

Article

Multi-Source Sensing and Interpretable Ensemble Learning for Cross-Validated Performance-Weighted Evaluation of Open-Pit Blasting Performance

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Abstract

Comprehensive evaluation of open-pit blasting is challenging because performance indicators originate from different sensing sources and are predicted with different levels of model performance. This study proposes a multi-source sensing and interpretable ensemble learning framework for model-performance-weighted blast-performance evaluation. Data from 70 production blasts were organized into 12 input variables and 10 indicators spanning fragmentation quality, muckpile morphology, safety and adverse effects, and operational efficiency. Random forest, XGBoost, LightGBM, and CatBoost models were developed separately for each indicator and compared using five-fold cross-validation, while SHAP was applied to interpret the selected models. The indicator-specific models achieved cross-validated R^2 values of 0.7812–0.9012; these are selection-conditioned cross-validated estimates obtained under the same five-fold partition that was used to select the model for each indicator, and they are not unbiased estimates of generalization performance. Powder factor and uniaxial compressive strength were influential for fragmentation, whereas maximum charge per delay strongly affected peak particle velocity and muckpile displacement. Cross-validated R^2 was then incorporated into AHP–entropy weighting as a relative model-performance coefficient that is not a confidence level, a probability of correctness, or an uncertainty estimate. In field application, engineering adjustment based on model feedback increased the comprehensive score from 65.4 to 87.5, improved the grade from III to II, and reduced D80 and PPV by 25.4% and 27.8%, respectively. The models are specific to the monitored mine rather than transferable, and the field implementation is an application case rather than an independent external validation. The framework provides an interpretable and model-performance-aware basis for site-specific blast-scheme comparison and iterative improvement.

Keywords: open-pit blasting; multi-source sensing; ensemble learning; SHAP; model-performance weighting; comprehensive evaluation; blast-performance prediction



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1. Introduction

Open-pit blasting is a key upstream operation in the drill–blast–load–haul–crush production chain. Its performance affects fragmentation, muckpile diggability, loading

efficiency, haulage, and downstream comminution. Fragment-size distribution influences secondary-breakage demand and crushing energy, whereas muckpile geometry affects excavator access and loading conditions. Blast-induced vibration, flyrock, and toe formation further constrain operational safety and production continuity. Blast design should therefore balance fragmentation quality, muckpile morphology, safety and adverse effects, and operational efficiency rather than optimize a single response in isolation [1–3].

Rock blasting is a transient and highly nonlinear process governed by the interaction of stress-wave propagation, detonation-gas expansion, crack growth, and rock movement. Empirical approaches, including Kuz–Ram-type fragmentation models and scaled-distance vibration equations, generally rely on a limited set of geometric, charging, or propagation variables. Their applicability may be restricted by rock-mass heterogeneity, blast geometry, and implementation deviations [3–6]. Conventional assessments also tend to examine fragmentation, peak particle velocity, or flyrock separately, although production blasts involve several interdependent quality, safety, and efficiency objectives [3]. Comprehensive evaluation methods have also been developed to integrate multiple blasting-performance indicators for open-pit mine assessment [7].

Advances in mine sensing and digitalization have enabled more comprehensive monitoring of blasting performance. UAV imagery and three-dimensional point clouds can characterize terrain change, muckpile geometry, and spatial displacement [8,9]. Image-based analysis provides estimates of fragment-size distributions, while triaxial vibration sensors record dynamic responses and support peak particle velocity extraction [10–12]. Loading records further indicate how blasting outcomes affect downstream operations. These data sources provide complementary spatial, fragmentation, dynamic, and operational information. However, they are often analyzed independently, and their outputs are rarely integrated into a unified prediction and evaluation workflow.

Machine learning methods have been increasingly applied to blasting-response prediction. Random forests, gradient-boosting models, support vector regression, and neural networks have been used for fragmentation, vibration, flyrock, toe, and muckpile-related tasks, demonstrating their ability to represent nonlinear field relationships [3,5,10–16]. Nevertheless, different indicators are governed by different mechanisms and exhibit different distributions and measurement uncertainties. Fragmentation is closely related to explosive-energy input and rock resistance, vibration is additionally affected by the maximum charge per delay and propagation conditions, and loading efficiency reflects the combined influence of fragmentation and muckpile geometry. Indicator-specific model comparison under a consistent validation procedure is therefore more appropriate than adopting a single algorithm for all outputs.

Considering the limited number of field blast samples in this study, tree-based ensemble algorithms were selected because of their robustness for small-to-medium tabular datasets and their suitability for feature-importance interpretation.

Predictive accuracy alone is insufficient for engineering decision-making. Model interpretation is needed to determine whether the learned relationships are physically plausible, and the relative predictive performance of the models should be considered when model outputs are used in comprehensive evaluation. SHAP has been widely used to quantify the direction and magnitude of feature effects in nonlinear models [17]. AHP, entropy weighting, and related combination methods have also been applied to multi-indicator engineering assessment [18,19]. However, several methodological gaps remain in current blasting-performance prediction and evaluation studies. Existing studies have improved the prediction of individual blasting responses or the comprehensive assessment of multiple indicators. Nevertheless, the integration of indicator-specific model selection, interpretable machine learning analysis, and performance-adjusted weighting

within a unified blast-scheme evaluation framework remains insufficient. A comparison of representative approaches and the proposed framework is summarized in Table 1.

Table 1. Comparison of representative blasting-performance prediction and evaluation approaches.

Approach	Multi-Indicator Evaluation	Machine Learning Prediction	Indicator-Specific Model Selection	Model Interpretation	Model-Performance-Weighted Evaluation
Empirical blasting models	Limited	No	No	No	No
Single-indicator ML prediction studies	No	Yes	No	Limited	No
Multi-indicator evaluation methods	Yes	Partial	No	Limited	No
ML-assisted blasting optimization methods	Partial	Yes	Partial	Limited	No
This study	Yes	Yes	Yes	SHAP-based	Yes

As summarized in Table 1, previous studies have provided valuable contributions to blasting-response prediction and engineering evaluation. However, most existing methods either focus on individual indicators or combine multiple indicators without considering differences in predictive performance among indicator-specific models. In this study, an integrated framework is developed to select appropriate models for different indicators, interpret model behavior using SHAP, and incorporate cross-validated model performance into comprehensive blast-scheme evaluation.

This study addresses these limitations by developing a multi-source sensing, interpretable ensemble learning, and cross-validated performance-weighted evaluation framework for open-pit blasting performance. Specifically, this study aims to answer three research questions: (1) whether different blasting-performance indicators require indicator-specific model selection rather than the use of a universal prediction model; (2) whether SHAP-based interpretation can reveal the dominant factors and physically meaningful relationships underlying model predictions; and (3) whether incorporating cross-validated model performance into indicator weighting can provide a more consistent comprehensive blast-scheme evaluation. Field data from 70 production blasts were collected using UAV-based LiDAR and imaging, image-based fragmentation analysis, triaxial vibration monitoring, and loading-operation records. The dataset contains blast-design and rock-mass inputs and performance indicators covering fragmentation quality, muckpile morphology, safety and adverse effects, and operational efficiency. Random forest, XGBoost, LightGBM, and CatBoost models are compared separately for each output using five-fold cross-validation. SHAP is then used to interpret the effects of key design and rock-mass variables. At the decision level, AHP and entropy weights are integrated through multiplicative normalization and adjusted using the cross-validated R^2 of the selected models. Comprehensive scoring is further combined with a critical-indicator constraint rule for blast-scheme assessment and field application.

