GEOPERSIA

Accepted Manuscript

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DOI: 10.22059/geope.2025.390443.648807

Receive Date: 13 February 2025
Revise Date: 02 May 2025
Accept Date: 08 May 2025

A comparative analysis data mining tools for predicting strength parameters of rocks by point load index

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Received: 13 February 2025, Revised: 02 May 2025, Accepted: 08 May 2025

Abstract
The most important criteria needed for the investigation and characterization of a rock mass on site in a geotechnical project are its uniaxial compressive strength (UCS) and tensile strength (TS). The UCS and TS of rocks are determined directly by complex laboratory or field tests that require specialized prepared samples and equipment. Therefore, the UCS and TS of rocks are estimated through several index parameters via regression analysis. The point load index (PLI) due to its simplicity and quickness is a common parameter for estimating the UCS and TS of rocks. In this study, data mining tools are used to estimate the UCS and TS [determined through the Brazilian tensile strength (BTS) test] of rock using PLI. The statistical parameters, including mean absolute error (MAE), root mean squared error (RMSE), and correlation coefficient (r), are used to evaluate the performance of each data mining tool. The validity and accuracy of platforms' data mining tools were verified according to the statistical parameters. The results indicated that all three platforms' data mining tools exhibited remarkable ability to predict UCS and BTS using PLI. Finally, using platforms' data mining tools obviates the need to perform the UCS and BTS tests as time-consuming and laborious efforts.

Keywords: Uniaxial Compressive Strength, Brazilian Tensile Strength, Regression Analysis, Machine Learning.

Introduction

In many rock engineering and rock mechanics field applications, the most important mechanical and geotechnical indicator is the strength parameter of the rock. When we consider the strength parameter of rock, the first consideration is the uniaxial compressive strength (UCS), and the second consideration is the tensile strength (TS). Both are the most widely used key parameters in the characterization of rock masses for underground operations such as excavation mechanics, fortification planning, tunnelling, and deformation analysis of underground openings (Afolagboye et al., 2023; Aksoy et al., 2010; Gao et al., 2021).

However, UCS and TS tests may not always be feasible due to their high cost and long sample preparation and testing processes (Abdelhedi et al., 2023; Lai et al., 2016). Accurate measurements of these parameters are performed in a labor-intensive and rigorous manner, in the field or the laboratory, following globally recognized standard testing protocols (ISRM, 2007). In addition, these tests cannot be performed due to the inability to obtain cores by the standards, especially from problematic rock masses such as highly fractured, very weak, etc. (Karaman & Kesimal, 2012). Therefore, accurate and fast estimation of these parameters is

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sometimes required (Abdelhedi et al., 2023; Lai et al., 2016).

In recent years, machine learning (ML) has emerged as a crucial tool for corporate and industrial applications in addition to academic study. A growing number of businesses in a wide range of industries have chosen to use ML technology to analyse the massive volumes of data they must handle due to advancements in hardware in recent years (Villarroya & Baumann, 2023).

Given that ever-increasing volume of data is produced daily, it is imperative to utilize the effectiveness of massive databases when analysing data for machine learning applications. To improve analysis skills across a wide range of application areas, including cancer diagnosis, pollution analysis, weather forecasting, and environmental classification, users will be able to leverage the most efficient data analysis techniques available (Villarroya & Baumann, 2023). Learning a prediction model based on training data that depicts the relationship between a set of input variables and a target variable is the standard problem in machine learning. The reason machine learning models are so potent is that they can accurately predict future examples once they have been trained. Such models are widely used because they allow for the automation of many challenging and/or time-consuming operations (Hendrickx et al., 2021).

The most preferred parameter for estimating UCS and TS [as determined using the Brazilian tensile strength (BTS) test] is the PLI. The reasons for the popularity of PLI are that the experiment can be performed both in the field and in the laboratory, it is easy to prepare samples conforming to the standard for the experiment, the experiment can even be performed on irregular samples, the experiment is simple, practical, and fast, the test device is simple and inexpensive, etc.

Bieniawski (Bieniawski, 1975) listed the advantages of the PLI as follows:

(1) Smaller forces are needed so that a small and portable testing machine may be used.
(2) Specimens in the form of cores or irregular lumps are used and require no machining.
(3) More tests may be performed for the same cost
(4) fragile or broken materials may be tested
(5) The results show less scatter than those for the uniaxial compression test
(6) The measurement of strength anisotropy is simplified.

The specific objective of this study is to predict the UCS and BTS of rocks from the PLI using open-source machine learning platforms. For this purpose, different free and open-source machine learning platforms were used, and the prediction ability of different machine learning platforms was measured with metrics such as the correlation coefficient (r), mean absolute error (MAE), and root mean square error (RMSE).

Previous studies

To date, many researchers have conducted numerous investigations to determine the UCS and BTS of rocks. In these studies, models have been developed to predict UCS using several rock properties, such as the PLI, Schmidt hammer rebound hardness, P-wave velocity, unit volume weight, and abrasiveness index (Andrea et al., 1965; Cargill & Shakoor, 1990; Yılmaz & Sendir, 2002; Aoki & Matsukura, 2008; Kayabali & Selcuk, 2009; Yilmaz, 2009; Minaeian & Ahangari, 2013; Karaman & Kesimal, 2015; Armaghani et al., 2016; Török & Czinder, 2017; Saedi et al., 2018; Wang & Wan, 2019; Aladejare, 2020; Teymen & Mengüç, 2020; Benavente et al., 2021; Fadhil et al., 2023).

The PLI is considered to be one of the best parameters for estimating the UCS and BTS. Most of these studies have focused on the use of simple and multiple regression and statistical techniques to establish many empirical relationships (Mahmoodzadeh et al., 2021; Ibrahim et al., 2023). Recent studies have proposed a large number of equations that estimate the UCS and BTS as a function of the PLI (Broch & Franklin, 1972; Ulusay et al., 1994; Basu & Kamran, 2010; Heidari et al., 2012; Kolapo & Munemo, 2021; Wang et al., 2022; Guan et al., 2024).

