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ORIGINAL PAPER

Estimation of Cutting Forces Acting on Conical Cutters Based on Rock Properties and the Contact Area Between Cutter Tip and Rock

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Abstract

This study aimed to investigate various models for predicting the cutting force in rock-cutting processes by conical tools or pick cutters. For this purpose, a database of rock cutting forces was established by utilizing full-scale cutting tests and analysis of the measured forces as a function of input parameters, such as uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), spacing, and the contact area between the pick cutter and rock. The study outlined the procedure for calculating the area of contact (AOC) between a conical pick cutter and rock surface, utilizing key parameters, including tip radius, tip cone angle, depth of penetration, and a fixed 45° attack angle. Six categories of regression models were employed, encompassing conventional regression models (linear, log–log linear, and polynomial), regularized models (LASSO, Ridge, and Elastic-Net), tree-based models (decision tree, random forest, and extreme gradient boost), complex models (SVR and ANN), probabilistic (Bayesian linear and Gaussian process), and Ensemble models (stacking and voting). As a result, the stacking technique within the ensemble models exhibited superior performance in predicting cutting forces, showing the highest Coefficient of Determination (R^2) score and the lowest Mean Absolute Error (MAE). To enhance the interpretability of the results, particularly from the ensemble methods, Explainable Artificial Intelligence (XAI) techniques, such as individual conditional expectation (ICE), partial dependence plots (PDPs), and SHAP (SHapley Additive exPlanations) analysis, were applied. The research offers reasonable prediction of cutting force based on specified parameters. This empowers engineers to make well-informed decisions regarding cutter selection, machine specifications, and cutting strategies, resulting in more efficient rock-cutting operations.

Highlights

- The study introduced the contact area between the pick cutter and the rock surface as a calculated input parameter for predicting cutting force.
- Six categories of regression models were used to predict cutting force, and their performances were compared with each other.
- The results highlight the efficacy of ensemble techniques, particularly the stacking model, in accurately predicting cutting force.

Keywords Cutting force · Area of contact · Machine learning · Explainable AI · Conical picks

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Abbreviations

FT	Total cutting force
FD	Drag/rolling force
FN	Normal force
STD	Standard deviation
MAE	Mean absolute error
CF	Cutting force
PCF	Peak cutting force
AOC	Area of contact
XGB	Extreme gradient boost
EMI	Earth mechanic institute
XAI	Explainable artificial intelligence
KDE	Kernel density estimation
PDPs	Partial dependency plots
BLR	Bayesian linear regression
ICE	Individual conditional expectation
SHAP	Shapley additive explanations

List of Symbols

σ	Standard deviation of the noise term
σ^2	Variance
α	Mean pf the intercept
μ	Expected (predicted) average value of the response variable
R^2	Coefficient of determination

1 Introduction

Mechanical fragmentation is a technique that involves applying force to a rock with a cutting tool, causing it to break into smaller pieces (Geng et al. 2022). The force creates a pressure bubble, leading to the development of subsurface cracks in the surrounding rock. In underground mining and tunneling operations where shearers, continuous miners, and roadheaders are used for rock fragmentation, efficiency and safety of the excavation process are controlled by the interaction between the cutting tool, most likely a pick cutter, and the rock surface. Accurate estimation of cutting force is crucial for equipment design and performance estimation. Existing theoretical models may have discrepancies caused by simplifications, and empirical models have limited applicability due to their limited data sets. The accurate prediction of cutting forces is paramount in the field of mechanical fragmentation for a variety of reasons. For example, understanding and estimating cutting forces is essential for designing and optimizing the equipment used in mining and tunneling operations (Liu et al. 2009). Oversized or underpowered machinery can lead to inefficiencies, increased operational costs, and safety hazards. Also, accurate predictions of cutting forces enable engineers and operators to select the appropriate cutting tools and tool materials, ensuring the longevity and performance of the equipment. Additionally, by knowing the expected cutting forces, operators can establish safe operating parameters and implement preventive maintenance schedules, reducing the risk of unexpected equipment failures and downtime. Moreover, precise control over cutting forces enhances the safety of the excavation process by minimizing the potential for overloading and structural damage to the surrounding rock and equipment.

The initial interaction and penetration of the cutting tool into the rock surface is known as indentation. This region is crucial for cutting efficiency and tool wear. As the cutting tool penetrates deeper into the rock, it creates a zone near the tool tip called bubble pressure due to the applied force. The rock is compressed and deformed within this bubble pressure zone, which is responsible for transferring cutting forces (Gertsch 2000; Rostami 2013). Raising the pressure causes the crushing and fracturing of the material beneath the cutting tool tip, which is known as the crushed zone. Within the crushed zone, high compressive pressure leads to the initiation and expansion of radial cracks, causing the formation of chips or small pieces of rock. These chips are then moved away from the cutting area. Notably, a sudden drop in the applied force can be seen once a chip is formed, often referred to as the "force drop" or "force reduction" effect. The crushed zone is the key to understanding the magnitude and variability of cutting forces. Initially, fine powder is generated around the cutting tool tip, which subsequently transforms into a fractured area within the rock body (Liu 2004; Huang et al. 2013; Li et al. 2019; Liu et al. 2019). Overall, smaller crushed zones are favored for improving cutting efficiency in terms of energy consumption and for generating lower amounts of fine powder (Rostami 2013).

Cutting force is a critical parameter in the study of rock cutting using conical pick cutters, as it directly influences efficiency and performance of the cutting process. It refers to the force the cutter exerts on the rock during the cutting operation. The cutting force on pick cutters is notably influenced by various factors, including the properties of the rock, depth of penetration, the distance between cuts, the geometry of the pick cutter, and the machine specifications (Morshedlou et al. 2023). Numerous researchers have extensively examined the cutting force, aiming to elucidate the cutting process by employing analytical approaches that consider the properties of the rock and the characteristics of the pick cutters (Potts and Shuttleworth 1958; Evans 1958, 1984; Nishimatsu 1972; Roxborough and Liu 1995; Goktan 1997; Copur et al. 2003; Goktan and Gunes 2005; Qayyum 2003).

Demou et al. (1983) conducted drag bit cutting tests using a uniquely designed instrumented rock cutting device to assess a continuous miner's performance across different rock types. They tested point attack and cutter bits on rocks with varying compressive strengths, determining that rock hardness significantly affects cutting forces, specific energy, and bit wear. Their findings suggest the feasibility of using continuous miners in certain rocks like Indiana limestone, while rapid bit deterioration limits their use in harder materials. Evans (1984) suggested that the ultimate failure of rocks occurs due to tensile forces. This theory assumes that when the cutting tool penetrates the rock perpendicularly, it creates radial compressive stresses on the surface and tensile hoop stresses. Evans pioneered developing a theoretical model to estimate conical picks' cutting force (CF). This groundbreaking study led to the establishment of various modified models and further investigations by many researchers. Modifications were required for this model because it had certain deficiencies. For instance, the model assumed an inverse relationship between cutting force and the uniaxial compressive strength (UCS) of the rock, and it also assumed that the cutter tool penetrates the rock perpendicular to its surface. Roxborough and Liu (1995) and Goktan (1997) found that the CF of a conical pick is, to some extent, affected by the friction angle between the pick and the rock. As a result, prediction models for conical pick CF were developed, considering the effect of the friction angle. Building on the work of Goktan (1997) and Roxborough and Liu (1995), Goktan and Gunes (2005) presented a semi-empirical model for predicting CF, demonstrating notable performance. In a distinct investigation, Bilgin et al. (2006) tested different rock samples with a linear cutting machine, spanning strengths from 10 to 170 MPa, observing a direct correlation between the compressive and tensile strength of the rock and the CF. Leveraging the data from Bilgin et al. (2006), Tiryaki (2008) used tensile strength, compressive strength, and density to predict CF. Kuidong et al. (2014) developed a theoretical model based on elastic fracture mechanics. The model was validated through numerical analysis and experiments and was compared with the Evans model. Dewangan et al. (2015) investigated the wear mechanisms of conical picks used in coal mining, employing scanning electron microscopy (SEM) and energy-dispersive X-ray (EDX) analysis to examine worn-out tools. They identified four primary wear mechanisms: coal/rock intermixing, plastic deformation, rock channel formation, and crushing and cracking, which contribute to the rapid deterioration of both the carbide tips and steel bodies of the picks. Li et al. (2018) determined the peak cutting force (PCF) during the initiation of the rock crack in contrast to existing models. Experimental validation confirmed the reliability and accuracy of the proposed model. Yasar and Yilmaz (2018) compared theoretical rock-cutting models to experimental results, finding inconsistencies. They suggested model improvements and emphasized the need for more experimental data to enhance understanding. Kang et al. (2020) investigated the impact of different cutting angles of conical picks on rock breaking efficiency, focusing on hard rock types. They constructed a rotary milling test bench to assess the performance of conical picks against four rock types at six different angles, discovering optimal angles that enhance machine operation efficiency based on the forces experienced and the brittleness of the rocks. Yasar (2020b) explored the impact of various rock properties on the performance of conical picks used in partial face rock excavation machines. Through rock cutting tests on six volcanic rock samples at varying depths and modes, the study established predictive plots correlating cutting force and specific energy with rock mechanical properties.

However, despite being evaluated against experimental and field data, these models have been observed not to replicate the actual cutting mechanism accurately. Consequently, their compatibility with real-world cutting phenomena needs to be improved. (Mellor 1977; Bilgin et al. 2006; Spagnoli et al. 2017).

Wang et al. (2017) developed empirical models to predict CF, experimenting with different cutting parameters. Subsequently, Wang et al. (2018a) introduced a prediction model for CF grounded in the Coulomb-Mohr Criterion and substantiated its validity through an orthogonal test. Wang et al. (2018b) also explored the effects of cutting parameters on specific energy in rock excavation, showing that cutting depth significantly influences specific energy, unlike other parameters. They developed validated empirical models to predict specific energy, enhancing roadheader efficiency at optimal cutting depths of 7–9 mm. Yasar (2020a) introduced a semi-theoretical method using 165 test samples but considered limited parameters. Tiryaki et al. (2010) created various models based on rock properties and cutting geometry attributes. The stepwise multiple linear regression they developed yielded satisfactory results, although their research indicated that nonlinear models are more effective in predicting CF. Yilmaz et al. (2007) employed multiple linear regression to formulate equations for predicting CF, utilizing input parameters, such as depth of cut, shear strength, sliding friction angle, rake angle, and UCS. Roxborough (1973) developed a nonlinear model for the prediction of CF using BTS, depth of penetration, and rake angle.

Several scholars have dedicated their efforts to investigating theoretical connections between cutting parameters and cutting force. They have aimed to enhance the pick design and cutter head by modeling the cutting process, identifying pertinent parameters related to cutting force, and assessing the impact of influencing factors (Balci and Bilgin 2007; Wang et al. 2021; Huang et al. 2022; Kim et al. 2012; Qiao et al. 2022b).

