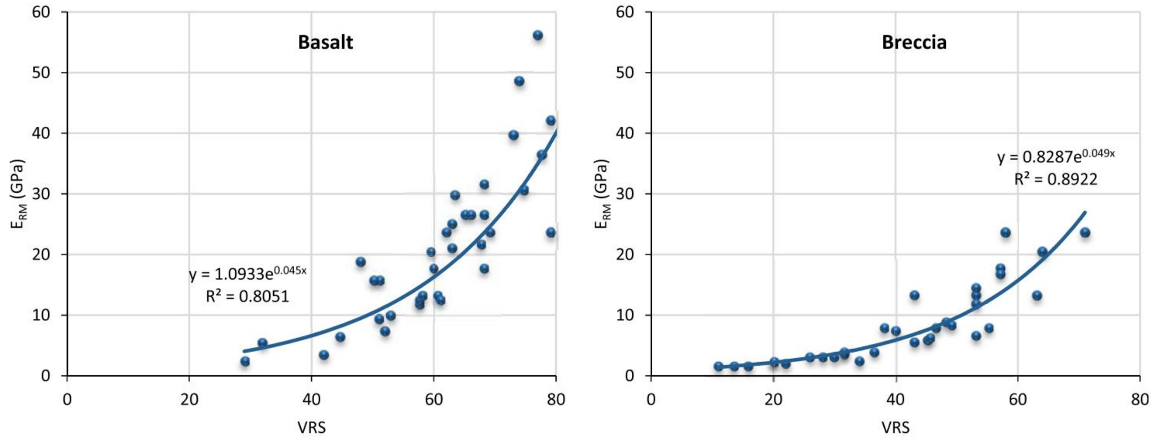


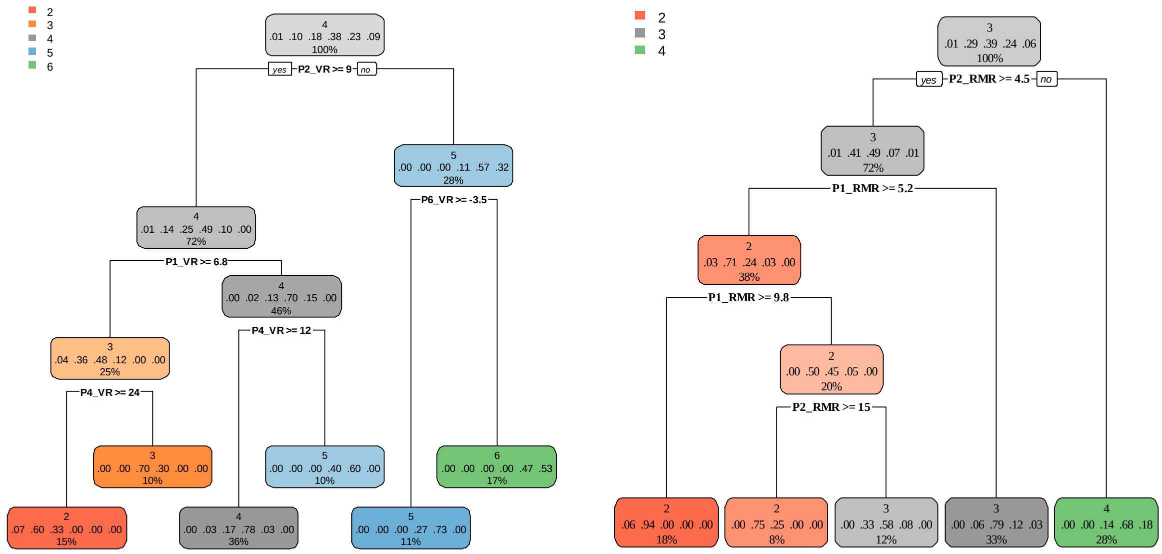
Fig. 4. Deformability modulus of the rock mass versus VRS for basalt and breccia formations.