Artificial neural networks (ANNs), which are soft computing-based methods, have also been extensively used for UCS estimations in recent years. Regression models have also been successfully used to predict UCS from observed data with satisfactory results (Moussas & Diamantis, 2021). Over the last 20 years, there has been rapid development in machine learning algorithms in the data science discipline, and a considerable amount of literature has focused on the theme of machine learning. Many studies have attempted to determine the design characteristics of rocks with the help of measured index properties (Hassan & Arman, 2023). Most of these studies have only been undertaken using a data tool to analyse the dataset. The studies in which UCS and BTS were predicted by machine learning with PLI as one of the input parameters are given in Table 1. When Table 1 is analysed, the scarcity of studies on the estimation of BTS is noteworthy.

When these studies are examined, it is seen that in analyzes using artificial intelligence, it is necessary to have detailed knowledge about the relevant artificial intelligence tool, to know coding, etc. However, for the data mining tools preferred in this study, such expertise, etc. is not needed. Whereas no-code tools are excellent for quickly building proof-of-concept models to validate the feasibility of a machine learning solution before investing significant time and resources in custom coding. In this way, researchers will be able to concentrate on the problem itself, away from the complexity of coding.

Materials and Methods

Dataset

The size of the dataset's samples affects how well machine learning models perform. Many examples that may be found in the literature are needed to create and compare high-accuracy models (Bansal et al., 2023; Erdal et al., 2013). To achieve the research objectives of the study, a database of more than 1200 data points, including UCS, BTS, and PLI values of the rocks from previous studies, was created (Table 2).

Data analysis using data mining tools

Correlation analysis for relationships and regression analysis to determine causality are fundamental and significant tasks in statistical data analysis when examining relationships between variables. Regression analysis and correlation analysis are commonly employed in traditional statistics. They are also crucial and significant as foundational analyses for machine learning analysis, including deep learning. This is because in deep learning analysis, variables with high correlation are chosen first, and to analyse the causal relationship, fundamental analyses such as regression analysis must first be performed (Yoon et al., 2023).

Data mining is the cornerstone of knowledge discovery. It is the process of searching through a large and disorganized dataset for new and useful information. To effectively extract any potential information, data need to be prepared (Pyle, 1999). After preparation, a variety of models are built, and common statistical methods are employed for analysis. Today, there are many big data mining programs and methodologies available for deriving insights from large amounts of data (Chahal & Gulia, 2019). Lausch et al. (Lausch et al., 2015) provided an overview of data mining tools and techniques. After analysis using sample implementation, it was shown that analysts with little to no programming experience would benefit most from using the RapidMiner and KNIME tools. The linked open data (LOD) technique was proposed as a unique option for data mining research. Jovic et al. (Jović et al., 2014) described the characteristics of free software that is often utilized.

Table 1. Soft computing-based methods for estimating the UCS and BTS using PLI

Reference	Input	Output	Method	r	Rock Type
(Gokceoglu & Zorlu, 2004)	BPI, BTS, PLI, Vp	UCS	FIS	0.819	Various rock types
(Yılmaz & Yuksek, 2008)	PLI, SHR, SDI, Vp	UCS	ANN	0.964	Sedimentary
(Yilmaz & Yuksek, 2009)	PLI, SHR, Vp, WC	UCS	ANFIS	0.970	Sedimentary
(Dehghan et al., 2010)	n, PLI, SHR, Vp	UCS	ANN	0.927	Sedimentary
(Sarkar et al., 2010)	d, PLI, SDI, Vp	UCS	ANN	0.995	Sedimentary Metamorphic
(Mishra & Basu, 2013)	BPI, Vp, PLI, SHR	UCS	FIS	0.990	Various rock types
(Mohamad et al., 2015)	BD, BTS, PLI, Vp	UCS	PSO-ANN	0.985	Several
(Momeni et al., 2015)	d, PLI, SHR, Vp	UCS	PSO-ANN	0.985	Sedimentary Igneous
(Madhubabu et al., 2016)	d, n, PLI, PR, Vp	UCS	ANN MLR	0.985 0.954	Sedimentary
(Jahed Armaghani et al., 2016)	PLI, SHR, Vp	UCS	ANFIS ANN NLMR	0.975 0.941 0.807	Igneous
(Ferentinou & Fakir, 2017)	BTS, d, LT, PLI	UCS	ANN	0.922	Sedimentary Igneous
(Heidari et al., 2018)	BPI, PLI, SHR, Vp	UCS	FIS	0.954	Sedimentary
(Matin et al., 2018)	n, PLI, SHR, Vp	UCS	RF	0.964	Sedimentary
(İnce et al., 2019)	d_{dry} ,d_{sat}, n, PLI	UCS	GEP MLR	0.938 0.911	Igneous
(Saedi et al., 2019)	CPI, BPI, BTS, n, PLI, Vp	UCS	FIS	0.954	Metamorphic
(Mahdiabadi & Khanlari, 2019)	BPI, CPI, PLI	UCS	ANFIS ANN MLR MNLR	0.978 0.959 0.935 0.950	Sedimentary
(Huang et al., 2019)	d_{dry}, PLI, SHR	BTS	IWO-ANN	0.958	Igneous
(Mahdiyar et al., 2019)	d_{dry}, PLI, SHR	BTS	PSO-ANN	0.966	Various rock types
(Barzegar et al., 2020)	n, PLI, SHR, Vp	UCS	ANN MARS M5P RF	0.889 0.831 0.574 0.490	Sedimentary
(Mahmoodzadeh et al., 2021)	n, PLI, SHR, Vp	UCS	DNN DT GPR KNN LSTM SVR	0.950 0.974 0.998 0.889 0.967 0.967	Various rock types
(Jing et al., 2021)	PLI, SHR, Vp	UCS	SFS-ANFIS	0.990	Various rock types
(Jin et al., 2022)	n, Vp PLI, SHR	UCS	GWO-ELM	0.973	Various rock types
(Hassan Arman, 2023)	PLI, SHR	UCS	HYFIS FMR LWR MLR	0.940 0.940 0.951 0.939	Sedimentary