Tang and Wang (2014) investigated the prediction of peak cutting force for conical picks, critiquing traditional theoretical models for their inaccuracy and complexity in calculation compared to experimental results. They employed an RBF

Neural Network to model the relationship between cutting forces and rock properties, demonstrating that this method significantly enhances prediction accuracy and reliability over traditional methods. Shao et al. (2017) used multiple linear regression and artificial neural networks (ANN) to predict CF. Their approach involved including various samples and parameters to formulate a comprehensive model. Zhou et al. (2022a) used machine learning algorithms to predict specific energy in roadheader excavation. They consider rock properties, pick geometry, and operation parameters. The sparrow search algorithm-random forest model performed best. Cutting depth, compressive strength, and tensile strength were found to be crucial for SE prediction. Zhou et al. (2022b) developed advanced predictive models for conical pick cutting force using chaos-optimized slime mold algorithm (COSMA) integrated with random forest (RF). The models, enhanced by chaos algorithms for initial positioning and hyperparameter tuning, outperformed traditional theoretical formulae and common machine learning techniques in predicting peak cutting force. Fathipour-Azar (2022) introduced a data-driven predictive model using extreme gradient boost (XGB) to estimate the CF. The study identified the cutting depth as the most influential parameter on CF. Zhou et al. (2023) proposed a new model, SSA-RF, combining the random forest algorithm and salp swarm algorithm (SSA), to predict mean cutting force of conical picks.

Some studies related to rock cutting with pick cutters can also help define the critical parameters in estimating cutting forces based on rock properties and geometry of the cutting tools (Bao et al. 2011; Hurt and Macandrew 1985). Rojek et al. (2011) presented a numerical rock-cutting model using the discrete element method validated with experimental data. The model accurately represented the cutting process and can aid in designing rock-cutting tools. Su and Akcin (2011) used numerical simulation to compare the PCF of conical picks with models established by Evans (1962), Roxborough and Liu (1995), and Goktan (1997). The results demonstrated a correlation between the PCF obtained through simulation and the empirical models. Li et al. (2015) investigated the strength of road header conical picks using finite element analysis. They identified failure forms, examined stress distribution, and highlighted the importance of the Pick geometry. The findings contributed to improving conical pick design and longevity. Kang et al. (2016) introduced a small-scale linear cutting machine (LCM) and a new force measurement method for rock-cutting performance assessment. The study confirmed their feasibility with 96.74% accuracy and established their cost-effectiveness for estimating excavation performance in soft to medium-strength rocks. Huang et al. (2016) examined the influence of lateral pressure on the cutting process of sandstone. The study proposed a modified cutting theory to account for lateral pressure, aiding in mining equipment design. Li et al. (2016) assessed the tool–rock interaction in underground excavations and the impact of confining pressure on cutting force and crack propagation. Higher confining pressure was found to lead to increased cutting forces and a transition from brittle to ductile failure. Liu et al. (2017) identified factors, such as asymmetrical cutting, carbide tip height, and pick tip angle, which affect pick wear and working life. The study emphasized the importance of optimizing cutting angles and highlighted the negative impact of worn picks on coal-rock fragmentation. Li et al. (2017) used numerical simulations with the discrete element method (DEM) to study the effects of confining pressure on rock fragmentation during cutting, revealing that increased confining pressure and rock strength limit the vertical crack propagation and enhance the rock's resistance to cutting. Their findings show a linear increase in cutting force and specific energy with rising confining pressure, indicating a more substantial impact on harder rocks. Lu et al. (2017) utilized LS-DYNA (3D) to simulate rock cutting interactions, focusing on predicting fragment separation with different cutting depths and rock properties. Their numerical simulations indicated a significant increase in cutting forces and fragment sizes with deeper cuts and higher rock compressive strength and elastic modulus. Lu et al. (2018) in another research developed a novel rock cutting method using increased free surface area to mitigate conical pick wear, employing numerical simulations in LS-DYNA to analyze various rock plate dimensions and cutting parameters. Their findings reveal that changes in rock plate size and cutting positions significantly affect peak forces, with the new method effectively reducing peak cutting forces compared to traditional techniques. Park et al. (2018) explored the efficiency and stability of point attack pick cutters for rock cutting. Optimal conditions were identified, including a positive skew angle, an attack angle of 60°, and a 12–18 mm cut spacing for depths of 4–6 mm. Gao et al. (2018) analyzed the dynamic characteristics of shearer drums in coal cutting. A model was created to simulate working conditions, revealing that rock distribution affects peak cutting forces.

Fan et al. (2019) improved the wear resistance of mining conical picks through accurate stress analysis using a three-dimensional edge-based smoothed finite element method (ES-FEM). ES-FEM demonstrated higher accuracy and convergence, making it suitable for practical mining engineering. Lu et al. (2019) introduced a combined cutting method using saw blades and conical picks to mitigate pick wear in rock cutting. Experimental and numerical analyses showed correlations between peak cutting force and factors, such as compressive strength and rock plate dimensions. The proposed method proved effective and provides insights into fracture processes and cutting forces.

Jeong et al. (2020) researched rock cutting with point attack picks, employing a numerical simulation technique of Smooth Particle Hydrodynamics (SPH), Drucker–Prager (DP) strength model, and Cumulative Damage (CD) model. The simulation results demonstrated good agreement with the experimental data, providing evidence for the suitability of SPH in this context. Wang et al. (2020) proposed a new method for breaking hard rocks using a circular sawblade and conical pick. Numerical simulations showed that the width, height, thickness, distance to the central axis, and cutting angle significantly affect the cutting force and rock fragment shape. Zeng et al. (2021) studied the influence of cutting parameters on conical pick performance and fatigue life. Findings show that increasing cutting depth and speed leads to more rock damage and higher forces, reducing fatigue life, but a 45° cutting angle is optimal for improved performance. Qiao et al. (2022a) studied the effects of confining pressure and cutting sequence on cobalt-rich crust cutting in ocean mining. The study emphasized the need to consider multiple factors in analyzing cobalt-rich crust fracture characteristics in the deep sea environment.

The contact area between the pick cutter and the rock surface is a crucial parameter that can substantially influence cutting force. The contact area refers to the portion of the cutter that is in direct contact with the rock during cutting. The size of the contact area is directly related to the force applied by the cutter, with a larger contact area generally resulting in higher forces (Rostami 2013). The interaction between the contact area and the force applied creates pressure zones on the rock surface. A larger contact area distributes the force over a broader surface area, leading to a lower pressure zone and reducing the likelihood of localized wear and damage to the pick cutter. On the other hand, a smaller contact area concentrates the force, resulting in a higher-pressure zone, which can lead to faster wear and increased cutting forces (Gertsch 2000; Rostami 2013; Liu et al. 2019; Huang et al. 2013; Liu 2004; Li et al. 2019).

This research is part of an ongoing study on the development of the Smart Bit. The original database of measured cutting forces that was developed by the Earth Mechanics Institute (EMI) at Colorado School of Mines (CSM) was updated by results of additional full-scale cutting tests for the current project. More experiments and testing are underway to further expand the dataset as part of the current project which is focused on evaluating the impact of tool wear on cutting forces. In this study, the primary objective was to develop a predictive model for rock cutting force by incorporating the contact area between the pick cutter and the rock while also considering crucial factors like rock mechanical properties, such as UCS and BTS, along with the geometry of the pick and spacing between cuts. This paper addresses a critical gap in the existing body of research by focusing on an area that has received limited attention in prior publications. The novelty of this study resides in its exploration and introduction of a meticulous approach to calculate the contact area between rock and pick cutter as a fundamental factor influencing the prediction of cutting force, considering critical parameters, such as tip radius, tip cone angle, and depth of penetration. The AOC calculation method presented in this study is versatile and not limited to specific bit configurations, allowing for the analysis of various other bit configurations, demonstrating the possibility of expanding the proposed method and a broader range of cutting tools and applications. The paper introduces a series of regression models, meticulously examines uncertainties within the dataset by applying probabilistic models, and notably advocates for using ensemble models as a viable and effective method for predicting cutting forces. Finally, Explainable Artificial Intelligence (XAI) techniques including individual conditional expectation (ICE), partial dependence plots (PDPs), and SHAP (SHapley Additive exPlanations) analysis were employed to improve the interpretability of the results and provide deeper insights into the model's performance. By encompassing these unique approaches, this study significantly contributes to a more thorough understanding of the dynamics between rock and pick cutters, paving the way for enhanced predictive models and practical applications in the field.

2 Methodology

The dataset used in this study was provided by the EMI at Colorado School of Mines. This dataset comprises a selection of cutting force measurements gathered during full-scale rock-cutting tests conducted over 30 years, encompassing

Table 1 Properties and strength attributes of rocks (Morshedlou et al. 2023)

Rock type	UCS (MPa)				BTS (MPa)			
	MIN	MAX	Average	STD	MIN	MAX	Average	STD
Limestone	16.50	186.40	122.80	62.30	1.99	14.96	6.44	4.00
Sandstone	50.45	177.30	110.17	47.69	3.35	9.71	6.80	2.40
Concrete	25.60	33.40	30.05	4.03	3.18	3.38	3.18	0.17
Kimberlite	43.66	67.40	57.50	8.90	2.95	5.23	4.00	0.92
Gypsum	17.56	22.69	20.77	2.25	2.80	4.95	3.39	1.05

numerous projects undertaken at EMI. In this paper, the analysis revolves around collecting data using conical pick cutters for various rock types, leading to the creation of a comprehensive database. Table 1 displays information concerning different rock types and their respective rock properties utilized in this research. Subsequently, the data was subjected to regression analysis to explore the correlation between the cutting force and input parameters. The estimation of the cutting forces is also a part of and prelude to the development of algorithms for the assessment of cutter wear and identification of the rock type by smart pick, which is a project funded by the National Institute of Occupational Safety and Health (NIOSH), currently underway at EMI.

2.1 Full-Scale Testing with Linear Cutting Machine

EMI has carried out extensive cutting tests for three decades using an LCM to replicate authentic cutting conditions for diverse rock-cutting tools. The tests measure cutting forces while cutting large rock samples at selected spacing and penetration, enabling the development of Force-Penetration curves for cutterhead operation simulation. This approach effectively represents the cutting actions of tools used in diverse excavation machines. The rock specimen is encased in concrete within a steel rock box to prevent disintegration during cutting, and a load cell records the cutting forces during the test. Figure 1 illustrates the experimental setup of rock cutting using LCM. The test utilized a load cell comprising four distinct load sensors, which captured forces by measuring strains on columns equipped with high-precision strain gauges. Calibration allows measuring relevant voltage outputs at preset force levels applied to the pick, covering the expected force range during cutting. Calibration data is compiled and analyzed to verify load cell linearity. The recorded voltages undergo conversion to force through calibration factors implemented in software. Analysis of cutting forces in the tested rock sample on the LCM is conducted for each line cut, encompassing normal, drag, and side forces. Mean, minimum, and maximum force values are assessed and examined for every line sharing the same penetration and spacing. This method enables the estimation of cutting forces for a specific cutting geometry utilizing a chosen cutting tool.