Based on these research questions, the main contributions of this study are summarized as follows:

(1) A multi-source indicator system is established by integrating UAV-based three-dimensional surveying, image-based fragmentation analysis, triaxial vibration monitoring, and loading-operation records across four blasting-performance dimensions.

(2) An indicator-specific ensemble learning framework is developed to compare and select models under a consistent validation procedure, with SHAP used to interpret nonlinear feature effects.

(3) A cross-validated performance-adjusted weighting method is proposed by combining AHP, entropy weighting, and cross-validated model performance, together with a critical-indicator constraint rule for scheme assessment and implementation decisions.

2. Materials and Data Acquisition

2.1. Study Area and Field Blast Dataset

This study was conducted at a large open-pit coal mine in Xinjiang, China. The mining area covers approximately 45.84 km² and has an approved annual production capacity of 40 million tons. The mine name and exact geographical coordinates are withheld for confidentiality. Field data were collected from 70 production blasts, with each blast treated as one sample for blasting-performance prediction and comprehensive evaluation. Because all blast records were collected from the same open-pit mine during the investigated production period, large-scale terrain differences and seasonal variations were relatively limited within the dataset. Therefore, terrain, precipitation, and seasonal factors were not introduced as independent input variables in the current prediction models. These blasts corresponded to different production operations conducted during the data-collection period, while representing the geological and operational characteristics within the investigated mine.

The study area is characterized by a gently inclined monocline with a northeast–east strike and a southeast–south dip. The principal coal seam belongs to the Xishanyao Formation and has an average thickness of approximately 76.84 m. Its roof and floor mainly comprise mudstone and sandstone. The representative lithologies exposed in the blasting areas include red mudstone, yellow mudstone, limestone, fine sandstone, coarse sandstone, and sandy mudstone, as shown in Figure 1.

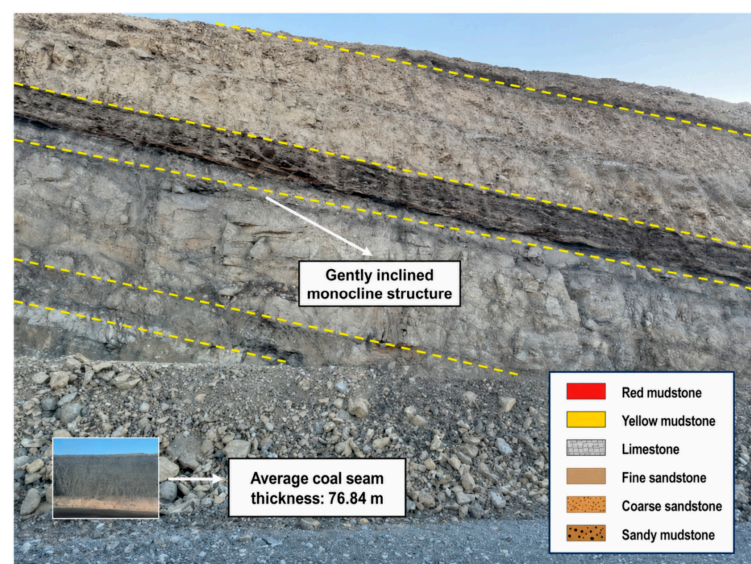


Figure 1. Field exposure of the gently inclined monocline and representative lithological units in the study area.

These lithologies differ markedly in strength, density, and integrity, which results in heterogeneous stress-wave propagation, crack development, and rock movement. Rock-mass properties were therefore considered together with blast-design variables in the subsequent modeling.

Data acquisition covered the pre-blast, blast-time, and post-blast stages. The pre-blast data comprised blasthole geometry, charge parameters, and rock-mass properties. During blasting, triaxial vibration-velocity time histories were recorded. Post-blast measurements covered fragmentation, muckpile morphology, safety and adverse effects, and loading-operation efficiency. The resulting dataset contained 12 input features and 10 output indicators, whose acquisition methods and definitions are provided in the following sections.

2.2. Rock Properties and Equivalent Parameters

Six representative lithologies exposed in the blasting areas—red mudstone, yellow mudstone, limestone, fine sandstone, coarse sandstone, and sandy mudstone—were sampled for laboratory characterization. The collected rock blocks were cut, end-ground, and prepared as standardized specimens. For each lithology, five cylindrical specimens ($\Phi 50 \times 100$ mm) were prepared for uniaxial compression, three disc specimens ($\Phi 50 \times 25$ mm) for Brazilian splitting, and cubic specimens ($50 \times 50 \times 50$ mm) for variable-angle shear testing. The specimen-preparation and testing procedures are illustrated in Figure 2.

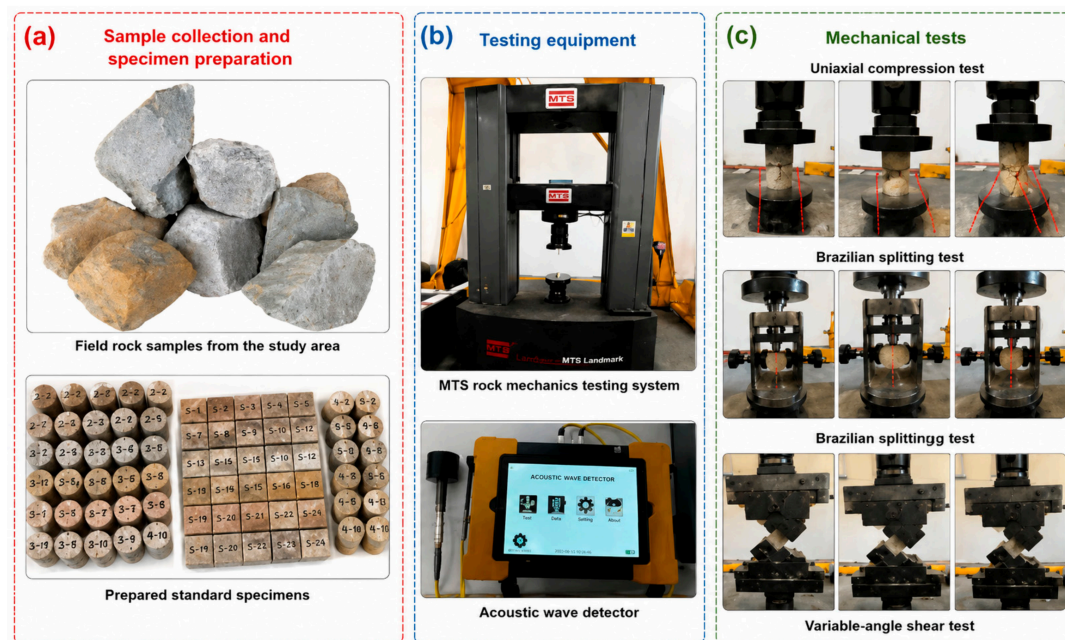


Figure 2. Preparation of rock specimens and laboratory testing procedures.