3. Application of DM techniques to the database

Prediction of geotechnical formation behavior in geoengineering is complex because of the uncertainties associated with the characterization of rock masses. The database can hold valuable information such as trends and patterns that can be used to improve decision making and optimization processes. It is however necessary to define standard ways of collecting, organizing and representing the data. AI tools and pattern recognition techniques enable one to analyze datasets to retrieve information there (Witten et al., 2011, Leskove et al., 2014). DM is an area of computer science that lies at the intersection of statistics, machine learning, data management and databases and pattern recognition. The formal and complete analysis process is called Knowledge Discovery from Databases (KDD) that defines the main procedures for transforming data into knowledge (Cortez, 2010).

All experiments were conducted using the R statistical environment (R Development Core Team, 2010) and supported through the *RMiner* package (Cortez, 2010), which facilitates the implementation of several DM algorithms, i.e. ANNs, MRs, SVMs and DTs algorithms, as well as different validation approaches such as cross-validation. For models' evaluation and comparison, three classification metrics were used based on the confusion matrix (Hastie et al., 2009, Miranda et al., 2018).

A hierarchical volcanic rock mass rating was developed based on a DT algorithm, taking as model inputs P_i (i=1,2 …6) variables from the classification system of VRS (from here named HVR). A similar approach was followed but considering instead attributes P_i (i=1,2 …6) variables from the RMR system (from here named HRMR). Fig. 5 depicts the decision trees for VRS and RMR systems.



(a) (b)

Fig. 5. Decision trees for (a) VRS and (b) RMR systems.

Fig. 6 shows the observed versus predicted classes using the HVR and HRMR models. For each observed class (x-axis), the percentage of each predicted class (y-axis) is shown. Fig. 6a shows that the HVR model is unable to correctly identify class 1 and its best performance is for class 4. Around 90% of VR identified as 1 (true condition) was classified by the HRV model as 2 and 10% classified as 3. Also, the HRMR model (Fig. 6b) is unable to correctly identify VR class. The proposed DT is not able to identify classes 1 and 5. The best performance is observed for class 2, for which an F1-score around 73% was achieved. For classes 3 and 4, the proposed system seems to perform slightly well.

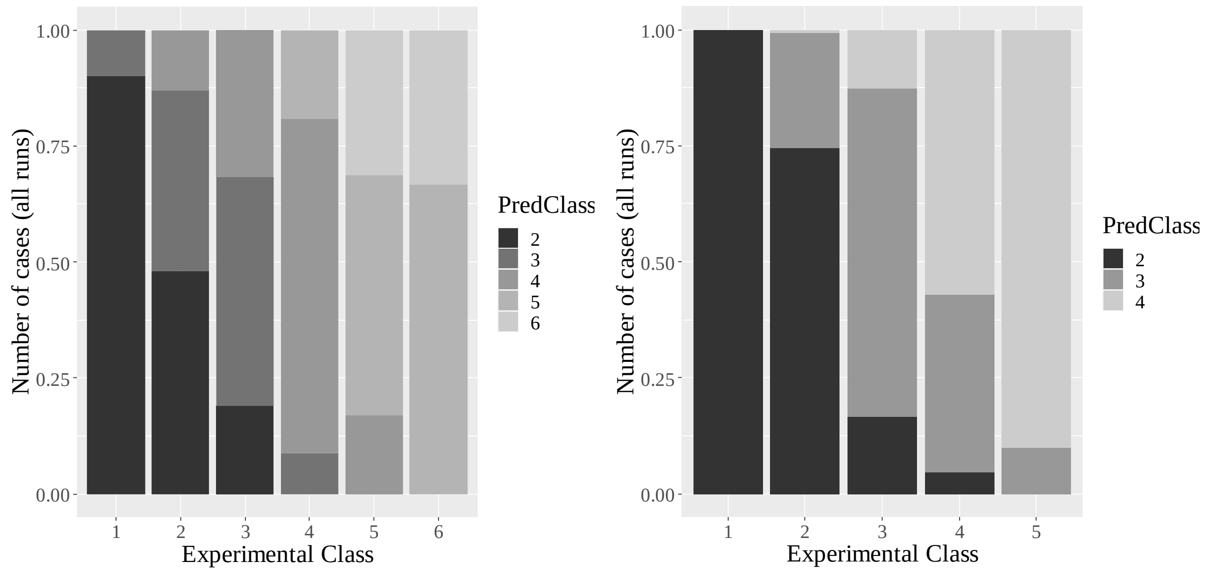
Finally, in Fig. 6 is illustrated the relative importance of each input variable for both HVR and HRMR models. According to the proposed DT based on the HVR system, the three most relevant variables are P2, P4 and P1 with an influence close to 30% each. Also, according to the DT based on the RMR system, the three most relevant variables are P1, P4 and P2, with a total influence around 94%.