This study integrates the rolling/drag force (FD) and normal force (FN) while using conical drag bits at a 45° attack angle. These forces are then referred to as the total force (FT). The mean total force (FT) is determined by calculating the average of the FT values. While FN, FD, and FS each provide valuable insights into the rock cutting process, our study specifically focuses on Total/Residual Force (FT). This is because the "Smart Pick" concept is based on a load sensor that measures the axial force on the cutting tool in real time, enabling the evaluation of tool wear and rock type. The axial force measured is directly correlated with FT, which is derived from the individual contributions of FN, and FD. FT offers a holistic view of the forces acting on a cutting tool, enhances the analysis of tool stress, and aids in optimizing cutting parameters to minimize wear and energy use. The focus on FT in many studies is attributed to its direct impact on the efficiency and energy requirements of rock excavation processes. Moreover, the ratio of FT to FN which is a critical parameter can vary based on several factors including rock type, cutting geometry, and operational

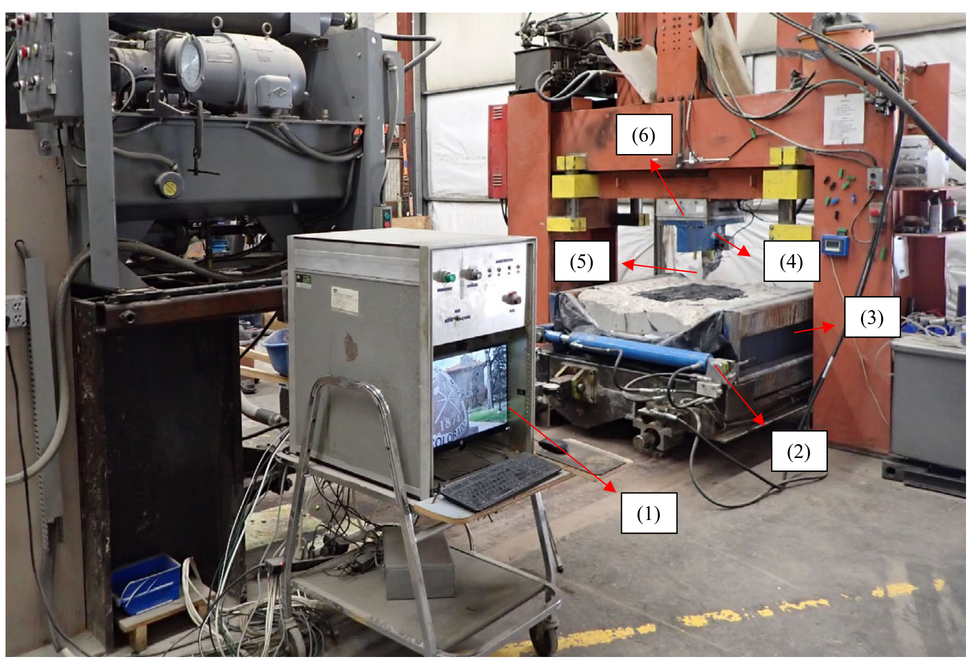


Fig. 1 Experimental setup of a rock-cutting test with LCM. **1** Data acquisition system and operator interface panel. **2** Hydraulic cylinders. **3** Rock box. **4** Saddle. **5** Conical pick cutter. **6** Load cell

conditions. These variables affect how these forces interact and are distributed, ultimately impacting the efficiency of rock cutting operations.

2.2 Area of Contact

Several important steps are followed in calculating the area of contact (AOC) between a conical pick cutter and the rock. First, the geometry of the conical cutter is defined, with its attack angle set at 45 degrees, representing the angle between the cutter's axis and the rock surface it is engaging. Next, a suitable Cartesian coordinate system was established, simplifying the analysis with the tip center as the origin and the z-axis perpendicular to the base.

The penetration depth is then determined, which signifies how deep the conical cutter enters the rock. At each level of penetration, the corresponding AOC is calculated. The contact area is projected onto the rock's surface in the front view to do this, forming a 2D geometric segment.

Several steps are undertaken to calculate the AOC at a specific penetration depth. The area of the segment (AOC) is calculated as a projection of the pick tip within the rock surface on a plane perpendicular to the direction of cutting, as shown in Fig. 2. This process is repeated for different penetration levels to obtain a range of AOCs between the conical cutter and the rock at varying penetration depths. By following these steps meticulously, one can accurately calculate the AOC between the cutting tool and the rock, which is essential for understanding the efficiency and effectiveness of the cutting process and optimizing the tool's design for specific rock types and conditions. The controlling parameters of the AOC are the tip radius, tip cone angle, depth of penetration, and attack angle, which, in this case, was set to 45°.

2.3 Data Exploration

The data utilized in this research were derived from the cutting force database involving roller cutters and drag bits. 192 tests involving the cutting force of conical pick cutters were incorporated in this analysis. The data was normalized using the Z-score normalization method. The correlation between variables is depicted in Fig. 3, while Fig. 4 illustrates the data screening process aimed at removing outliers from the dataset. The identification of outliers involved the application of the interquartile range method (IQR). Table 2 presents an overview of the statistical analysis of the utilized data after outlier removal.

3 Data Analysis

This step applied regression analysis to the dataset after identifying and addressing outliers, followed by normalization. The data set was then divided into 80% train and 20%

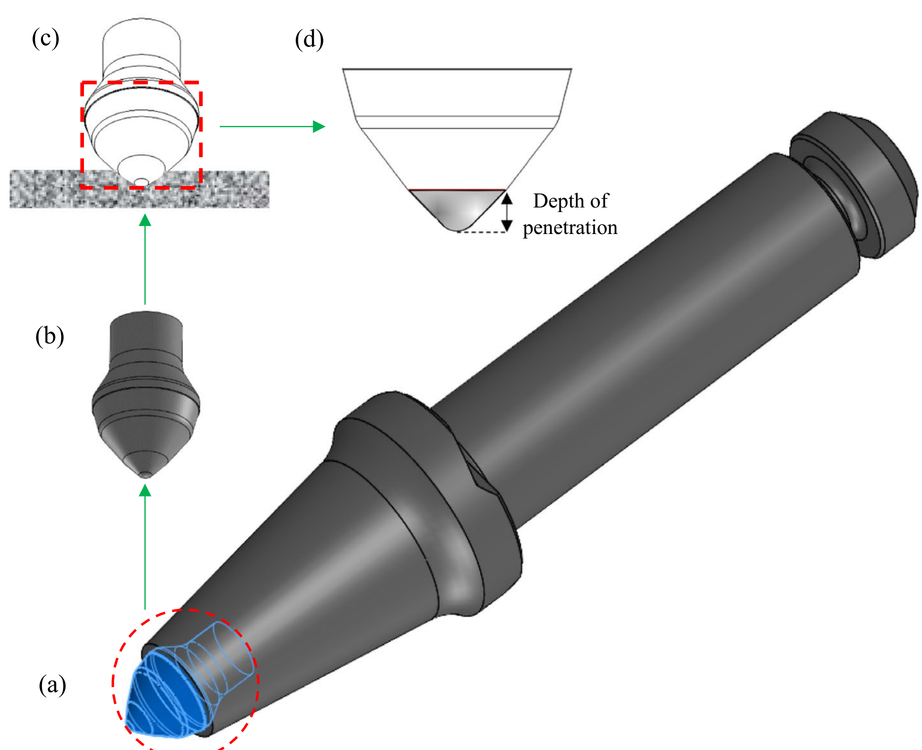


Fig. 2 Geometric analysis and AOC calculation for a conical cutter. **a** 3D model of the U92 conical pick cutter. **b** Front view: 3D model at a 45° attack angle. **c** Front view: 2D model at a 45° attack angle. **d** Projected 2D model showing the AOC between the cutter tip and rock for a given depth of penetration

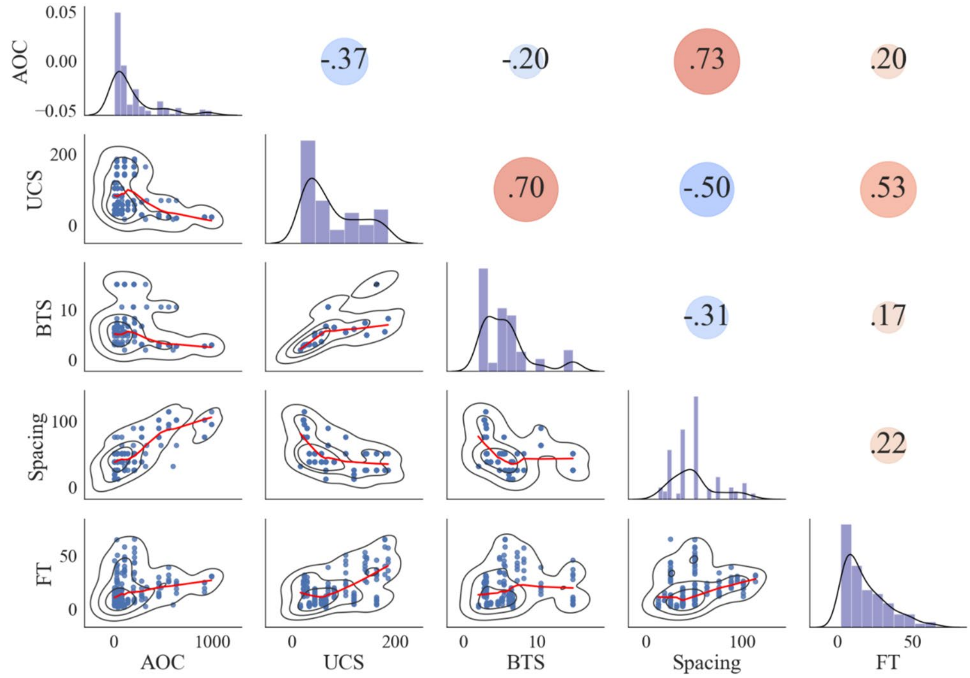


Fig. 3 Exploratory data analysis: The lower triangle includes the scatter plot, Kernel density estimation (KDE) plot, and regression lines showing the relationship between the variables, providing insights into the shape and spread of the data distribution, and best-fit linear regression model for variable pairs, respectively. The diagonal contains the probability density function of each variable. The upper triangle consists of correlation coefficient annotations, which quantifies the strength and direction of the linear relationship between pairs of variables. FT (KN); BTS (MPa); spacing (mm); AOC (mm^2); UCS (MPa)

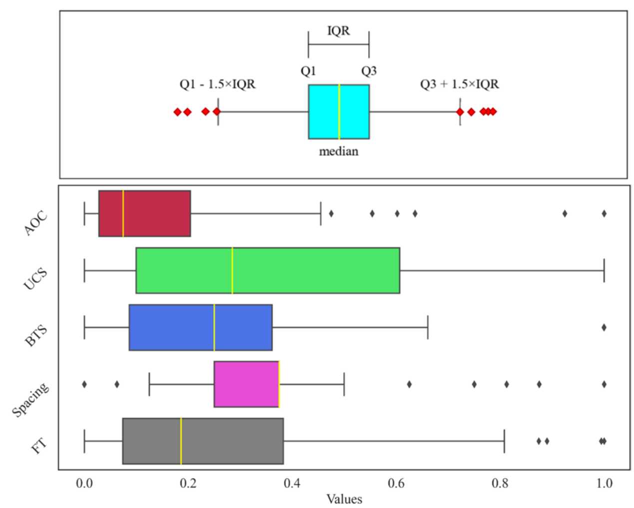


Fig. 4 Identifying outliers through the utilization of boxplots and the interquartile method: The area between Q1 and Q3 includes the middle 50% of the data, represented as the blue-shaded region. Outliers are commonly identified beyond the bounds of Q1 − 1.5 × IQR on the lower end and Q3 + 1.5 × IQR on the upper end, which is depicted as the red-shaded area in the distribution