The mechanical tests were conducted using an MTS rock-mechanics testing system in accordance with GB/T 50266-2013 [20]. Uniaxial compression tests provided the uniaxial compressive strength and elastic modulus, Brazilian splitting tests provided the tensile strength, and variable-angle shear tests provided the cohesion and internal friction angle. Natural density was measured by hydrostatic weighing, and the P-wave velocity of the intact rock was measured using standardized specimens. Only uniaxial compressive strength, natural density, and rock-mass integrity coefficient were used as model inputs; these properties are summarized in Table 2. The remaining laboratory properties were used only for lithological characterization and were not included as independent input features. Therefore, only parameters with direct relevance to blasting-response prediction were retained as model inputs.

Table 2. Rock properties used as model inputs for the representative lithologies.

Lithology	σ_c (MPa)	ρ (t/m ³)	K_v
Red mudstone	5.70	2.30	0.55
Yellow mudstone	6.50	2.35	0.52
Limestone	77.50	2.70	0.75
Fine sandstone	65.90	2.50	0.68
Coarse sandstone	4.14	2.40	0.50
Sandy mudstone	6.80	2.38	0.58

Note: σ_c , uniaxial compressive strength; ρ , natural density; K_v , rock-mass integrity coefficient.

As shown in Table 2, the uniaxial compressive strength varied from 4.14 MPa for coarse sandstone to 77.50 MPa for limestone, while K_v ranged from 0.50 to 0.75. Limestone and fine sandstone exhibited substantially higher strength and integrity than the mudstone-dominated lithologies, which indicates pronounced mechanical heterogeneity within the blasting areas.

The integrity coefficient of lithology l was calculated from the field and laboratory P-wave velocities as

$$K_{v,l} = \left(\frac{V_{field,l}}{V_{lab,l}} \right)^2 \quad (1)$$

where $V_{field,l}$ is the P-wave velocity obtained from field sonic logging and $V_{lab,l}$ is the P-wave velocity measured using an intact laboratory specimen of the corresponding lithology.

Because individual blasting areas commonly contained multiple lithological layers, the density and integrity coefficient of a single lithology could not represent the overall rock-mass conditions. The thickness weight of each layer was therefore determined from the blasthole lithological logs:

$$\omega_l = \frac{h_l}{\sum_{l=1}^L h_l}, \sum_{l=1}^L \omega_l = 1 \quad (2)$$

where h_l is the thickness of layer l , L is the number of lithological layers within the blasting area, and ω_l is the corresponding thickness weight. The equivalent density and equivalent integrity coefficient were then calculated as

$$\rho_{eq} = \sum_{l=1}^L \omega_l \rho_l, K_{v,eq} = \sum_{l=1}^L \omega_l K_{v,l}, \quad (3)$$

where ρ_l is the measured natural density of lithology l . This weighting procedure accounts for both the properties of the constituent lithologies and their proportions within each blasting area. The uniaxial compressive strength recorded for each blast, together with ρ_{eq} and $K_{v,eq}$, was used to characterize the rock-mass conditions in the subsequent models. The remaining mechanical properties were retained for lithological characterization but were not used as separate model inputs.

2.3. Multi-Source Monitoring of Blasting Performance

Blasting data were obtained from field design records, rock-property measurements, UAV surveying, image-based fragmentation analysis, triaxial vibration sensing, and loading-operation records. Blast-design parameters were retrieved from the construction plans, whereas the rock-mass variables were derived from the laboratory tests and field sonic logging described in Section 2.2. The acquisition procedure for the blast-design variables, rock-mass properties, fragmentation indicators, and muckpile-morphology indicators is shown in Figure 3.

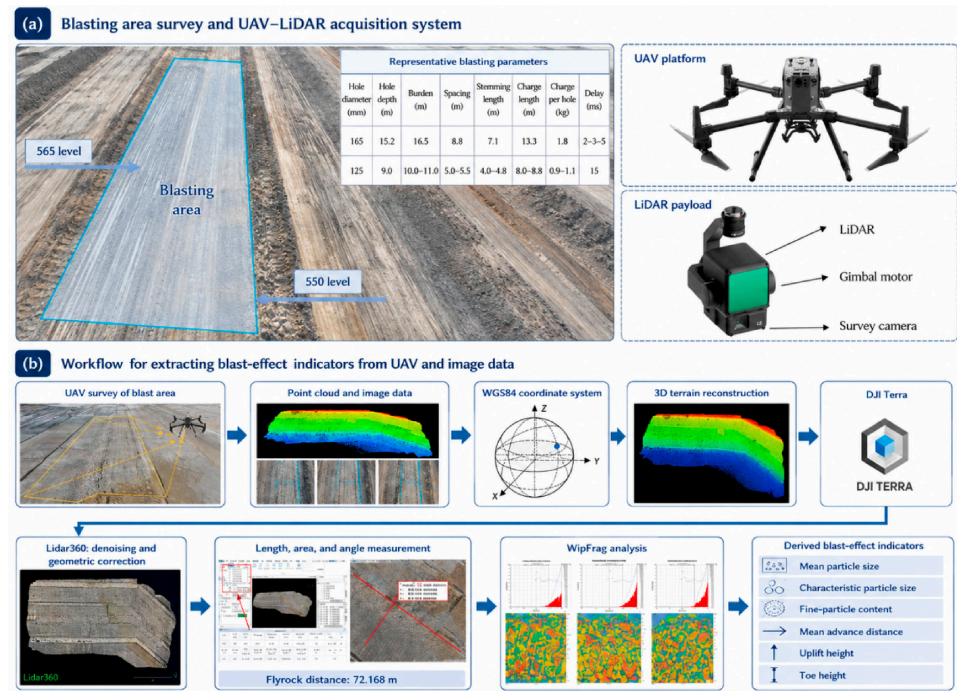


Figure 3. Acquisition workflow for blast-design parameters, rock-mass properties, fragmentation indicators, and muckpile-morphology indicators.

Pre- and post-blast surveys were conducted using a DJI Matrice 350 RTK UAV (DJI, Shenzhen, China) equipped with a LiDAR scanning system and a high-resolution mapping camera. The acquired data were reconstructed in DJI Terra (v5.0, DJI, Shenzhen, China) within the WGS84 coordinate system and subsequently processed in LiDAR360 (v7.0, Beijing GreenValley Technology Co., Ltd., Beijing, China). Noise, vegetation, and anomalous points were removed before digital elevation models (DEMs) were generated. The aligned pre- and post-blast DEMs were compared to determine the mean muckpile advance distance, muckpile uplift height, toe height, and flyrock distance. Mean muckpile advance distance was measured relative to the pre-blast bench-toe line, uplift height was obtained from the maximum elevation increase near the muckpile center, toe height was defined as the maximum residual protrusion above the bench floor, and flyrock distance was measured from the blast-area boundary to the farthest identified fragment.