4. Conclusions

The VRS empirical geomechanical classification system was developed specifically for volcanic rocks by adapting the more traditional RMR system. A database of volcanic rocks was created using mainly geomechanical information from different archipelagos. The VRS was calibrated and correlated with RMR system.

DM techniques were applied to predicting VR classes. Different DM algorithms were used that include MR, ANN and SVM. All experiments were conducted using R environment and supported by the software *RMiner*. ANN models were used to compare observed and predicted values. Parameter P_4 (discontinuity conditions) from the VRS is the most relevant variable and P_2 (rock weathering characteristics) is the second most influential parameter. Considering variables from the VRS and RMR systems, two main observations can be made: a better performance is achieved using attributes from the VRS; and ANN and MR algorithms present very similar performances that are superior to the SVM.

Considering hierarchical models, the HVR model was unable to identify correctly class 1 and its higher performance is observed for class 4. Also, the HRMR model was unable to correctly identify VR classes. Indeed, the proposed DT is not able to identify classes 1 and 5. The best performance is observed for class 2. For classes 3 and 4, the proposed system seems to perform slightly well. Although the initial classification attempt requires further improvements, this first attempt shows that the use of DM tools in the study of volcanic rocks could be very useful, with important costs reduction. Moreover, the use of sensitivity analysis can help in the clarification (human understanding) of the high complexity of these models, in particular by measuring the relative importance of model attributes.



(a) (b)

Fig. 6. (a) HVR (a) and (b) HRMR performance.

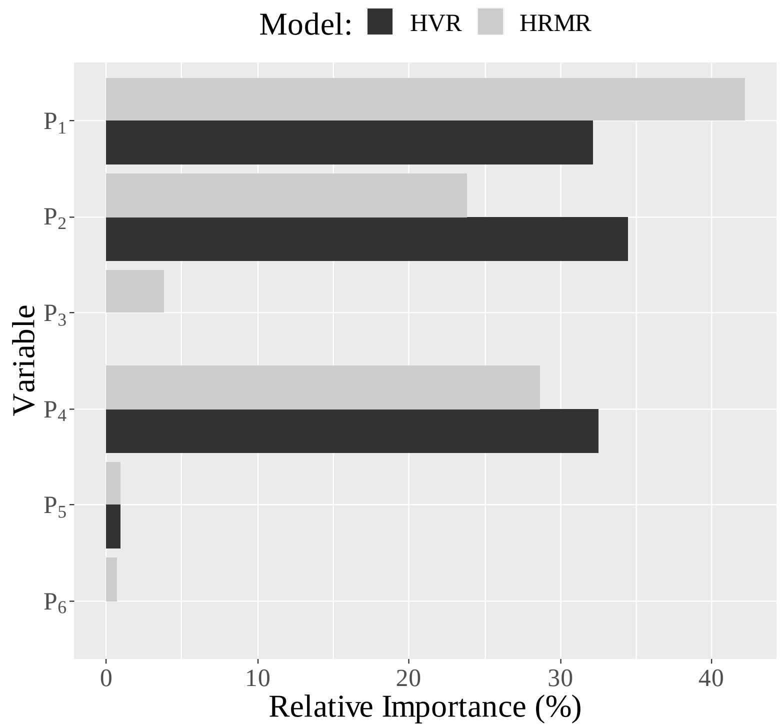


Fig. 7. HVR and HRMR relative importance.

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