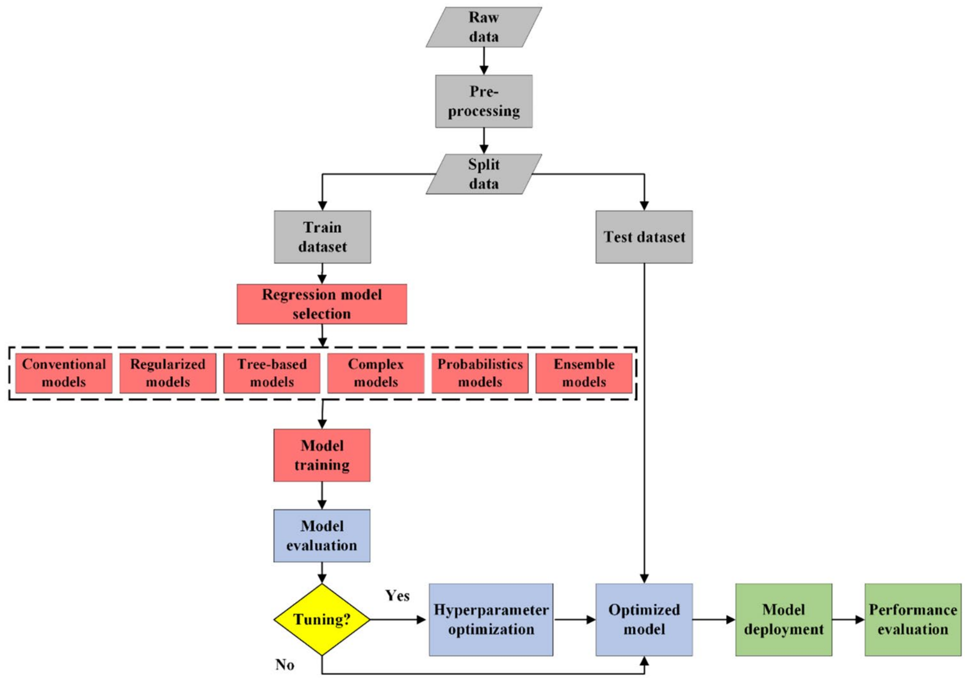
Table 2 Statistical overview of key parameters

Variable	Quantity	Average	STD	MIN	MAX
AOC (mm^2)	168	183.52	236.31	9.12	991.47
BTS (MPa)	168	5.71	3.29	1.99	14.96
UCS (MPa)	168	77.68	52.19	16.47	186.43
Spacing (mm)	168	52.50	25.68	12.70	114.30
FT (KN)	168	20.23	16.63	1.90	93.54

testing. The analysis involved six sets of regression techniques to determine the most effective models for predicting FT using UCS, BTS, spacing, and AOC. The first set involved conventional regression methods, such as linear, log–log, and second-degree polynomial regression. The second set consisted of regularized regression models, including LASSO, Elastic-Net, and Ridge regression. The third set utilized tree-based regression models, such as decision trees, random forests, and XGB regression. The fourth set encompassed probabilistic methods, including Bayesian linear and Gaussian process regression. The fifth set contained complex regression models, such as Support Vector Regression and ANN regression. Finally, ensemble models were used as the sixth regression models, including stacking and voting techniques. All models are trained with five cross-validations to avoid overfitting and improve generalization. Additionally, a random state of 42 is kept for all to ensure consistency in the results. The flowchart of the analysis used in this paper is depicted in Fig. 5. In this study, we utilized Mean Absolute Error (MAE) and the coefficient of determination (R^2) as the primary evaluation metrics for our regression models. MAE was chosen due to its interpretability and its robustness to outliers, ensuring that our model's performance is not unduly influenced by extreme values when predicting cutting force.

The following section discusses the regression algorithms, outlining the steps and presenting the results from various techniques in predicting the FT. All the developed regression models have undergone hyperparameter optimization using grid search.

Fig. 5 Flowchart of analysis used for prediction of FT



3.1 Conventional Regression Models

Linear regression is a simple but effective statistical method. However, it has limitations, such as handling boundary values effectively (Afifi et al. 2003). To address nonlinearity, using linear regression on log-transformed variables is effective for rock engineering, managing data gaps, and revealing input interactions (Agresti 2002). Log-linear modeling, achieved through logarithmic transformations of the dependent variable, offers flexibility for capturing nonlinear relationships, making it a superior choice for predicting rock mechanics problems without being hindered by zero input values (Peng et al. 2002; Hosmer et al. 2013). Polynomial regression fits data using an nth-degree polynomial to model relationships between variables. Yet, it is important to acknowledge that if the selected degree for polynomial regression is excessively high in relation to the dataset's size, overfitting can become a concern (Cheng 2018). Polynomial regression offers advantages over linear and log–log linear regression because it flexibly captures intricate, nonlinear relationships between variables. Furthermore, it can effectively manage shifts in relationships' direction, a capability that log–log linear regression might not capture adequately (Sagar et al. 2021). The downside of the polynomial equations is that away from the range of the input data, it can generate a much higher level of errors. The result of the equations for each regression model is presented in Table 3. Figure 6 demonstrates the comparative results of the conventional regression models with the measured values.

Figure 6 indicates that the 2nd-degree polynomial regression model outperforms other conventional regression methods, achieving an R^2 score of 0.61. Despite this improved performance, it falls short of being considered desirable.

Table 3 Summary of the best equations for FT

Regression method	R^2	MAE(KN)	Equation	
Linear	0.55	4.84	$FT = -13.98 + 63.36(UCS) - 31.49(BTS) + 37.02(S) + 8.82(AOC)$	(1)
Log–log linear	0.57	4.83	$FT = \frac{0.001.AOC^{0.20}.S^{1.05}.UCS^{1.59}}{BTS^{0.98}}$	(2)
Polynomial 2nd-degree	0.61	4.58	$FT = -27.75 + 14.84(AOC) + 50.87(UCS) + 16.78(BTS) + 67.44(S)$ $+1.02\left(AOC^2\right) + 27.99\left(UCS^2\right) + 25.20\left(BTS^2\right) - 34.06\left(S^2\right)$ $+58.53(AOC)(UCS) - 39.97(AOC)(BTS) + 1.10(AOC)(S) - 92.63(UCS)(BTS)$ $+28.51(UCS)(S) - 27.47(BTS)(S)$	(3)

FT (KN), UCS (MPa), AOC (mm^2), BTS (MPa), S (mm)

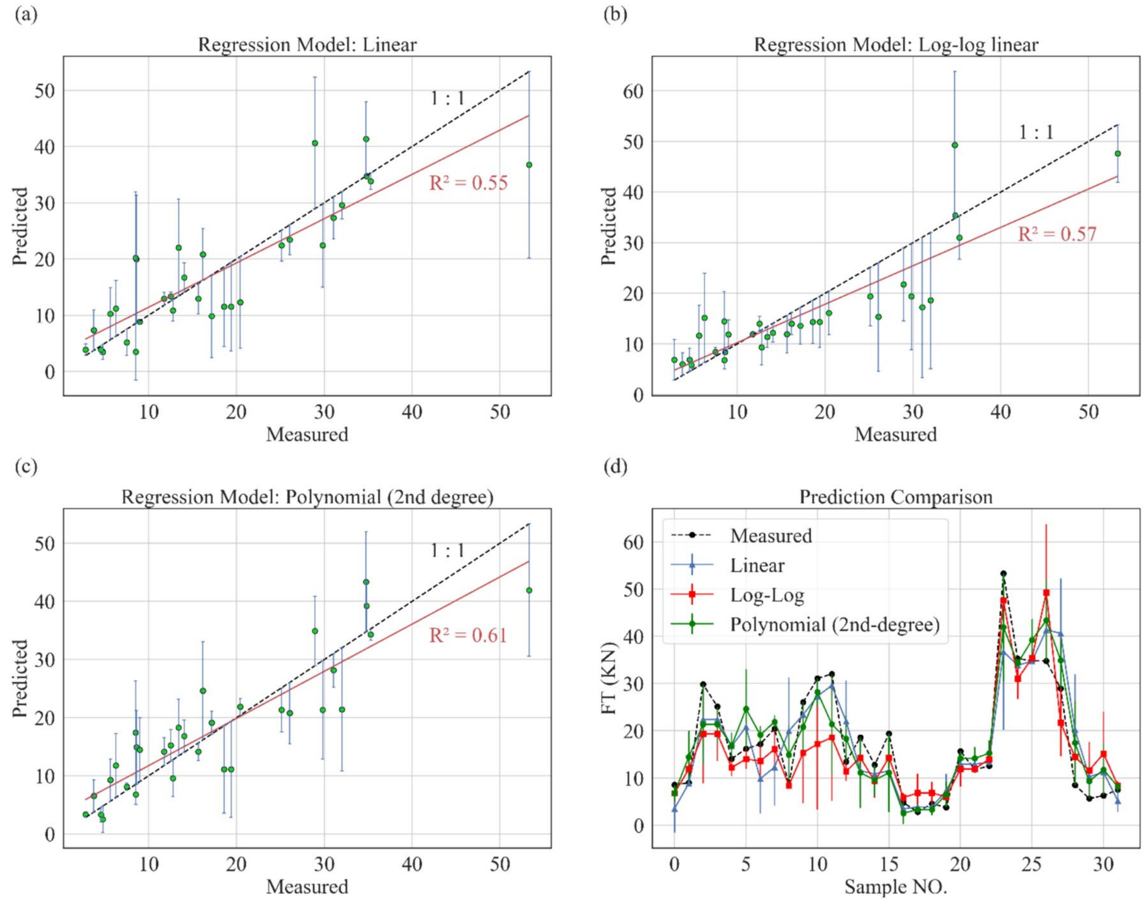


Fig. 6 Comparison of conventional regression methods for predicting FT. Prediction versus measured values for **a** Linear. **b** Log–log. **c** Polynomial (2nd-degree). **d** Overall prediction performance

3.2 Regularized Regression Models

The least absolute shrinkage and selection operator (LASSO), a statistical and machine learning method, integrates regularization and variable selection to enhance predictive accuracy and improve the interpretability of the model. Initially developed in geophysics and later introduced by Robert Tibshirani (Tibshirani 1996), LASSO employs shrinkage, pulling data towards a central point like the mean, to achieve more precise predictions. By favoring simplicity and sparsity in models, it is especially effective in cases of multicollinearity and automating aspects of model selection, such as variable elimination. LASSO uses L1 regularization (Agresti 1990; Tibshirani 1996).

Ridge regression is a model-tuning technique aimed at handling multicollinearity issues in data analysis. By applying L2 regularization, this method addresses situations where independent variables are highly correlated, which commonly arises in fields like econometrics, chemistry, and engineering. Developed by Hoerl and Kennard in 1970, Ridge regression efficiently estimates coefficients in linear regression models with many parameters, counteracting bias, and variance tradeoffs. This approach proves especially valuable for reducing the impact of multicollinearity, ultimately enhancing parameter estimation precision (Hoerl and Kennard 1970; Saleh et al. 2019).

The Elastic-Net technique enhances regression models by merging the L1 and L2 regularization penalties from the LASSO and Ridge methods. It addresses the constraints of the LASSO approach, which relies solely on absolute coefficient values for its penalty function. The Elastic-Net method offers an improved means of regularization by introducing a combined penalty term integrating both L1 and L2 penalties. This approach combines insights from both LASSO and Ridge regression techniques, leveraging their strengths to mitigate each other's weaknesses and optimize the regularization of statistical models (Zou and Hastie 2005). The results from regularized regression models are presented in Fig. 7, allowing for a direct comparison with the measured values.