Fragmentation indicators were extracted from UAV orthophotos of the muckpile surface. Following scale calibration in WipFrag (v3.3, WipWare Inc., Hamilton, ON, Canada), the particle-size distribution was analyzed to obtain the mean fragment size, characteristic fragment size D80, and image-derived fine-particle content below 5 mm. These indicators describe the overall fragmentation level, the coarse-fragment component, and the fine-fragment component, respectively. The fine-particle content below 5 mm is derived from image-based particle segmentation and is therefore treated as an image-derived fragmentation indicator for comparative evaluation among blast schemes. Its quantitative accuracy may be influenced by image resolution, particle exposure conditions, and segmentation performance during image processing. Therefore, this indicator was interpreted as a relative measure of fine-fragment variation rather than an absolute measurement of all particles below 5 mm. The effective ground sampling resolution of these images was quantified from the survey configuration. The mapping camera used for the fragmentation surveys records 5280×3956 pixels with a 24 mm equivalent focal length, so the ground sampling distance is $GSD = H \times 36 / (24 \times 5280) = 2.84 \times 10^{-4} H$, where H is the flight height above the terrain in meters. For the surveys used in this study, H ranged from about 20 m to about 90 m. The ground sampling distance was therefore about 2.1–2.6 cm per pixel for the

flights at 75–90 m that provided most of the muckpile orthophotos and about 0.6 cm per pixel for the lowest-altitude passes. A particle of 5 mm consequently corresponds to less than one pixel in every configuration used here: about 0.2 pixels at the 75–90 m altitudes and about 0.9 pixels for the lowest-altitude passes. The 5 mm class therefore lies below the resolvable scale of the imagery, and the value returned by WipFrag for this class is obtained by extrapolating the fitted particle-size distribution beneath the resolution limit rather than by delineating individual fine particles. $F < 5$ is therefore used only as a relative, image-based index of fine-fragment variation among schemes surveyed and processed with the same chain, and its absolute value carries no sieving-equivalent meaning.

The field arrangement and data processing procedures for vibration and operational-efficiency monitoring are shown in Figure 4.

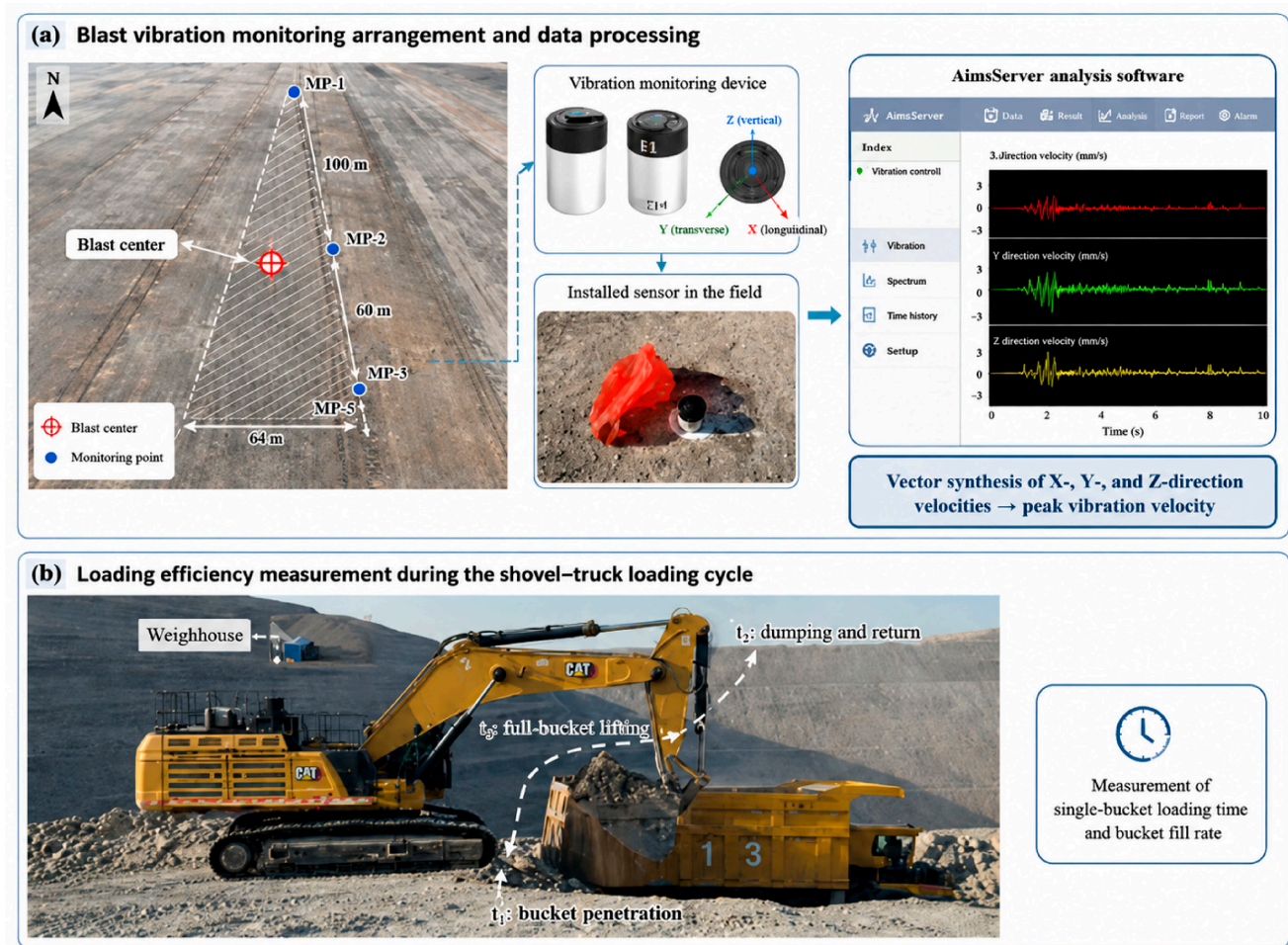


Figure 4. Monitoring workflow for blast-induced vibration and operational-efficiency indicators.

Blast-induced vibration was recorded using three-channel iSensor vibration monitors manufactured by Top Instruments, Sichuan, China. For each blast, two monitoring points were arranged 1 m apart at a nominal distance of 30 m from the blast source. The instruments were fixed with gypsum to cleaned bedrock, with the x-axis directed toward the blast center, the y-axis oriented tangentially, and the z-axis directed vertically upward. The three velocity components were recorded at 4000 Hz using automatic triggering and offline acquisition. Peak particle velocity (PPV) was defined as the largest absolute peak among the three components:

$$PPV = \max \left\{ \max_t |v_x(t)|, \max_t |v_y(t)|, \max_t |v_z(t)| \right\} \quad (4)$$

where $v_x(t)$, $v_y(t)$, and $v_z(t)$ are the vibration velocity time histories along the three measurement axes. The two instruments provided duplicate measurements for field consistency checking.

Operational efficiency was characterized by single-bucket loading time and truck payload utilization. A loading cycle comprised bucket penetration into the muckpile, full-bucket lifting, swinging, dumping, and return to the initial position. Fifteen consecutive standard cycles were timed for each blast, and their arithmetic mean was used as the single-bucket loading time. Truck payload utilization was calculated from weighbridge records for ten randomly selected trucks:

$$\eta_p = \frac{100}{n} \sum_{i=1}^n \frac{m_{g,i} - m_{t,i}}{m_{r,i}}, \quad n = 10 \quad (5)$$

where η_p is the mean truck payload utilization (%) and $m_{g,i}$, $m_{t,i}$, and $m_{r,i}$ are the gross mass, tare mass, and rated payload of truck i , respectively. The monitoring procedures yielded ten output indicators across fragmentation quality, muckpile morphology, safety and adverse effects, and operational efficiency. Their definitions and units are summarized in Section 2.4.