BD: bulk density; BPI: block punch index; BTS: Brazilian tensile strength; CPI cylindrical punch index; d: density; LAAV: Los Angeles aggregate value; LT: lithology; n: porosity; PLI: point load index; PR: Poisson's ratio; SDI: slake durability index;SHR: Schmidt hammer rebound value; UCS: uniaxial compressive strength; Vp: P-wave velocity;WC: water content; ANN: artificial neural network; DT decision tree; ELM: extreme learning machine; FIS: fuzzy inference system; FMR: finite mixture regression model; GEP: gene expression programming; GPR: Gaussian process regression; GWO-ELM: grey wolf algorithm - extreme learning machine; HYFIS: hybrid fuzzy inference systems model; IWO: invasive weed optimization; KNN: K-nearest neighbor; LSTM: long short term memory; LWR: locally weighted regression; M5P: M5 model tree; MARS: multivariate adaptive regression splines; MLR: multiple linear regression; PSO: particle swarm optimization; PSO: particle swarm optimization; RF: random forest; SFS: stochastic fractal search algorithm; SVR: support vector regression

Various algorithms have been used for analysis in different data mining sectors. Weka, R, RapidMiner, and KNIME were found to be the finest data mining and analytical tools. (Chahal & Gulia, 2019). Data mining tools are powerful tools that work by combining traditional statistical methods with artificial intelligence techniques. Their main purpose is to make meaningful inferences from large and complex datasets, make predictions, and improve decision-making processes. In general, all these tools (1) prepare for user-supplied data, (2) develop and train appropriate statistical prediction models, (3) analyse user-supplied data and make predictions, and (4) evaluate the performance of the developed model.

In the analysis, three different machine learning platform data mining tools were used. Regression tools were used for the analyses. A comparative study was conducted on the accuracy of regression analysis between KNIME, RAPIDMINER, and WEKA.

KNIME

The open-source KNIME Analytics Platform was used in the data analysis so that anyone could access, integrate, analyse, and visualize the data without knowing any code. Nodes are used by the KNIME Analytics Platform to symbolize different jobs. Every node is represented by a multicoloured box with input and output ports. Nodes are capable of reading and writing files, manipulating data, training models, generating visualizations, and much more. A group of interconnected nodes defines a workflow (Figure 1). By connecting nodes via their input and output ports, a process can be constructed. After a workflow is executed, its data flows either continuously or sequentially from left to right along the links (Berthold et al., 2008).

Table 2. Studies from which the dataset was compiled

References	Rock type (sample number)
(Gunsallus & Kulhawy, 1984)	Sedimentary (8)
(Aston et al., 1991)	Sedimentary (1)
(Tuğrul & Zarif, 1999)	Igneous (19)
(Altındağ, 2000)	Igneous (1), Metamorphic (3), Sedimentary (3)
(Kahraman et al., 2000)	Sedimentary (15)
(Lashkaripour, 2002)	Sedimentary (1)
(Yenice, 2002)	Sedimentary (12)
(Basarir & Karpuz, 2004)	Sedimentary (9)
(Balcı & Bilgin, 2005)	Sedimentary (2)
(Kılıç & Teymen, 2008)	Igneous (10), Metamorphic (2), Sedimentary (7)
(Tahir et al., 2011)	Sedimentary (30)
(Heidari et al., 2012)	Sedimentary (15)
(Heidari et al., 2013)	Igneous (2)
(Yesiloglu-Gultekin et al., 2013)	Igneous (1)
(Mishra & Basu, 2012)	Igneous (19), Metamorphic (20), Sedimentary (18)
(Yarali & Soyer, 2013)	Igneous (18), Sedimentary (11)
(Khanlari et al., 2015)	Sedimentary (15)
(Ghobadi & Babazadeh, 2015)	sedimentary (9)
(Tripathy et al., 2015)	Metamorphic (7), Sedimentary (3)
(Jamshidi et al., 2016)	Sedimentary (15)
(Fakir et al., 2017)	Igneous (1)
(Capik et al., 2017)	Igneous (15), Sedimentary (26)
(Masoumi et al., 2017)	Sedimentary (1)
(Minaeian & Ahangari, 2017)	Sedimentary (1)
(Singh et al., 2017)	Igneous (8)
(Akbay, 2018)	Igneous (3), Metamorphic (1), Sedimentary (3)
(Fereidooni & Khajevand, 2018)	Sedimentary (6)
(Khajevand & Fereidooni, 2018)	Sedimentary (15)
(Jamshidi et al., 2020)	Sedimentary (10)

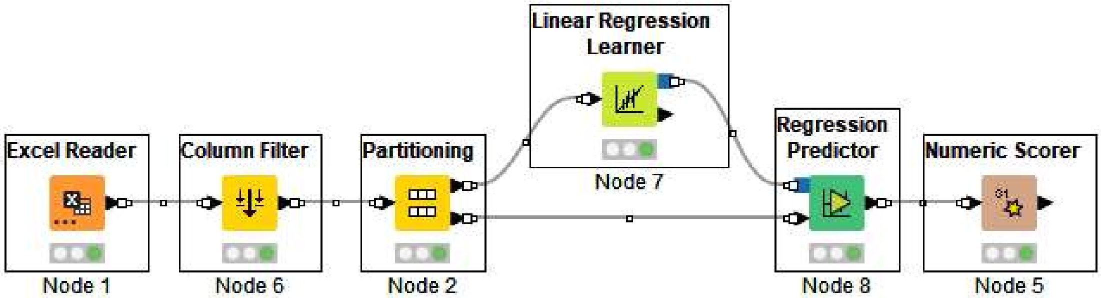

Figure 1. Workflow created in KNIME for this study

RapidMiner

RapidMiner is a data mining analytics application that supports multiple data mining techniques and is used for data analysis (Hofmann & Klinkenberg, 2013). Applications in industry, research, education, training, and application development are all included. There are more than 100 learning methods available for regression analysis, classification, and clustering. Additionally, it supports the majority of database formats, allowing users to import data for examination and analysis within the application from a variety of database sources. Faculty and students can obtain renewable 1-year educational licences from RapidMiner. (Javadpour, 2022). As illustrated in Figure 2, the operator can be used to build a process by arranging them on a canvas and connecting their input and output ports. (Ristoski et al., 2015).

WEKA

A variety of machine learning algorithms and data preprocessing tools are combined on the WEKA workbench. It enables users to rapidly and easily test current techniques on fresh datasets in a variety of ways. It offers comprehensive assistance for the entire experimental data mining process, which includes preparing the input data, statistically assessing learning schemes, and visualizing both the learning outcome and the input data. This approach involves a large selection of preprocessing tools in addition to a broad range of learning methods. Through a single interface, users may access this extensive and varied toolbox and compare various approaches to determine which is best suited for the given challenge. The WEKA was developed at the University of Waikato in New Zealand; the name stands for the Waikato Environment for Knowledge Analysis (Frank et al., 2016). Weka is open-source software issued under the GNU General Public Licence (The University of Waikato, 2024).