The performance of regularized methods is comparable, as illustrated in Fig. 7. Ridge regression stands out with a

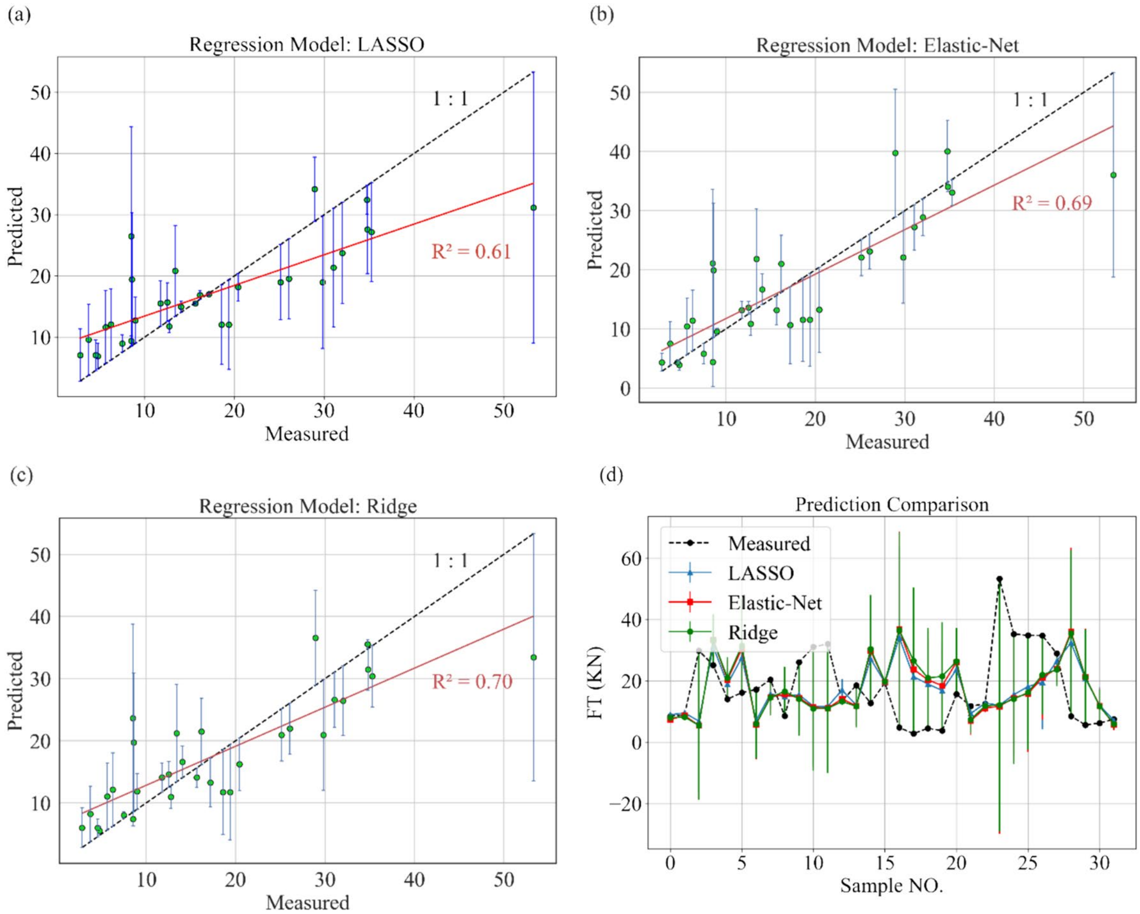


Fig. 7 Comparison of regularized regression methods for predicting FT. Prediction versus measured values for **a** LASSO. **b** Elastic-Net. **c** Ridge. **d** Overall prediction performance

superior performance, boasting an R^2 of 0.70. Despite the improvement over traditional methods, the obtained result falls short of the desired outcome.

3.3 Tree-Based Models

In this section, decision tree, random forest, and XGB are used as the tree-based models. Decision tree employs adaptive tests influenced by previous results to understand algorithmic trends and patterns in data. It excels in regression tasks, dividing data into subsets based on features and calculating outputs from average target values (Wu et al. 2008; Liaw and Wiener 2002; Hastie et al. 2009). Random forests combine multiple decision trees to enhance accuracy, capturing data intricacies and patterns while avoiding overfitting. They handle large, high-dimensional, and missing datasets (Ho 1995; Breiman 2001; Zhou et al. 2023). XGB, a powerful technique, utilizes decision trees for classification and regression, excelling in efficiency and scalability for large datasets. In this method, selecting features, tuning hyperparameters, and data quality significantly affect the model's performance (Chen et al. 2015; Chen and Guestrin 2016). Overfitting is mitigated through techniques like early stopping and reducing model complexity. Model tuning is done via the GridSearchCV technique and then evaluated using R^2 and MAE. Comparative results between the measured values and tree-based regression models are depicted in Fig. 8.

Figure 8 illustrates that XGB displays the most effective performance among the tree-based approaches, achieving an R^2 of 0.84. It is essential to highlight that all tree-based models demonstrate satisfactory outcomes, lower (MAE) values, and higher R^2 scores.

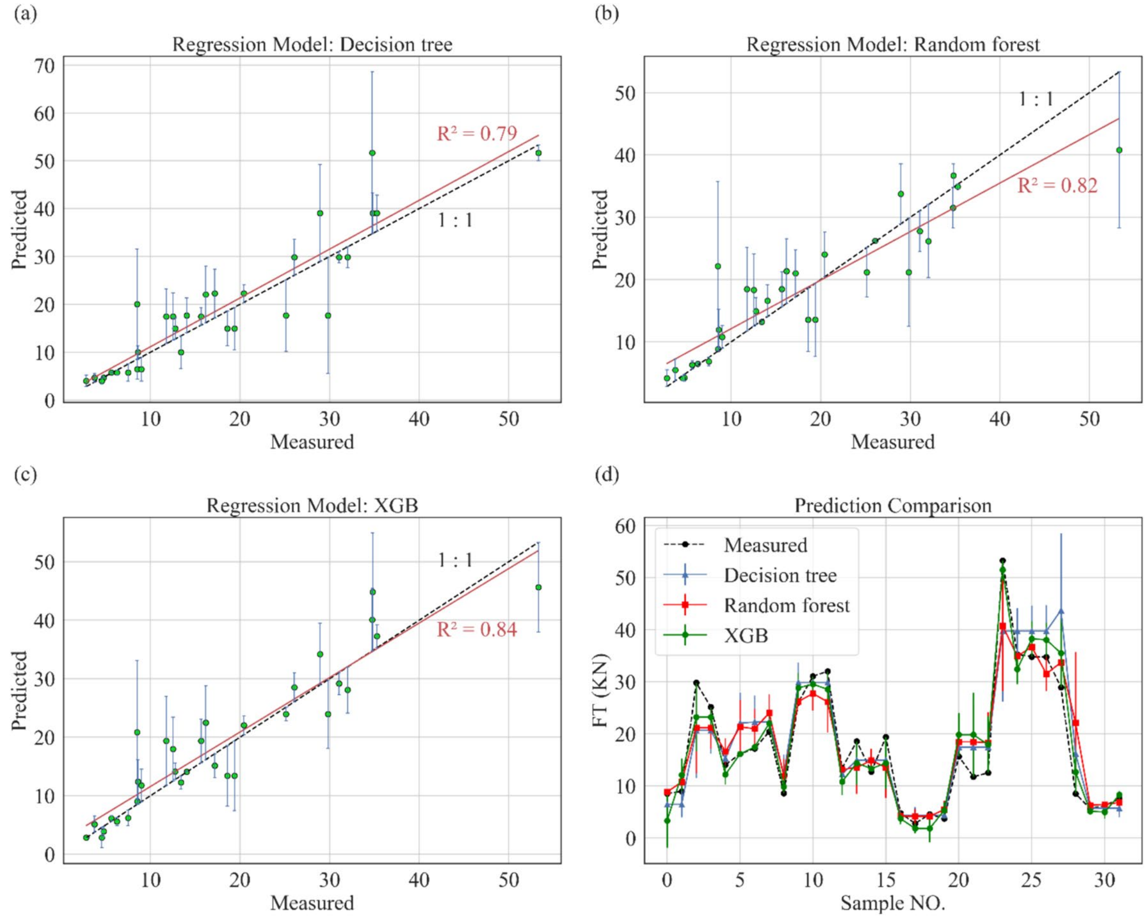


Fig. 8 Comparison of tree-based regression methods for predicting FT. Prediction versus measured values for **a** Decision tree. **b** Random forest. **c** XGB. **d** Overall prediction performance

3.4 Complex Models

Support Vector Regression (SVR) is a regression technique stemming from Support Vector Machines (SVMs) that caters to both linear and nonlinear regression tasks. Unlike traditional regression, which minimizes error rates, SVR focuses on constraining errors within a predefined threshold. This approach involves adjusting coefficients to fit data and predicts continuous ordered variables. SVR's flexibility lies in its choice of linear or nonlinear kernels based on data complexity. The method optimizes a function to approximate values while maintaining error margins dictated by epsilon ε (Schölkopf et al. 1998; Smola and Schölkopf, 2004; Awad et al. 2015).

McCulloch and Pitts (1943) introduced ANNs which excel in nonlinear tasks like classification and pattern recognition through interconnected neurons. A Keras neural network (KNN), constructed using the Keras library, simplifies the creation, training, and evaluation of neural models (McCulloch and Pitts 1943; Ferentinou and Sakellariou 2007; Dimitraki et al. 2019). Figure 9 presents a side-by-side examination of the complex regression models and the measured values.

While certain expectations propose that complex models, particularly neural networks, generally deliver superior results, Fig. 9 provides evidence to the contrary. It reveals that SVR achieves the best performance among the complex models with an R^2 of 0.79, which is lower than the tree-based models.