2.4. Input Features and Output Indicators

Each blast was represented by 12 candidate input features, comprising nine blast-design variables and three rock-mass variables. The blast-design features describe blasthole geometry, charge configuration, and explosive-energy input, whereas the rock-mass features characterize the strength, integrity, and density of the blasted material. Specifically, blasthole geometry was represented by parameters including blasthole diameter, depth, spacing-to-burden ratio, stemming length, and subdrilling depth. Explosive-energy input was characterized indirectly through charge-related parameters, including charge length, powder factor, and maximum charge per delay, because these variables describe the charging conditions associated with explosive loading during blasting. The rock-mass variables were characterized as follows: uniaxial compressive strength was obtained from laboratory uniaxial compression tests, equivalent density was determined by hydrostatic weighing and thickness-weighted averaging of lithological units, and the equivalent integrity coefficient was derived from the ratio between field and intact-rock P-wave velocities. Their definitions, symbols, units, and data sources are listed in Table 3. The candidate features were screened for completeness and potential outliers, after which indicator-specific input subsets of four to six variables were defined a priori from the governing physical mechanism of each response and held fixed across folds (Section 2.5). The complete candidate set was retained only for the descriptive correlation analysis reported in Section 3.1.

Table 3. Candidate input features used for blasting-performance prediction.

Group	Input Feature	Symbol	Unit	Data Source or Calculation
Blast design	Blasthole diameter	D	mm	Drill-bit diameter specified in the blast design
Blast design	Blasthole depth	H	m	Actual drilled length from collar to hole bottom
Blast design	Spacing-to-burden ratio	R_{sb}	–	Blasthole spacing divided by burden
Blast design	First-row-to-crest distance	L_c	m	Horizontal distance from the first-row blasthole center to the bench crest
Blast design	Subdrilling depth	J	m	Drilled length below the designed bench-floor elevation
Blast design	Stemming length	L_s	m	Length of the stemming column

Table 3. *Cont.*

Group	Input Feature	Symbol	Unit	Data Source or Calculation
Blast design	Charge length	L_q	m	Length of the explosive column
Blast design	Powder factor	q	kg/m ³	Explosive mass per unit volume of blasted rock
Blast design	Maximum charge per delay	$Q_{\max}$	kg	Total explosive mass initiated within one delay interval
Rock mass	Uniaxial compressive strength	σ_c	MPa	Laboratory uniaxial compression test
Rock mass	Equivalent integrity coefficient	K_v, ρ_q	–	P-wave velocity ratio and thickness-weighted averaging
Rock mass	Equivalent density	ρ_{eq}	t/m ³	Hydrostatic weighing and thickness-weighted averaging

Note: The equivalent rock-mass parameters were calculated using the procedures defined in Equations (1)–(3).

The ten output indicators were organized into four dimensions: fragmentation quality (B_1), muckpile morphology (B_2), safety and adverse effects (B_3), and operational efficiency (B_4). This structure separates directly measured responses according to their engineering functions while retaining each indicator as an independent prediction target. The indicator definitions and measurement sources are summarized in Table 4.

Table 4. Output indicators used to characterize blasting performance.

Dimension	Output Indicator	Symbol	Unit	Measurement or Calculation
Fragmentation quality (B_1)	Mean fragment size	d	mm	WipFrag analysis of UAV orthophotos
Fragmentation quality (B_1)	Characteristic fragment size	D80	mm	Particle size at 80% cumulative passing
Fragmentation quality (B_1)	Image-derived fine-particle content below 5 mm	$F < 5$	%	WipFrag-derived image-based particle-size distribution (comparative image-based index; see Section 2.3)
Muckpile morphology (B_2)	Mean muckpile advance distance	L_a	m	Pre- and post-blast DEM comparison
Muckpile morphology (B_2)	Muckpile uplift height	H_u	cm	Maximum central elevation increase from DEM differencing
Safety and adverse effects (B_3)	Peak particle velocity	PPV	cm/s	Maximum absolute peak of the three velocity components
Safety and adverse effects (B_3)	Toe height	H_t	cm	Maximum residual protrusion above the bench floor
Safety and adverse effects (B_3)	Flyrock distance	L_f	m	Distance from the blast-area boundary to the farthest identified fragment
Operational efficiency (B_4)	Single-bucket loading time	T_b	s	Mean of 15 consecutive standard loading cycles
Operational efficiency (B_4)	Truck payload utilization	η_p	%	Mean net payload-to-rated-payload ratio for 10 trucks

Note: D80 denotes the particle size at which 80% of the analyzed material passes. PPV denotes peak particle velocity. $F < 5$ denotes the image-derived fine-particle content below 5 mm; it is a comparative image-based index whose ground sampling resolution and interpretation are described in Section 2.3 and whose influence on the evaluation is quantified in Section 3.4.

All ten indicators were modeled separately because they differ in physical origin, scale, and measurement process. No composite score was used during model training. The

indicators were combined only at the subsequent evaluation stage through the weighting and model-performance adjustment procedure described in Section 2.8.

2.5. Overall Framework and Data Preprocessing

The proposed framework comprises six stages: multi-source data acquisition, data quality control, indicator-specific feature screening, ensemble-model development, SHAP-based interpretation, and performance-adjusted evaluation and field application. The 12 input features and 10 output indicators defined in Section 2.4 were processed independently for each prediction task rather than being fused into a single response variable. The complete analytical workflow is shown in Figure 5.

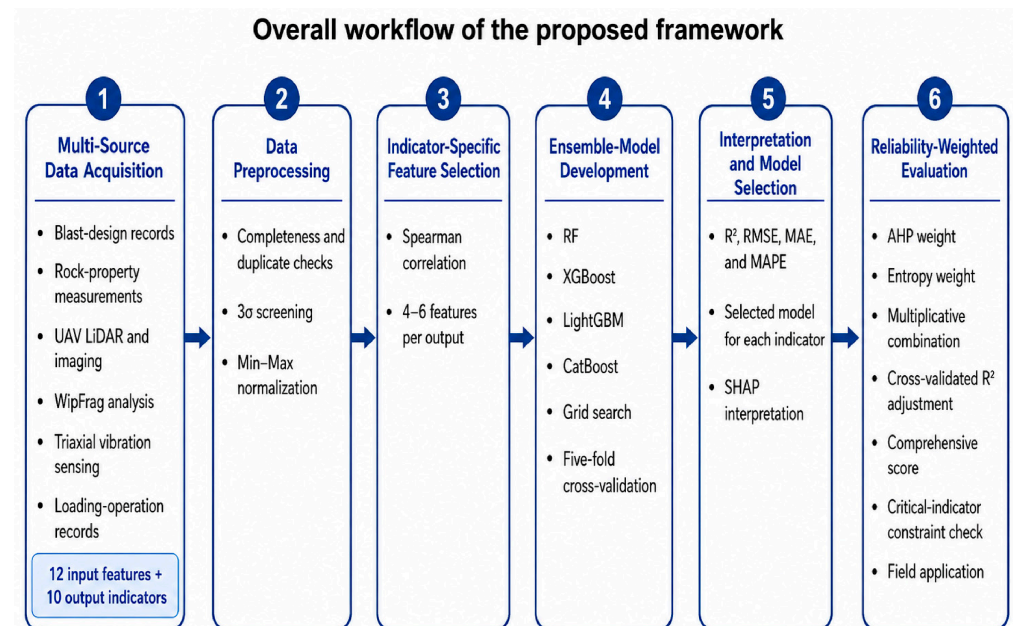


Figure 5. Overall workflow of the proposed framework, comprising multi-source data acquisition, data preprocessing, indicator-specific feature selection, ensemble-model development and selection, SHAP interpretation, performance-adjusted evaluation, and field application.