The Waikato Environment for Knowledge Analysis is referred to as the WEKA. It is an open-source tool used in the daily work of a data scientist to carry out various machine learning and data mining tasks. There are two ways you can use WEKA. Nonetheless, the graphical user interface, or GUI, is the most effective method of using it. You may easily complete the tasks by using the provided controls while using the tool through a graphical user interface (GUI). For instance, the open file dialogue box makes it simple to load datasets from an existing file. All that is needed to complete the classification process is loading the dataset and choosing the right classification technique. WEKA offers the "Explorer" interface for this purpose. KnowledgeFlow is an additional graphical user interface that allows the use of icons to accomplish various data mining operations (Figure 3). Various components, such as datasets, algorithms, and visualization techniques, may be represented by distinct icons. As the name suggests, WEKA's third interface, the Experimenter, assists you in conducting various experiments, such as determining which classification algorithm works best for a given dataset and which parameters boost accuracy. Workbench and SimpleCLI are the names of two more interfaces (Qamar and Raza, 2023).

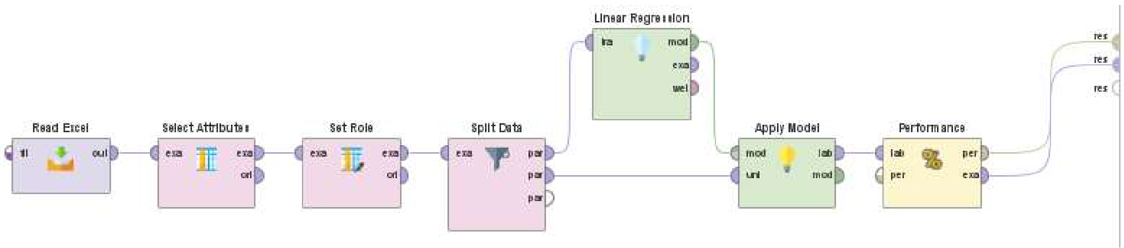

Figure 2. Workflow created in RapidMiner for this study

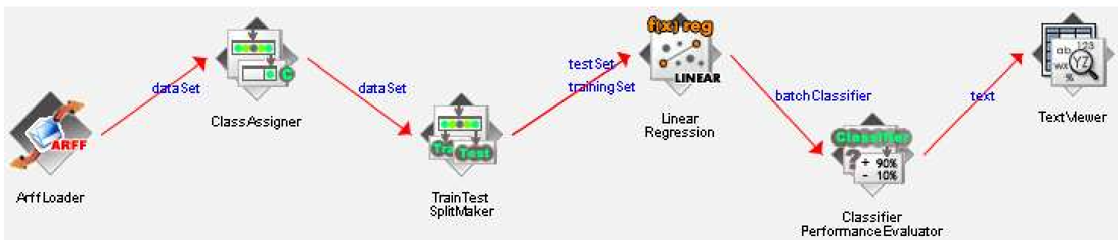

Figure 3. Workflow created in WEKA for this study

Discussion

The UCS and BTS were the dependent variables, and the PLI was the independent variable. For the purpose of the study for each tool, the input table was randomly divided into two partitions: 70% training data and 30% test data. To make the results more meaningful and easier to evaluate, all the rocks were evaluated collectively before being categorized and examined according to their geological origins (igneous, metamorphic, and sedimentary). The prediction performances of the data mining tools were measured with the metric correlation coefficient (r), mean absolute error (MAE), and root mean squared error (RMSE).

The question of whether the RMSE or MAE is better is covered in two seminal publications in the geoscientific modelling literature: Willmott and Matsuura (Willmott & Matsuura, 2005) and Chai and Draxler (Chai & Draxler, 2014). Two often used metrics for assessing prediction models are the mean absolute error (MAE) and the root-mean-square error (RMSE). A common statistical tool for assessing model performance in studies on climate, air quality, and meteorology is the root mean square error (RMSE). Another helpful metric that is frequently used in model evaluation is the MAE. There is no agreement on the best metric for model errors, although they have both been used for many years to evaluate model performance (Hodson, 2022).

Let x_i and y_i represent the predicted and actual values, respectively, at data point i, and N be the total number of data points. MAE and RMSE were defined using equations (1) and (2) (Chai & Draxler, 2014):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|x_i - y_i| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \tag{2}$$

Figures 4-9 depict a comparison between the actual and predicted UCSs. These results aptly demonstrate the model's impressive capacity to forecast UCS and BTS by PLI with remarkable precision based on well logging data. In the figures, it is shown that the r values for all assessments are significant. When all the rocks are evaluated together, r ranges between 0.72 and 0.75 for UCS-PLI and between 0.78 and 0.80 for BTS-PLI. For igneous rocks, r values ranging between 0.77 and 0.91 for UCS-PLI and between 0.87 and 0.92 for BTS-PLI were calculated. For metamorphic rocks, the r values between UCS-PLI and BTS-PLI vary from 0.88 to 0.93 and from 0.93 to 0.95, respectively. In sedimentary rocks, WEKA's prediction ability is better than that of other platforms. The r values for KNIME, RapidMiner, and WEKA between UCS-PLI were 0.57, 0.55, and 0.64, respectively, and those between BTS-PLI were 0.68, 0.62 and 0.73, respectively.

According to the performance evaluation metrics in the figures, similar to the correlation values, values that are close to each other are calculated. Only the MAE and RMSE values of KNIME calculated for UCS-PLI in metamorphic rocks were very low. The MAEs were 37.99 and 32.57 for RapidMiner and WEKA, respectively, and 1.56 for KNIME. The RMSE values were 44.98 and 40.77 for RapidMiner and WEKA, respectively, while it was 2.04 for KNIME. All the statistical metrics are summarized in Tables 3 and 4.

The MAEs and RMSEs in Tables 3 and 4 show that the various data mining technologies' performance measures yield reasonable results. According to the analysis of the MAEs and RMSEs, each instrument effectively predicted both the BTS and UCS.