3.5 Probabilistic Models

Probabilistic regression methods offer an alternative approach to traditional linear regression by utilizing probability distributions instead of singular point estimates. Among these methods, Bayesian linear regression (BLR) and Gaussian process regression stand out as popular choices, employing probability distributions for both the response variable and model parameters. BLR considers inherent uncertainties in data and knowledge, providing a robust framework for decision-making (Deisenroth et al. 2020). The BLR process involves three key

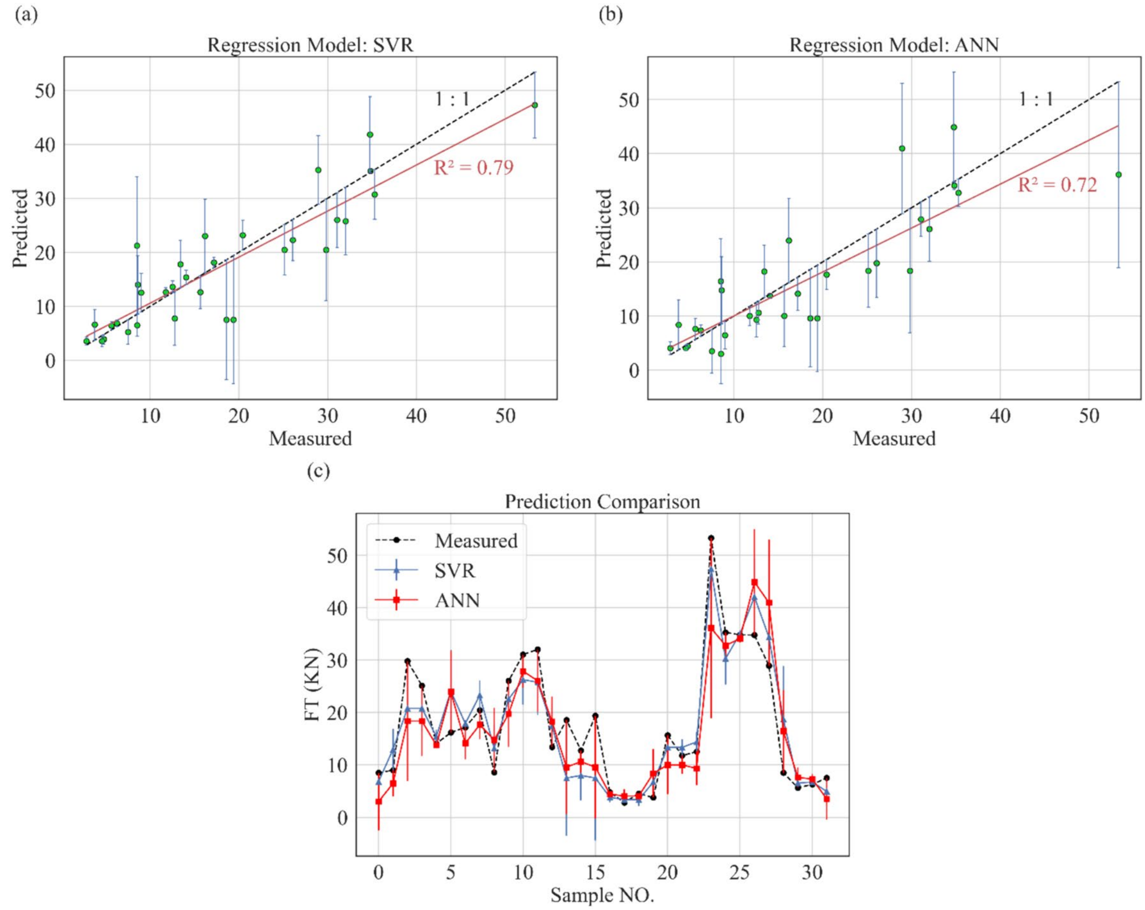


Fig. 9 Comparison of complex regression methods for predicting FT. Prediction versus measured values for **a** SVR. **b** ANN. **c** Overall prediction performance

steps, including defining a probabilistic model for data and parameter generation, inferring parameters by computing the posterior distribution, and using the posterior distribution for predicting new, unseen inputs, estimating parameters of the output's posterior distribution rather than point predictions (Minka 2000; Deisenroth et al. 2020). Gaussian process regression is a method for predicting real-valued outcomes using a flexible and probabilistic approach. It treats functions as random variables and models their relationships with data using a Gaussian distribution (Deisenroth et al. 2020). It is powerful for capturing complex patterns in data without assuming a fixed equation and is helpful in various fields. However, it can be computationally intensive and requires choosing the proper kernel function and hyperparameters. A Gaussian Process is like a more flexible version of Bayesian linear regression (Williams 1996; Seeger 2004; Rasmussen and Williams 2006).

As presented in Fig. 10, probabilistic models demonstrate promising results in predicting cutting force, especially Gaussian process regression, with an R^2 of 0.8. However, the most effective models are still tree-based models.

3.6 Ensemble Regression

Ensemble techniques involve combining multiple individual models to produce a more robust, more accurate predictive model than any individual model could on its own. The basic idea is to harness the collective intelligence of diverse models to achieve better predictive performance (Dietterich 2000; Zhou 2012). In this paper, two ensemble techniques, voting and stacking, are employed. The voting ensemble technique combines multiple individual models with its own methodology and predictions. These models can be diverse. The voting ensemble then aggregates the predictions made by each model and combines them through a voting mechanism (Leon et al. 2017). Stacking, commonly referred to as stacked generalization, includes training various models with diversity and subsequently employing a meta-model to acquire knowledge on how to amalgamate the predictions from these diverse models. Instead of simply averaging or

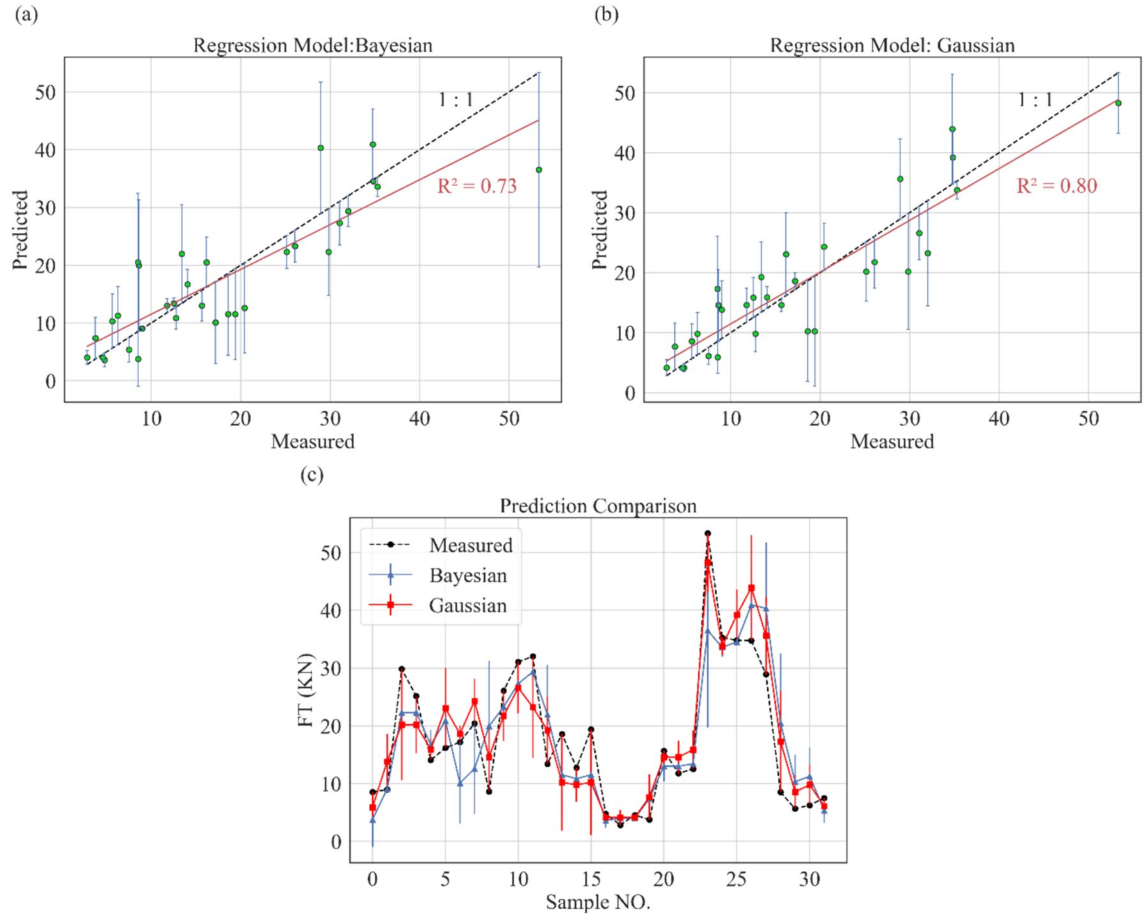


Fig. 10 Comparison of probabilistic regression methods for predicting FT. Prediction versus measured values for **a** Bayesian. **b** Gaussian. **c** Overall prediction performance

voting, stacking builds a new model that takes the outputs or predictions of the individual models as inputs and learns how to combine best or weigh these predictions to make a final prediction (Zhou 2012). Various combinations of utilized models were experimented with to create an ensemble model to alleviate bias and variance. Optimal outcomes for the voting model arose from merging SVR, tree models, and a second-degree polynomial. Conversely, the most favorable results emerged from the fusion of tree models exclusively for the stacking model. Figure 11 showcases the outcomes yielded by these ensemble models.

In the comparative analysis of predictive models for rock cutting force, the ensemble model—particularly the stacking technique—has exhibited outstanding performance, with an R^2 score of 0.92. It has consistently outperformed other models, including the tree-based ones, showcasing a notably higher degree of accuracy, robustness, and reliability in predicting cutting force.

4 Discussion

Six categories of regression methods were employed to predict rock-cutting forces with conical drag bits. Table 4 demonstrates the performance of all regression models. Figure 12 shows the MAE values and R^2 scores of the best models in each category of applied regression models in the train and test data set.

The ensemble techniques performed superior to all other methods, with the tree-based models showing the most promising results. The leading model, ensemble (stacking), a fusion of tree-based models including decision tree and XGB, notably enhanced the R^2 score to 0.92 while reducing the MAE value to 2.71 KN. The information on the used models in the ensemble (stacking) is provided in Table 5. These findings strongly indicate that employing tree-based models individually and in combination as an ensemble substantially augments model accuracy. Considering the outcomes, future investigations aiming to forecast the FT should consider utilizing an ensemble (stacking), incorporating a

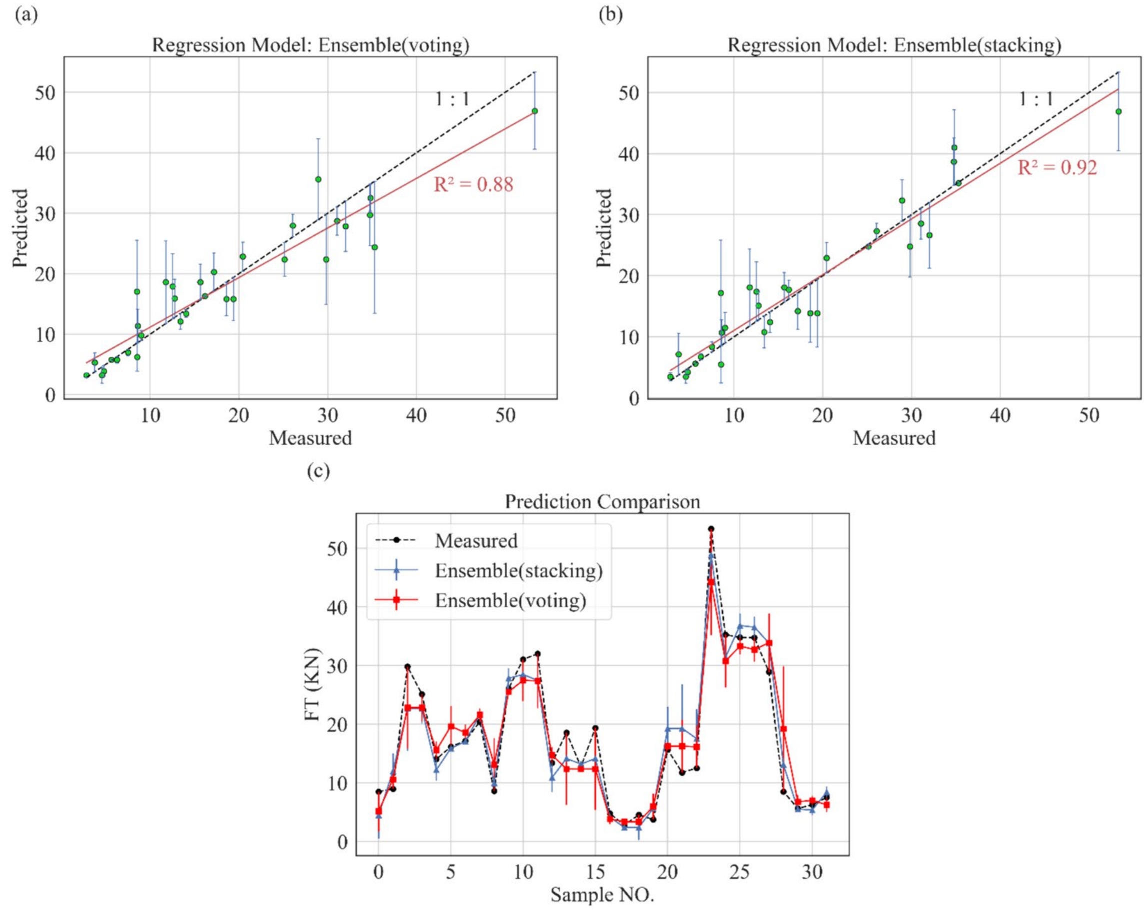


Fig. 11 Comparison of ensemble regression methods for predicting FT. Prediction versus measured values for **a** Ensemble (voting). **b** Ensemble (stacking). **c** Overall prediction performance