The dataset contained 70 complete blast records, with no missing values or duplicate observations. Potential outliers were screened for each input and output variable using the three-standard-deviation criterion.

The 70 blast records were drawn from production blasts distributed across several bench levels and over an extended period of the mining operation, and they represent the range of blast-design parameters and rock-mass conditions that were actually applied at the mine during the monitoring campaign. The records were not grouped by bench or by blasting area for the purpose of cross-validation; folds were assigned at the level of individual blast records. The selection-conditioned cross-validated results therefore describe the predictive performance that can be expected within the population of blasts sampled at this mine, conditional on the model-selection step, and the models should be regarded as site-specific within the parameter ranges represented by the collected data rather than as general models transferable to other geological settings. Three further points clarify the status of the fold assignment. First, the compiled modeling table retains only the design, rock-mass and response variables of each blast; bench identifiers and blasting-area coordinates were not carried into the modeling dataset, so a spatially blocked or grouped partition cannot be reconstructed retrospectively from the records as they stand. Second, the records are not near-duplicates of one another: in the standardized twelve-dimensional input space, the closest pair of the 70 blasts is separated by 1.17 standard deviations and

the mean nearest-neighbor distance is 2.39 standard deviations, so the fold assignment does not place effectively identical blast conditions into both the training and the validation subsets. Third, part of the local geological variation is represented explicitly, because uniaxial compressive strength, equivalent integrity coefficient and equivalent density were measured for every blast. The dependence that remains between folds is therefore the shared geological setting and the shared design practice of one mine, which is precisely the population within which the models are intended to be used. This does mean that the reported metrics describe prediction within one mine rather than transfer to unseen geological conditions, and it is in this sense that the framework is presented as site-specific. A grouped validation based on retained bench and location labels is the first requirement for extending the framework to other sites (Section 4.4). This numerical check establishes only that the records are not near-duplicates of one another; it does not establish spatial or geological independence of the validation folds. Because bench identifiers and blasting-area coordinates were not retained in the compiled modeling table, spatial autocorrelation between the training and the validation folds can no longer be tested retrospectively, and a spatially blocked partition cannot be reconstructed from the records as they stand. The independence of the folds is therefore an assumption that rests on the design and rock-mass covariates recorded for every blast rather than a verified property of the partition, and the reported accuracy may be optimistic if neighboring blasts share unrecorded local geological or operational conditions. This distinction is retained explicitly as a limitation in Section 4.4.

$$[\mu_j - 3\sigma_j \leq x_{ij} \leq \mu_j + 3\sigma_j] \quad (6)$$

where x_{ij} is the value of variable j for blast i and μ_j and σ_j are the corresponding sample mean and standard deviation, respectively. Values outside this interval were treated as potential outliers requiring examination. All observations fell within their respective intervals; therefore, no sample was removed or imputed.

Because the input variables had different units and numerical ranges, each feature was rescaled to $[0, 1]$ using min–max normalization:

$$[x_{ij}' = \frac{x_{ij} - x_{j,\min}}{x_{j,\max} - x_{j,\min}}] \quad (7)$$

where x_{ij}' is the normalized value and $x_{j,\min}$ and $x_{j,\max}$ are the minimum and maximum values of feature j , respectively. The same preprocessing procedure was applied consistently to the inputs supplied to all four learning algorithms. Normalization was used to provide a common numerical scale for feature comparison and model implementation, rather than as a requirement specific to tree-based models.

To limit redundant inputs relative to the available sample size, indicator-specific input sets were defined a priori from the governing physical mechanism of each blasting response and were held fixed across all five folds. No statistic computed from the response variable was used to select the inputs, and the feature sets were therefore identical in every fold. Four to six features were retained per output indicator, and the retained input sets are reported in the corresponding results section. Fragmentation indicators (d and $D80$) are governed by the energy delivered per unit rock mass and by the resistance of the rock mass and therefore share the same five inputs (q , $Q_{\max}$, σ_c , $K_{v,eq}$, ρ_{eq}). The image-derived fine-particle content $F < 5$ is additionally controlled by the geometry of the explosive column and is described by H , L_q , q and ρ_{eq} . Muckpile morphology (La , Hu) reflects the spatial redistribution of the broken rock and is described by the charge configuration together with the rock-mass properties. The safety indicators (PPV , Ht , Lf) are controlled by the charge concentration near the bench floor and by the maximum charge per delay and are described

using J , Q_{max} , σ_c , $K_{v,eq}$ and ρ_{eq} . The operational-efficiency indicators are governed by blast geometry and rock resistance: loading time T_b is described by L_c , q , Q_{max} , σ_c , $K_{v,eq}$ and ρ_{eq} and truck payload utilization η_p by R_{sb} , q , σ_c , $K_{v,eq}$ and ρ_{eq} . This target-specific procedure allowed different outputs to use different input subsets, reflecting their distinct physical mechanisms and data characteristics. The Spearman correlation matrices reported in Section 3.1 are descriptive; they were computed after model fitting and were not used to select the input sets. Nonlinear interactions among blasting parameters may also contribute to the prediction of blasting responses; however, their identification requires larger datasets and more advanced feature-selection techniques. This limitation is discussed in Section 4.4.

Because several candidate inputs describe related aspects of the same blasting process, multicollinearity among them was examined using the variance inflation factor (VIF), defined for input j as $VIF_j = 1/(1 - R_j^2)$, where R_j^2 is the coefficient of determination obtained by regressing input j on the remaining inputs considered. For the full set of 12 candidate inputs, VIF ranged from 1.07 to 25.96 (Table S3). The largest values were obtained for blasthole depth (H) and charge length (L_q), which showed a strong association because the explosive column occupies only part of the blasthole length and the recorded designs followed the relationship $H = L_q + L_s + J$. High values were also observed for uniaxial compressive strength (σ_c), which was associated with the integrity coefficient and the density of the lithologies represented in the dataset.

Within the indicator-specific input subsets actually used for model training, the maximum VIF ranged from 9.54 to 13.00 (Table S4). Values above the conventional threshold of 10 were obtained for the fine-particle-content and mean-muckpile-advance-distance subsets, which contain both H and L_q , and marginally for the three safety-related subsets (10.41), owing to the association among σ_c , $K_{v,eq}$, and ρ_{eq} . The rock-mass variables were nevertheless retained, because uniaxial compressive strength, rock-mass integrity, and density describe physically distinct properties of the blasted material and are the only rock-mass information available for the investigated blasts; removing them would eliminate the rock-mass characterization from the prediction models altogether. The correlated inputs are therefore reported transparently, and their SHAP contributions are interpreted jointly rather than as independent effects: for the fragmentation and vibration indicators, σ_c , $K_{v,eq}$, and ρ_{eq} are consistently identified as a combined rock-mass contribution (Section 3.3). Because each indicator-specific model uses only four to six inputs, the number of simultaneously correlated predictors within any single model remains limited, and the residual influence of multicollinearity on feature attribution is acknowledged in Section 4.4.