To summarize, the performance measures demonstrate that the data mining algorithms employed in this investigation were successful in estimating the UCS and BTS of rock, which aligns with previous research findings in the literature. In the UCS calculation of several sedimentary and igneous rocks, for example, (Madhubabu et al., 2016; İnce et al., 2019; Mahdiabadi & Khanlari, 2019; Hassan & Arman, 2023) reported the high prediction accuracy and precision of linear regression models utilizing the PLI as the input parameter. High r values varying between 0.911 and 0.954 were obtained by the authors, indicating a virtually perfect fit between the expected and actual UCS values of the examined rock samples.

Table 3. The statistical metrics for UCS-PLI analysis

UCS-PLI					
Performance metric	**Tool**	**All rocks**	**Igneous**	**Metamorphic**	**Sedimentary**
r	Knime	0.72	**0.91**	**0.93**	0.57
	RapidMiner	0.74	0.77	0.92	0.55
	Weka	**0.75**	0.88	0.88	**0.64**
MAE	Knime	25.86	14.99	**1.56**	23.65
	RapidMiner	**23.34**	23.32	37.99	23.94
	Weka	26.84	**12.08**	32.57	**23.57**
RMSE	Knime	35.03	20.23	**2.04**	31.03
	RapidMiner	**32.87**	33.27	44.98	**29.60**
	Weka	37.17	**18.42**	40.77	32.78

Table 4. The statistical metrics for BTS-PLI analysis

BTS-PLI					
Performance metric	Tool	All rocks	Igneous	Metamorphic	Sedimentary
r	Knime	**0.80**	**0.92**	**0.95**	0.68
	RapidMiner	**0.80**	0.87	0.93	0.62
	Weka	0.78	0.87	**0.95**	**0.73**
MAE	Knime	2.41	2.30	**1.33**	1.93
	RapidMiner	**2.31**	**1.30**	1.66	**1.43**
	Weka	2.74	2.40	1.38	1.91
RMSE	Knime	**3.16**	2.84	1.75	2.44
	RapidMiner	3.17	**1.64**	2.30	**1.79**
	Weka	3.63	2.83	**1.64**	2.68