Table 4 R^2 scores and MAE values of all used regression models

Regression models	R^2 score		MAE value (KN)	
	Test	Train	Test	Train
Linear	0.55	0.65	7.18	6.89
Log–log linear	0.57	0.63	6.65	6.41
Polynomial (2nd-degree)	0.61	0.78	6.41	5.22
LASSO	0.61	0.61	5.66	6.79
Ridge	0.70	0.71	5.05	5.87
Elastic-Net	0.69	0.70	5.10	5.90
Decision tree	0.79	0.80	3.98	4.58
Random forest	0.82	0.83	3.53	3.99
XGB	0.84	0.91	3.35	2.83
SVR	0.79	0.79	4.22	4.52
ANN	0.72	0.75	4.81	5.18
Bayesian	0.73	0.74	4.84	5.72
Gaussian	0.80	0.80	4.46	4.85
Ensemble (voting)	0.89	0.82	3.03	4.13
Ensemble (stacking)	0.92	0.84	2.71	3.99

combination of tree-based models, for more favorable and reliable results.

Table 4 shows that in some models, such as ensembles (stacking and voting), the model performance is better for the test dataset than for the training dataset. It is worth noting that while this behavior might be unusual, it does not significantly affect the performance of the models to the point of invalidating the results. This phenomenon could be attributed to various reasons. Data characteristics may cause such differences, as the test dataset sometimes contains better information, leading to improved model generalization. The small dataset used in this study may not adequately represent the underlying population or distribution of the data to learn complex relationships between features and the target variable. This may lead to biased model predictions and unreliable insights. Additionally, the randomness of small datasets could contribute to this outcome. The ensemble method demonstrates greater resilience to noisy data and outliers, resulting in better performance on the test dataset. The nature of ensemble models, which can be considered as a form of normalization, may contribute to improved

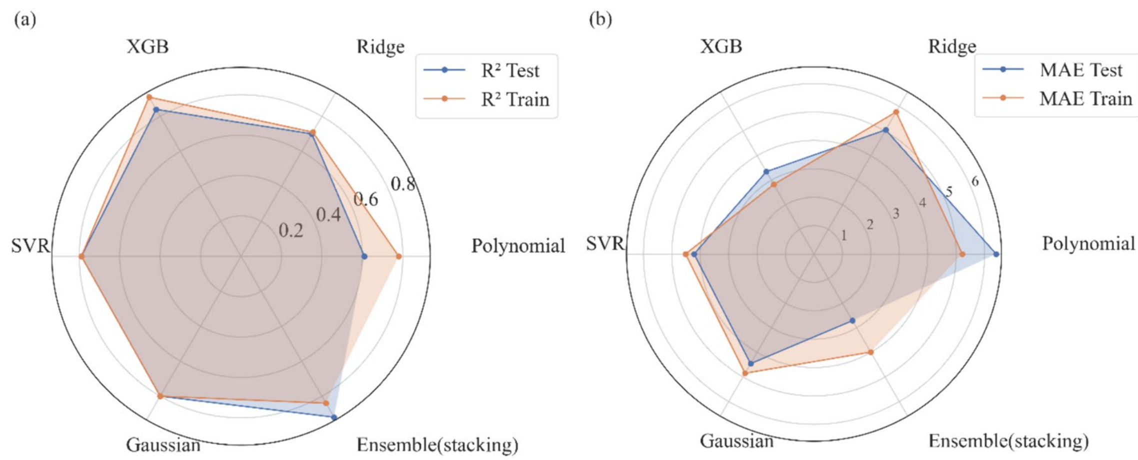


Fig. 12 Performance comparison of regression techniques in test and train dataset predicting FT. **a** R^2 scores. **b** MAE values

Table 5 Hyperparameters of the regression models used in the ensemble (stacking)

Regression model	Hyperparameters	
Decision tree	max_depth	14.00
	max_features	log2
	min_samples_leaf	4.00
	min_samples_split	4.00
XGB	colsample_bytree	0.499
	gamma	0.159
	learning_rate	0.093
	max_depth	8.00
	min_child_weight	8.00
	n_estimators	300
	reg_alpha	0.162
	reg_lambda	0.565
	subsample	0.659

generalization. Overfitting is another potential cause, which will be examined further to elucidate whether the best model exhibits this issue or remains free from it. Several actions including shuffling the data, outlier removals, different train-test splitting percentages (80–20, 70–30, etc.), random state of 42, hyperparameter optimization using grid search, cross-validation, etc. were taken to address this issue. Finally, to ensure the robustness of our findings, additional analyses using Explainable Artificial Intelligence (XAI) techniques are conducted throughout the paper to validate the models' performance.

XAI aims to make AI systems transparent and understandable, allowing for better comprehension of the process and results. XAI enhances transparency, where most AI algorithms are considered to be black box. It addresses challenges like the interpretability of complex models through methods, such as feature importance, individual conditional expectation (ICE), and partial dependence plots (PDPs). XAI also mitigates biases and model drift by promoting continuous monitoring and management, using techniques like SHAP (SHapley Additive exPlanations) to explain individual predictions (Arrieta et al. 2020; Gunning et al. 2021; Yang et al. 2021; Clancey and Hoffman 2021).

Regression equations display coefficients with negative values (such as the BTS coefficients illustrated in Table 2), signifying inaccuracies in estimating FT trends. This prompts an analysis of the data to uncover the underlying cause of this erroneous trend. Figure 13 shows this investigation focusing on examining the alterations in output linked to each input. The pair plot provides a comprehensive view of relationships between the specified quantitative variables, aiding in identifying trends (represented by the red regression line), patterns, and correlations in the dataset. Each subplot contributes to understanding how pairs of input variables interact with the output variable, along with the 95% confidence interval represented by the shaded area.

Figure 13 displays the expected trends aligning with rock mechanics principles, indicating that an increase in UCS, BTS, spacing, and AOC should correspond to an increase in cutting force. However, there is an irregularity in the data, particularly concerning the BTS parameter, which necessitates further investigation. Potential explanations for these irregularities encompass measurement inaccuracies due to the anisotropy and heterogeneity of the tested rocks, recording errors, and valid outliers, which denote authentic yet infrequent incidents within the data. This could also be due to the fact that the Brazilian method is an indirect method for measuring the tensile strength of the rock. Direct tensile strength measurements could help in this regard. Moreover, these anomalies could also indicate genuinely unusual

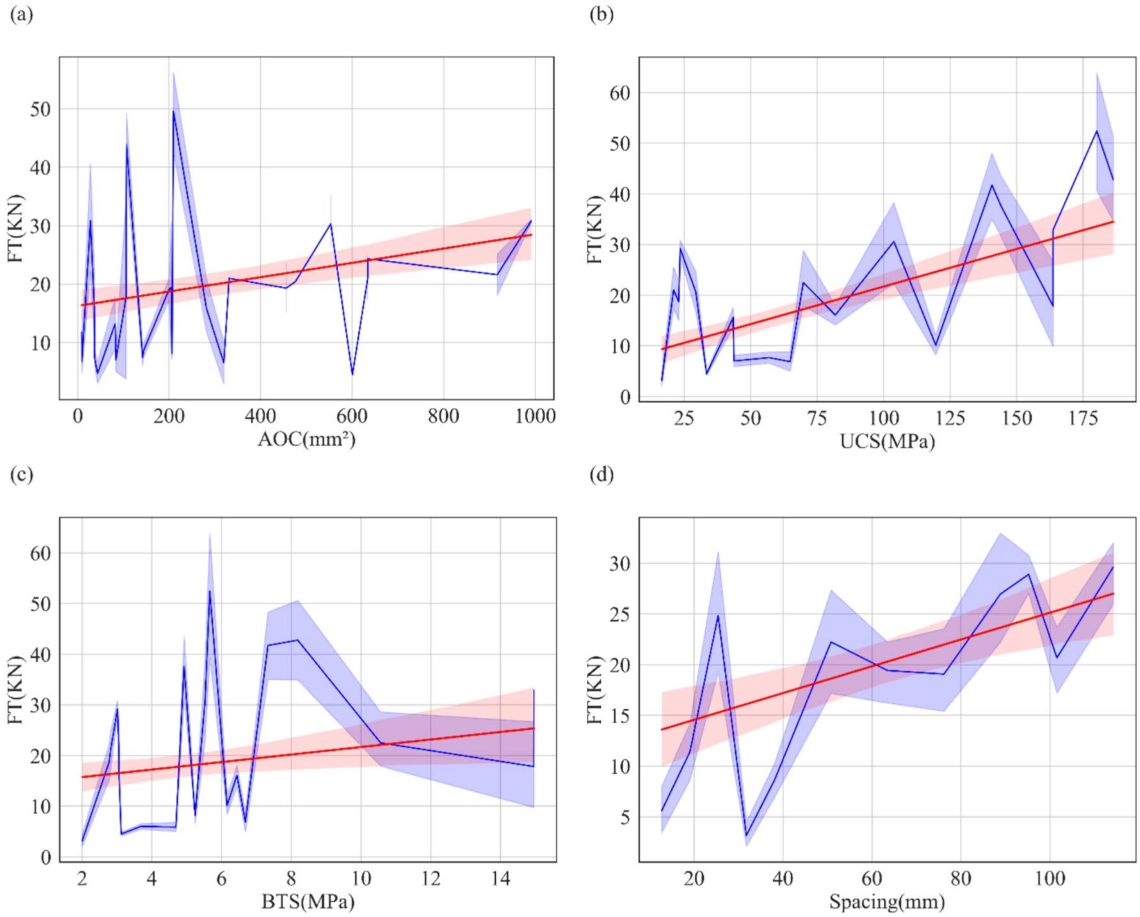


Fig. 13 Comparative analysis of input variables over FT showing trends. **a** FT as a function of AOC. **b** FT as a function of UCS. **c** FT as a function of BTS. **d** FT as a function of Spacing

observations, possibly highlighting specific conditions or instances that notably diverge from the prevailing majority of observations.