The preprocessed, indicator-specific datasets were subsequently used for model training, hyperparameter search, and five-fold cross-validation, as described in Section 2.6.

2.6. Ensemble Learning and Model Evaluation

Four tree-based ensemble algorithms—random forest (RF), XGBoost, LightGBM, and CatBoost—were evaluated for each output indicator. Linear models were not considered as primary candidates because the blasting process involves complex nonlinear interactions among blast-design parameters, rock properties, and response indicators. Neural networks and support vector regression were not included in the final comparison because the available dataset size was relatively limited, which may restrict their generalization ability and increase the risk of unstable model selection. RF reduces prediction variance through bootstrap aggregation and random feature screening [21]. XGBoost introduces regularized gradient boosting [22], LightGBM uses histogram-based learning and leafwise tree growth [23], and CatBoost applies ordered boosting to reduce prediction bias [24]. The four algorithms were trained separately for each indicator using the corresponding feature subset identified in Section 2.5.

Hyperparameters were optimized independently for every model–indicator combination using grid search. The search domains were selected to regulate tree complexity, learning rate, sampling ratio, and regularization, as summarized in Table 5. The final models used for prediction corresponded to the optimal parameter combinations identified through the grid-search process for each model–indicator combination.

Table 5. Hyperparameter search domains for the ensemble-learning models.

Model	Hyperparameter Search Domain
RF	n_estimators: 100–1000; max_depth: 3–12; min_samples_leaf: 1–10; max_features: 0.6–1.0
XGBoost	max_depth: 3–12; min_child_weight: 1–10; learning_rate: 0.01–0.15; subsample: 0.6–1.0; colsample_bytree: 0.6–1.0; reg_alpha: 10^{-3} –10; reg_lambda: 10^{-3} –10
LightGBM	num_leaves: 15–63; min_child_samples: 1–10; learning_rate: 0.01–0.15; subsample: 0.6–1.0; colsample_bytree: 0.6–1.0; L ₁ and L ₂ regularization: 10^{-3} –10
CatBoost	depth: 4–10; learning_rate: 0.01–0.15; l ₂ _leaf_reg: 10^{-3} –10; iterations: up to 1000

Note: The hyperparameter combination providing the most favorable mean cross-validation performance was retained separately for each output indicator. No early-stopping split was used in any of the boosting implementations: the number of boosting rounds was treated as a hyperparameter and selected within the same grid search as the domains listed above, so no separate early-stopping validation set was reserved and no data outside the training folds contributed to the fitting of the models.

Because only 70 field blast samples were available, model development and evaluation were based on five-fold cross-validation without a separate hold-out test set. Therefore, the reported results should be interpreted as cross-validated estimates within the investigated dataset rather than independent evaluations on completely unseen blasting conditions. The samples were divided into five non-overlapping subsets. In each iteration, four subsets were used for training and the remaining subset for validation such that every sample was used once for validation. The same fold structure was applied to all four algorithms for a given output to ensure a consistent comparison. Hyperparameter selection and model comparison were conducted using five-fold cross-validation, and the reported metrics represent the mean performance across the validation folds. Two different roles of this partition should be distinguished explicitly. The partition was used both to select the hyperparameter configuration and the algorithm for each output and to obtain the corresponding performance values. The reported metrics are therefore conditioned on the model-selection step: they describe how the candidate models compare with one another under one common protocol, but they should not be read as an unbiased estimate of the absolute accuracy that would be obtained on blasts outside the analyzed population. A nested protocol in which the hyperparameter search is repeated inside every outer training fold and a separate outer partition is reserved for evaluation would remove this conditioning. Such a protocol was not adopted here as a deliberate design choice rather than as a technical impossibility: nested cross-validation can be applied to a dataset of 70 records, but with the correspondingly smaller inner training sets, the resulting estimates would carry a substantially higher variance and would not provide a more informative comparison for a dataset of this size. The single-partition protocol was retained so that the four algorithms are compared on exactly the same folds and so that the reported values remain directly comparable with the scheme-level analysis that follows. The conditioning of the reported values on the model-selection step is therefore treated as a limitation of this study (Section 4.4) rather than as a property that has been removed. Because all four algorithms were evaluated on exactly the same partition and with the same preprocessing, the comparison among

them remains internally consistent, and this comparative use is the only role that the R^2 values play in the decision framework. In Equation (20), the cross-validated R^2 enters as a relative coefficient that expresses how the ten indicator-specific models compare with one another under an identical protocol, not as a statistical confidence level. The influence of the coefficient on the final result is bounded, because the ten selected models span the narrow range of $R^2 = 0.7812\text{--}0.9012$; Section 2.8 and Supplementary Table S1 show that replacing the coefficient by the squared R^2 , by the square root of R^2 , by R^2 reduced by one or two fold-level standard deviations, by R^2 capped or floored at 0.85, or by equal model-performance weighting leaves the ranking of the 70 schemes essentially unchanged, with a Spearman coefficient of at least 0.9995 and a maximum rank shift of two places out of seventy. Nested cross-validation with repeated outer partitions is identified as the preferred methodological extension in Section 4.4. The performance values reported in the model evaluation results are referred to throughout this work as selection-conditioned cross-validated estimates. The term is used consistently in Sections 2.6, 3.2 and 4.4 and in the Conclusions to indicate that the estimates were obtained under the same five-fold partition that was also used to choose the hyperparameter configuration and the algorithm for each output so that they are conditional on that selection step rather than unbiased estimates of generalization performance.

Prediction performance was evaluated using the coefficient of determination (R^2), root-mean-square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE):

$$[R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}] \quad (8)$$

$$[RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}] \quad (9)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (10)$$

$$[MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|] \quad (11)$$

where y_i and $\hat{y}$ are the measured and predicted values for observation i , respectively; $\bar{y}$ is the mean measured value; and N is the number of observations in the validation fold. Each metric was calculated for every fold and then averaged over the five folds.

A higher R^2 indicates that a larger proportion of the response variability is represented by the model. RMSE assigns greater influence to large deviations, MAE quantifies the mean absolute prediction error, and MAPE expresses the error relative to the measured value. The selected model for each indicator was determined from the joint performance of the four metrics. Preference was given to models with a higher R^2 and consistently lower RMSE, MAE, and MAPE. When no model dominated all four metrics, the four metrics were weighed jointly, with R^2 treated as the primary criterion and RMSE, MAE, and MAPE used as supporting criteria. The cross-validated R^2 of each selected model was subsequently used as a model-performance adjustment factor in the weighting procedure described in Section 2.8.