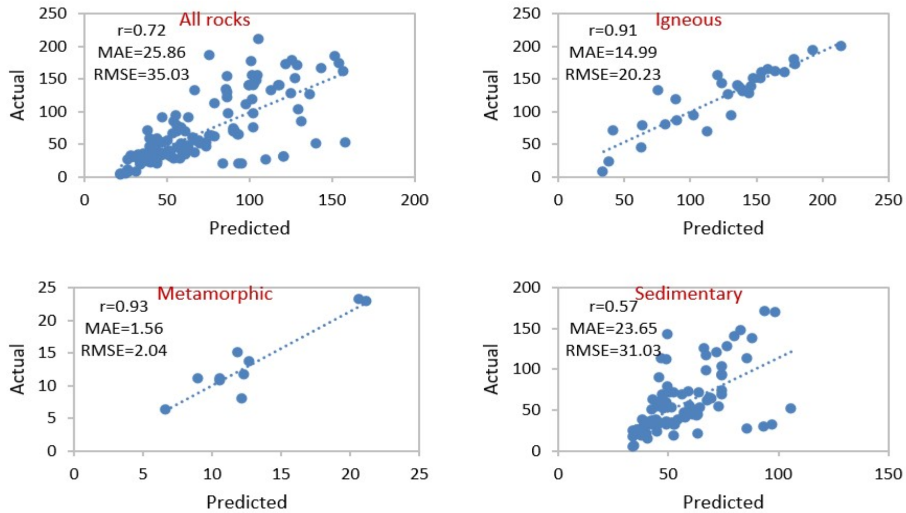

Figure 4. UCS prediction results in KNIME

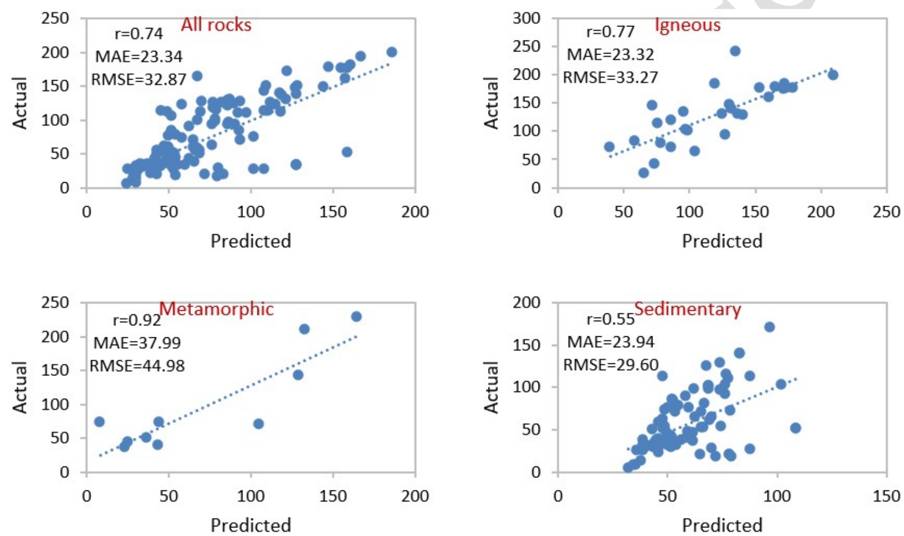

Figure 5. UCS prediction results in RapidMiner

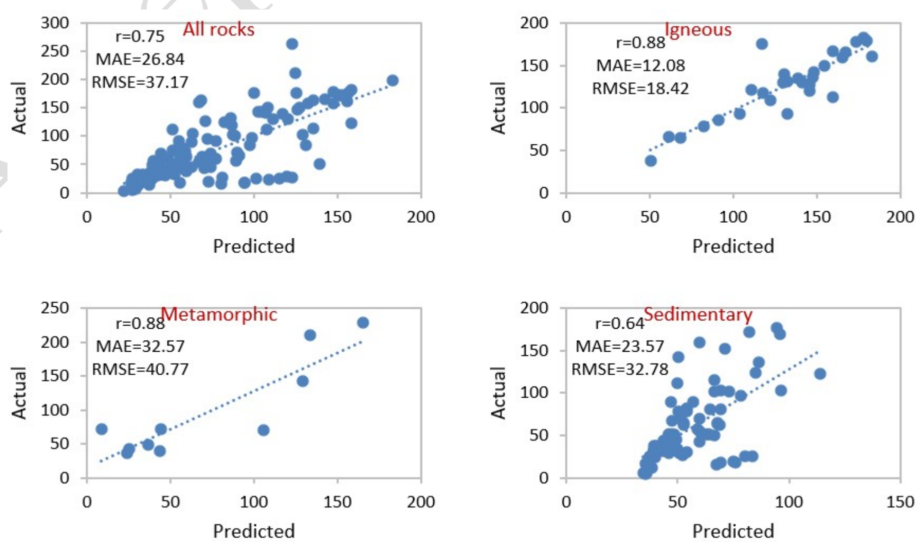

Figure 6. UCS prediction results in WEKA

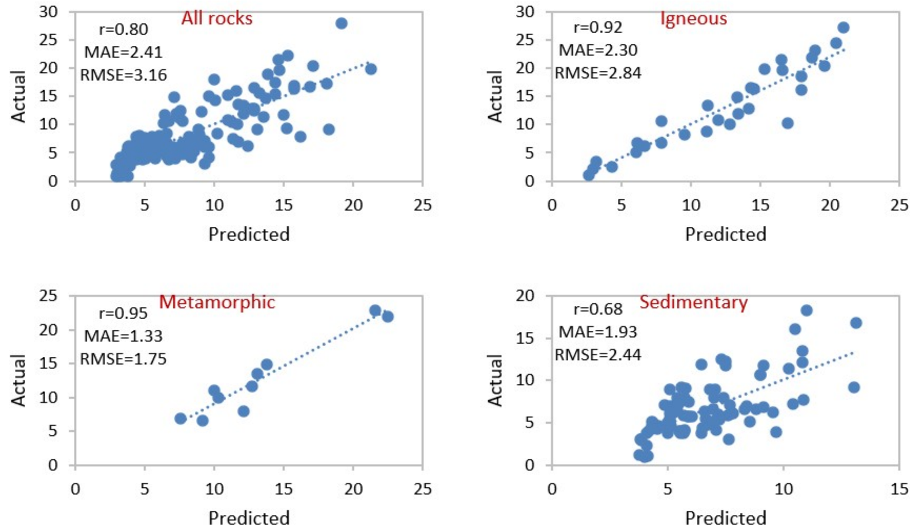

Figure 7. BTS prediction results in KNIME

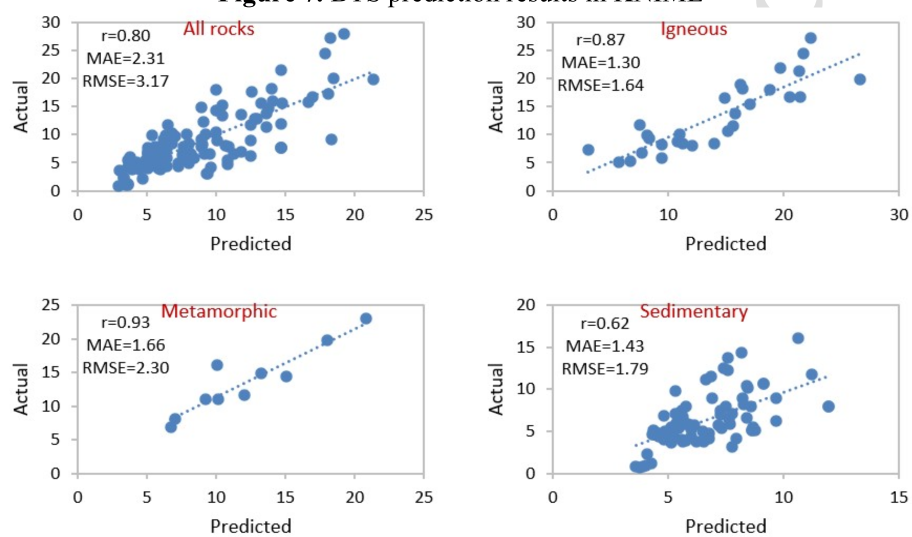

Figure 8. BTS prediction results in RapidMiner

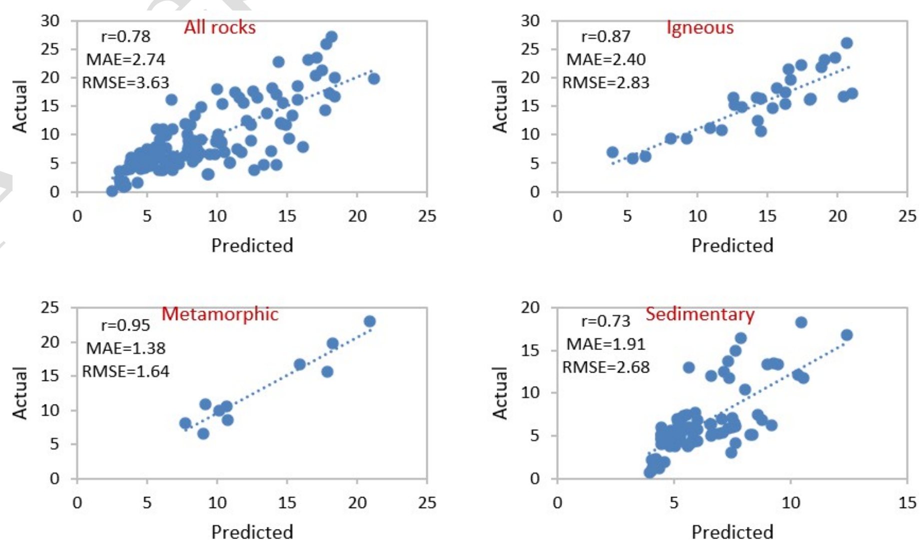

Figure 9. BTS prediction results in WEKA

According to figures 10-15, the r values for the sedimentary rock group are lower than those for the igneous and metamorphic rock groups when the prediction performances according to the rock origin are examined. In contrast to the igneous and metamorphic rock groups, the sedimentary rock group had lower r values for UCS and BTS predictions; however, this was not the case for the MAE and RMSE values chosen for the performance measures. Compared to those of the igneous and metamorphic rock groups, the MAE and RMSE values of the sedimentary rock group were lower. This is assumed to be because the sedimentary rock group has more data than the igneous and metamorphic rock groups. This demonstrates that while the r-value declines somewhat in large datasets, the prediction tools' error rate-that is, the discrepancy between the predicted and actual values-decreases.