The assumption that employing complex models would invariably lead to improved outcomes was not borne out in this instance. Precisely, the anticipation that the implementation of an ANN, due to its intricate structure, would yield superior results did not align with the actual outcome. The unexpected performance of complex models like the ANN model could be attributed to several factors. Having a dataset with a low number of observations for both training and testing, alongside a scattered feature, likely influenced the results. Small datasets can hinder complex models like ANNs from generalizing effectively. The scattered feature might have complicated pattern recognition, potentially resulting in the model capturing noise rather than meaningful information.

The ensemble model, particularly the stacking method, demonstrated superior performance to all other regression models, outperforming even the tree-based models. This suggests that ensemble stacking could significantly enhance the accuracy of predictions, specifically for the cutting force estimation. However, subjecting this model to further evaluation is imperative to ensure its validity and guard against potential overfitting.

Although ensemble is a valuable technique to increase accuracy, it is not immune to overfitting issues if not correctly tuned or if the base models are too complex and highly correlated. Figure 14 shows the learning curve and SHAP value of the best model ensemble (stacking). The learning curve analysis provides a comprehensive insight into the performance of the ensemble stacking model. It vividly illustrates the model's learning capability as more data is introduced. A particularly encouraging sign is the convergence of the training and cross-validation curves as the volume of data increases. This convergence indicates that the model's performance steadily improves with more data, as reflected in the diminishing gap between the two curves. The parallel nature of these lines towards the conclusion of the learning curve suggests that the model has almost reached its learning capacity or has effectively captured the underlying patterns in the data. Moreover, the minimal distance between

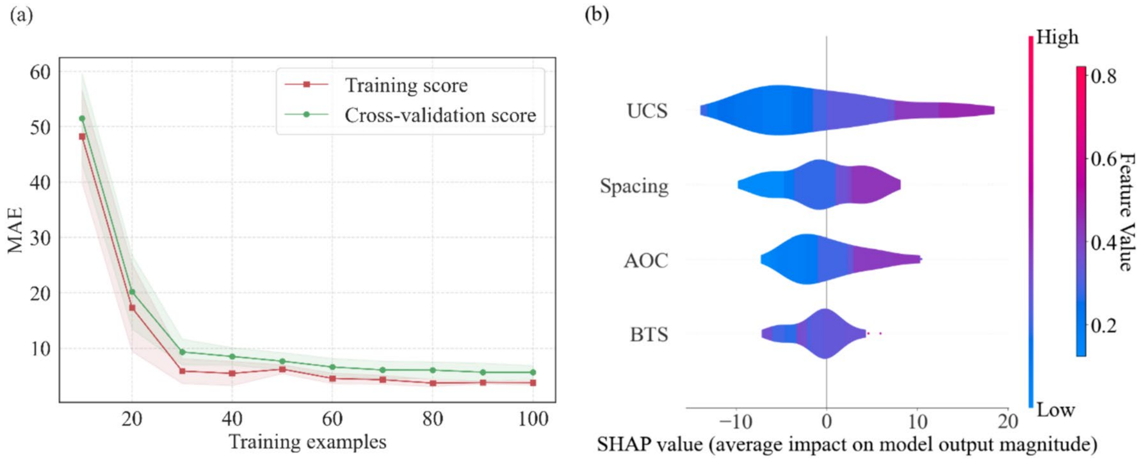


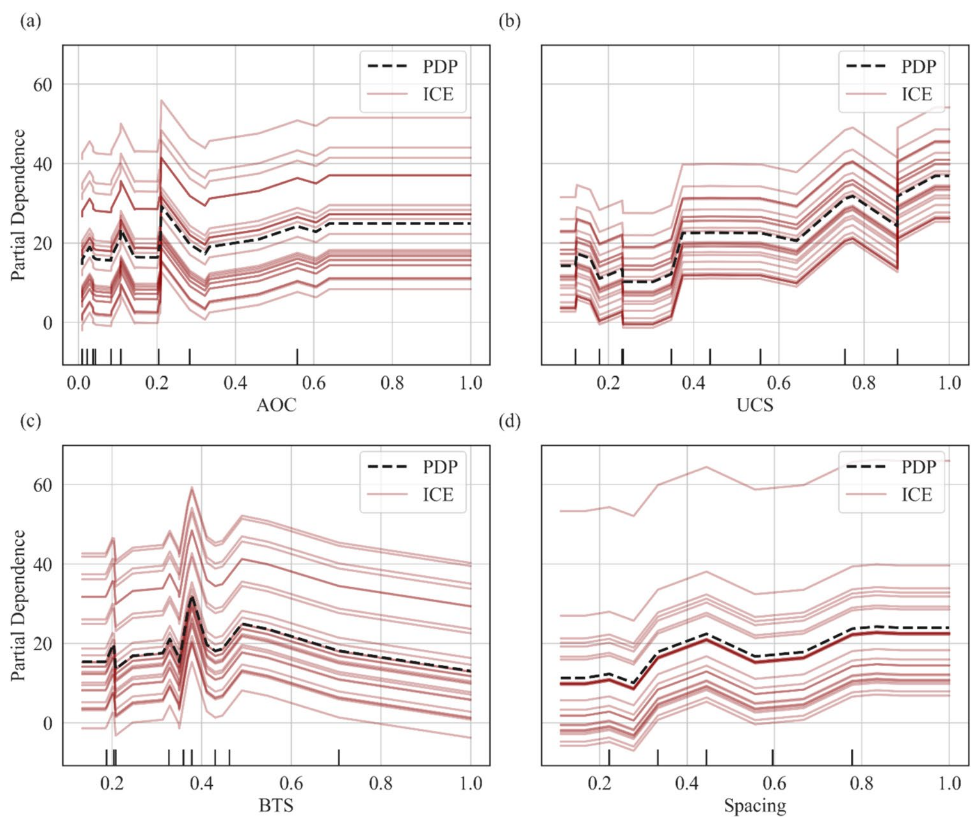
Fig. 14 Unveiling the ensemble (stacking) model behavior. **a** Learning curve. **b** SHAP analysis

the training and cross-validation curves at the end implies that the model exhibits a low variance and is less prone to overfitting. It signifies the model generalizes well to new, unseen data, making it a reliable predictor for cutting force estimation.

SHAP helps understand the parameters' importance and influence on the output results (Hunter 2007). Figure 14b shows that the most important parameter for the best model is UCS. In all parameters, the higher values of input parameters have a more significant influence on the prediction results.

One crucial aspect to consider in the evaluation process is how the complexity of the data influences the model's performance. High complexity in the data might lead to challenges in the model's ability to generalize well to new, unseen data. Understanding and managing the impact of data complexity on the model's predictive ability is crucial in

Fig. 15 ICE and PDPs for input parameters in the best model, ensemble (stacking). The values on the X-axis are normalized



interpreting its overall performance and reliability. This can be done through ICE and PDPs.

In machine learning, ICE and PDPs are techniques used to interpret and understand the behavior of models. PDPs simplify complex models by showing how the target variable reacts to changes in a specific input while keeping other features constant (Hastie et al. 2009; Greenwell 2017; Greenwell et al. 2018). ICE plots help to understand the effect of a single feature on the predicted outcome. PDPs, on the other hand, illustrate the average effect of a feature on predictions while taking into account the impact of all other features in the model. Figure 15 exhibits the ICE (blue lines) and PDPs (orange dash line), revealing the relationship between input parameters and the target value within the top-performing model, the ensemble (stacking). The findings indicate that even the best model struggles to capture the influence of BTS due to the unique scattering caused by data distribution (Figs. 3 and 13). UCS, AOC, and spacing exhibit correct increasing patterns. The absence of parallel ICE lines suggests the model is identifying interactions among the features, and this absence can be attributed to the selection of an appropriate gradient-boosting model. In this scenario, the absence of this phenomenon can be attributed to the selection of an appropriate gradient-boosting model. All curves consistently follow a similar trajectory, signifying the absence of evident interactions. This implies that the PDP effectively summarizes the relationships between the featured variables and the predicted cutting force.

The ensemble model developed in this paper exhibits superior performance across all metrics. This enhanced performance, when compared to the models introduced by Morshedlou et al. (2023), is attributed to the combination of parameters, such as pick cutter tip angle, tip radius, and depth of penetration, which collectively define the AOC, as well as the ensemble of tree-based models using a stacking approach.

The research acknowledges constraints in the size and collection of data, as well as the potential influence of methodology choices on the validity of the findings. The dataset focuses on specific rock types and cutter models, potentially leading to inaccuracies. While the chosen input parameters are suitable, more data could improve model generalization and help with the model's performance. However, if interpretability of the results and models' performance is still a concern, one should use simpler models like traditional regression models (linear, log–log linear, and polynomial), especially when dealing with small datasets since they have performed as expected in both training and test dataset, as shown in Table 4. Transfer learning could adapt these models to different scenarios. Environmental factors not considered in model development pose challenges for predicting cutting force under field conditions. Employing physics-informed machine learning can enhance model accuracy by integrating physics-based insights and addressing data limitations for broader predictions.

5 Conclusions

The primary objective of this study was to explore and compare a spectrum of regression models for predicting FT in rock-cutting processes acting on conical pick cutters using UCS, BTS, spacing, and the contact area between the pick cutter and rock as input parameters. The study aimed to assess model performance, identify anomalies, and evaluate the effectiveness of different regression techniques. The conclusions can be summarized as follows:

- The application of statistical analysis to derive linear and nonlinear formulas for estimating FT from input parameters has demonstrated reasonable accuracy. However, it is imperative to acknowledge that these formulas inherently exhibit lower accuracy than the more sophisticated regression models.
- The findings indicate that ensemble techniques, especially the stacking ensemble of tree-based models, displayed superior performance in predicting FT, significantly enhancing accuracy with an R^2 score of 0.92 and an MAE of 2.71 KN.
- The learning curve analysis of the ensemble stacking model highlighted its capability to generalize well and predict FT accurately.
- The analysis of regression equations revealed potential inaccuracies, particularly in the BTS feature, urging further investigation to understand and rectify these discrepancies for more accurate predictions.
- Potential explanations for these irregularities encompass interrelationships between parameters, measurement inaccuracies, a small number of data points and range of variability of input parameters, recording errors, and outliers, which could denote authentic yet infrequent incidents within the data. Moreover, these anomalies could also indicate genuinely unusual observations, possibly highlighting specific conditions or instances that notably diverge from the prevailing majority of observations.
- Complex models, exemplified by ANN, did not offer superior performance due to limitations related to a small dataset and scattered features, impeding their ability to generalize effectively.
- In this study, ICE, PDPs, and SHAP analyses were employed as key Explainable AI methods to interpret and validate the results obtained from the ensemble technique, specifically stacking, ensuring a thorough understanding of the model's decision-making process.

The identified superior performance of ensemble techniques, specifically the stacking ensemble of tree-based models, holds great potential for improving the accuracy of FT prediction. This study paves the way for future advancements in predicting cutting force in rock-cutting processes by highlighting the necessity for an ongoing investigation, larger datasets, and advanced methodologies. It emphasizes the need for a comprehensive and multifaceted approach to enhance accuracy and reliability in predictive models, thereby influencing and guiding future research and applications in this field.

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Declarations

Conflict of Interest The authors have no competing interests to declare that are relevant to the content of this article.

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