The exceptional prediction performance of these machine learning models for a range of input parameters, as demonstrated by our study and the literature review, demonstrates their proficiency and resilience in UCS and BTS prediction. Nevertheless, disparities in prediction accuracy were found when comparing the performance of the models employed in this investigation with those in other investigations.

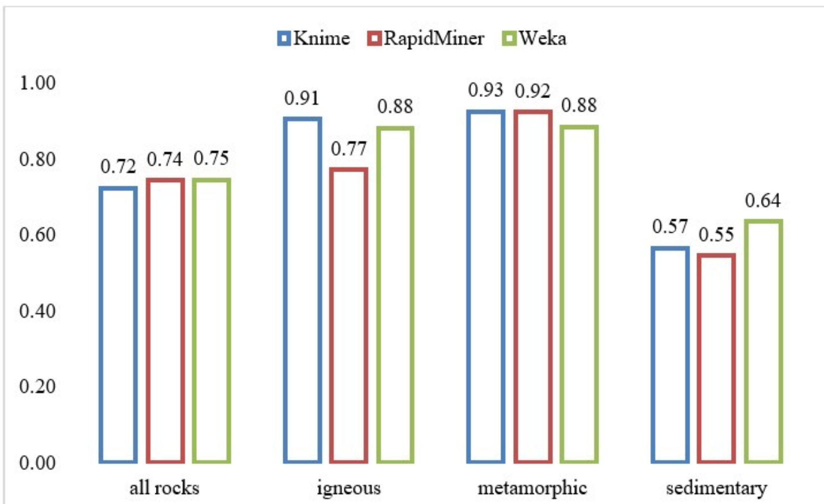

Figure 10. r values of machine learning platforms for UCS-PLI

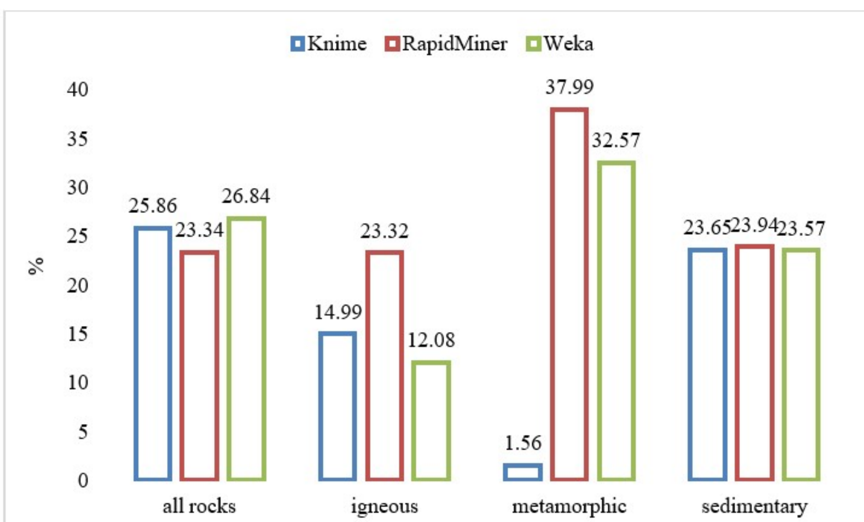

Figure 11. MAEs of machine learning platforms for UCS-PLI

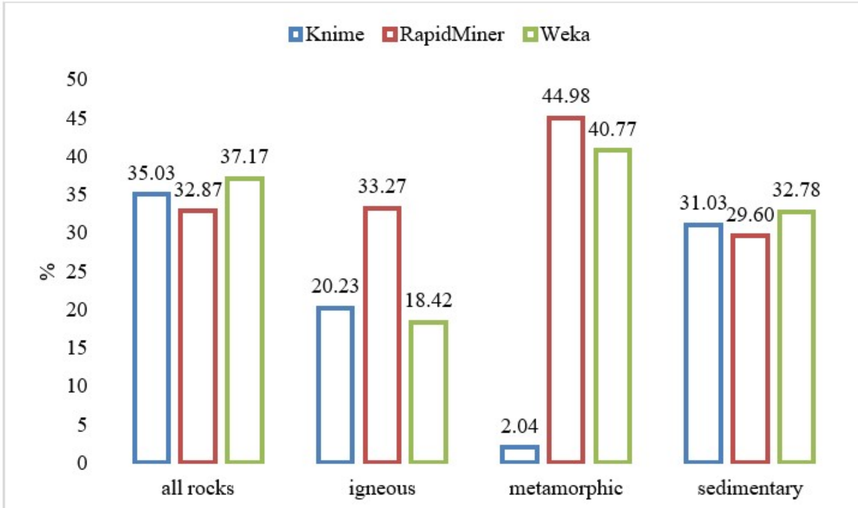

Figure 12. RMSEs of machine learning platforms for UCS-PLI

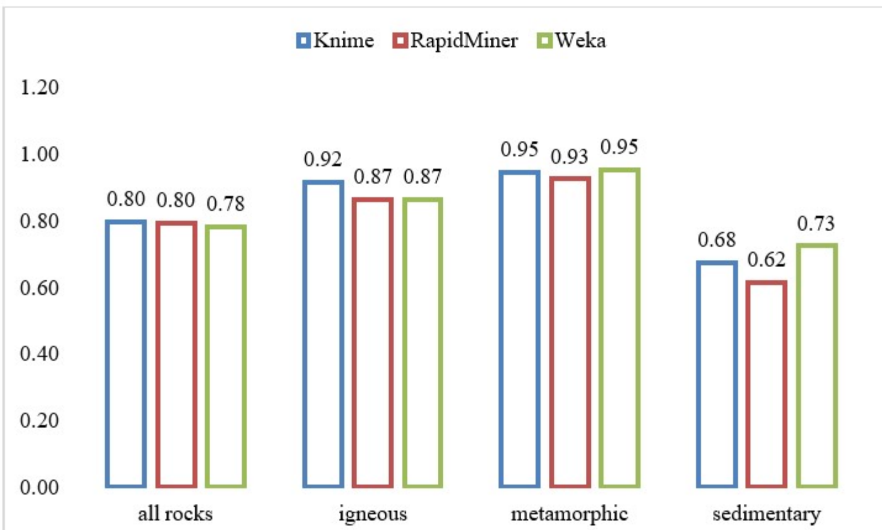

Figure 13. r values of machine learning platforms for BTS-PLI

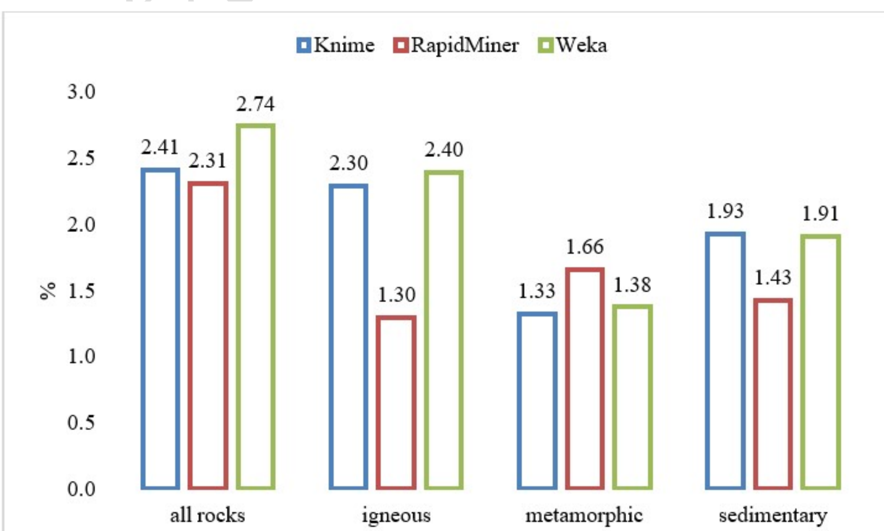

Figure 14. MAEs of machine learning platforms for BTS-PLI

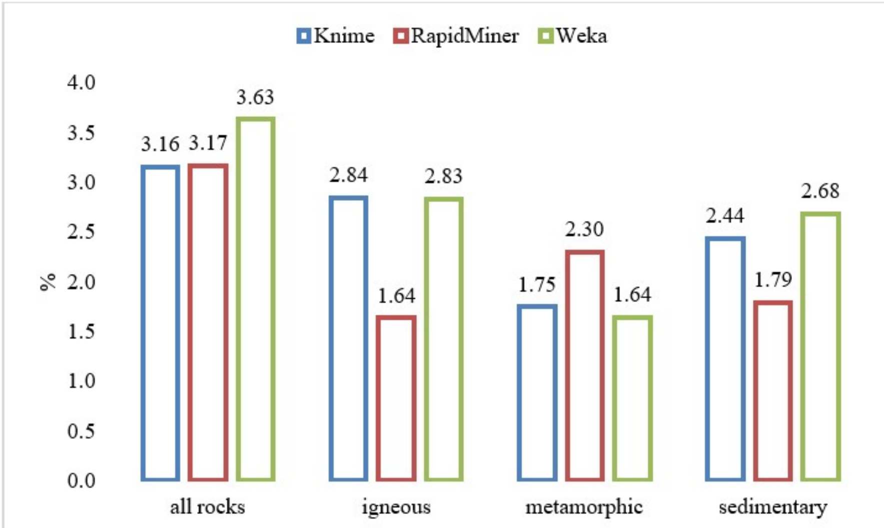

Figure 15. RMSEs of machine learning platforms for BTS-PLI

The reason for this disparity may be traced back to the selection of input parameters and the size of the dataset (Althnian et al., 2021). Studies differ in the input parameters they choose, which could account for some of the models assessed in the literature having higher prediction accuracy than our study. This could be a result of some input features producing more accurate predictions due to their better association with UCS and BTS than the input features employed in this investigation. Furthermore, it is possible that some models were applied using particular optimization techniques other than those employed in this investigation, which may have increased the accuracy of their predictions.

Conclusion

This paper investigated the predictability of UCS and BTS with PLI using different machine learning platform data mining tools without writing any code. This is thought to significantly lower the barrier to entry for machine learning. Domain experts, business analysts, and researchers who understand their data deeply but lack coding skills can directly build and experiment with machine learning models. This will foster innovation and allow for faster iteration. By removing the complexity of coding, users will be able to focus on the important aspects of the problem. The data from studies that assessed UCS, BTS, and PLI values together in the literature were collected to create a database. The key findings are summarized as follows. The results of this study indicate that all three platforms' data mining tools exhibited remarkable proficiency in predicting UCS and BTS using PLI. In other words, all three platforms' prediction tools can be successfully and reliably used to predict the UCS and BTS using PLI. The r values are quite high for igneous and metamorphic rocks, high for all the rocks considered together, and acceptable for sedimentary rocks. According to the results, the relationship between BTS and PLI is better than the relationship between UCS and PLI. Utilizing machine learning platforms in the estimation of rock parameters such as UCS and BTS is thought to offer an economical and fast solution, especially for industry. For such platforms, it is very important to recognize that large datasets need to be created from the work of scientists, and with wide applicability, different geological formations and more experiments need to be performed. In addition, this study has shown that instead of multi-input parameter estimation models, single-input parameter estimation models also yield good results with high accuracy and can be used in the estimation of UCS and BTS. This will save time and effort. In the future, it will be important to investigate the usability of other open-source machine platforms not used in this study for predicting the UCS and BTS of rocks.

Conflict of interest

The authors declared that they have no known competing financial interests or personal relationships that could have appeared to influence the study reported in this paper.

Authors' contributions

Conceptualization, Deniz Akbay; methodology, Deniz Akbay; validation, Deniz Akbay and Amin Jamshidi; formal analysis, Deniz Akbay and Amin Jamshidi; investigation, Deniz Akbay and Amin Jamshidi; writing—original draft preparation, Deniz Akbay writing—review and editing, Deniz Akbay and Amin Jamshidi; visualization, Deniz Akbay and Amin Jamshidi; supervision, Deniz Akbay. All authors have read and agreed to the published version of the manuscript.

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