2.7. SHAP-Based Model Interpretation

SHapley Additive exPlanations (SHAP) was used to interpret the selected model for each blasting-performance indicator [17]. The analysis was conducted after model comparison so that feature contributions were derived from the best-performing model for

each prediction task rather than from all candidate models. For observation i , the model output was decomposed as

$$[f(\mathbf{x}_i) = \phi_0 + \sum_{j=1}^p \phi_{ij}] \quad (12)$$

where $f(\mathbf{x}_i)$ is the predicted value, ϕ_0 is the baseline prediction, p is the number of input features, and ϕ_{ij} is the contribution of feature j to the prediction for observation i . A positive SHAP value indicates that the feature increases the predicted response relative to the baseline, whereas a negative value indicates a decreasing contribution.

The global importance of feature j was quantified by the mean absolute SHAP value:

$$I_j = \frac{1}{N} \sum_{i=1}^N |\phi_{ij}| \quad (13)$$

where N is the number of blast records. Features with larger I_j values exert a greater overall influence on the corresponding model output.

SHAP summary plots were used to present global importance and sample-level contribution patterns simultaneously. Features were ranked by their mean absolute SHAP values, while the horizontal position of each point represented the magnitude and direction of its contribution. Feature values were encoded from low to high to identify whether increases in a variable were associated with increases or decreases in the predicted indicator and whether the response was monotonic or nonlinear.

The interpretation focused on the consistency between the learned feature effects and established blasting mechanisms, including explosive-energy input, blasthole geometry, rock strength, and rock-mass integrity. SHAP values were used to explain model behavior and identify influential associations; they were not interpreted as direct evidence of causality. The global rankings and summary plots are presented with the prediction results in Section 3.3.

2.8. Model-Performance-Weighted Evaluation and Decision Rules

The ten predicted indicators were converted into a scheme-level assessment using a three-stage weighting procedure. AHP was first used to represent engineering priorities, while the entropy-weight method was applied to quantify the objective information contribution of the predicted indicators based on their data variability. Entropy weighting is an objective weighting approach in which indicators with greater variation and stronger discrimination ability contain more information and therefore receive larger weights. In this framework, R^2 does not represent statistical confidence, prediction uncertainty, or the probability of obtaining a correct prediction for an individual blast. Instead, it is used as a relative model-performance indicator derived from the same cross-validation procedure. Because all indicators were predicted independently by different models, the cross-validated R^2 provides a consistent criterion for comparing their predictive performance under the same validation strategy. Therefore, incorporating R^2 into the weighting process allows indicators predicted with stronger generalization performance to contribute more substantially to the comprehensive evaluation.

Pairwise comparisons were established based on the judgments of two experts who were directly involved in open-pit blasting management and production decision-making at the investigated mine: one blasting technician and one chief blasting engineer, both with more than five years of experience in open-pit blasting. Both experts had practical experience in blast design, production control, and performance evaluation. The experts independently assessed the relative importance of the evaluation criteria according to their engineering knowledge and field experience. The two judgments were aggregated by consensus; in the cases where the two assessments differed, the judgment of the chief

blasting engineer was adopted, reflecting the senior engineering responsibility for scheme approval. The aggregated judgments were used to construct the pairwise comparison matrices, and the consistency ratio was subsequently calculated to verify the reliability of the aggregated judgments. For judgment matrix A , the criterion-weight vector was obtained from

$$[Aw^{AHP} = \lambda_{\max} w^{AHP}] \quad (14)$$

where $\lambda_{\max}$ is the maximum eigenvalue and w^{AHP} is the normalized principal eigenvector. Matrix consistency was evaluated using

$$[CI = \frac{\lambda_{\max} - n}{n - 1}, CR = \frac{CI}{RI}] \quad (15)$$

where n is the matrix order and RI is the corresponding random consistency index. The criterion-level judgment matrix and weights are presented in Table 6.

Table 6. Criterion-level AHP judgment matrix and derived weights.

Criterion	B_1	B_2	B_3	B_4	Weight
Fragmentation quality (B_1)	1	5	1	3	0.3936
Muckpile morphology (B_2)	1/5	1	1/5	1/2	0.0753
Safety and adverse effects (B_3)	1	5	1	3	0.3936
Operational efficiency (B_4)	1/3	2	1/3	1	0.1375

Note: The calculated consistency ratio was $CR = 0.0015 < 0.1$.

Within B_1 , the local weights of mean fragment size, D_{80} , and fine-particle content were 0.4286, 0.4286, and 0.1429, respectively. The two indicators within B_2 were assigned equal local weights; the three indicators within B_3 were equally weighted; and the two indicators within B_4 were also equally weighted. Global AHP weights were obtained by multiplying each local indicator weight by its corresponding criterion weight. After the expert judgments were integrated, the consistency of the resulting comparison matrices was evaluated using the consistency ratio (CR). The criterion-level matrix yielded $CR = 0.0015 < 0.1$, and the consistency ratio of the B_1 sub-matrix was $CR = 0$, indicating acceptable consistency of the aggregated judgments.

Before entropy weighting and comprehensive scoring, the predicted indicators were transformed to dimensionless benefit scores $z_{ij} \in [0, 1]$. Truck payload utilization was treated as a benefit-type indicator. Mean fragment size, D_{80} , fine-particle content, PPV, toe height, flyrock distance, and single-bucket loading time were treated as cost-type indicators. Mean muckpile advance distance and muckpile uplift height were treated as interval-type indicators because both insufficient and excessive displacement are undesirable. The normalization was defined as

$$[z_{ij} = \begin{cases} \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}}, & \text{benefit-type indicator,} \\ \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}}, & \text{cost-type indicator,} \\ \frac{x_{ij} - x_j^{\min}}{a_j - x_j^{\min}}, & \text{interval-type indicator and } x_{ij} < a_j, \\ 1, & \text{interval-type indicator and } a_j \leq x_{ij} \leq b_j, \\ \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - b_j}, & \text{interval-type indicator and } x_{ij} > b_j, \end{cases}] \quad (16)$$

where x_{ij} is the predicted value of indicator j for blast scheme i ; $x_j^{\min}$ and $x_j^{\max}$ are the minimum and maximum values observed among the 70 production blasts, respectively; and $[a_j, b_j]$ is the preferred range for an interval-type indicator. The preferred interval for

mean muckpile advance distance was 39–43 m, whereas the preferred interval for muckpile uplift height was 110–150 cm.

The entropy weights were calculated from the normalized predicted-indicator matrix. The proportion and entropy of indicator j were calculated as

$$[p_{ij} = \frac{z_{ij}}{\sum_{i=1}^m z_{ij}}, e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij}] \quad (17)$$

where m is the number of evaluated blast records. For $p_{ij} = 0$, the term $p_{ij} \ln p_{ij}$ was defined as zero. The entropy weight was then obtained from

$$[w_j^E = \frac{1 - e_j}{\sum_{j=1}^J (1 - e_j)}] \quad (18)$$

where $J = 10$ is the number of output indicators.

Rather than applying a linear weighted average, the AHP and entropy weights were integrated through multiplicative normalization, following previous entropy-AHP-based multi-criteria decision-making studies [25]:

$$w_j^C = \frac{w_j^A w_j^E}{\sum_{k=1}^J w_k^A w_k^E} \quad (19)$$

where w_j^A , w_j^E , and w_j^C are the AHP weight, entropy weight, and combined weight of indicator j , respectively.

The mean five-fold cross-validated coefficient of determination of the selected model for indicator j , denoted by R_j^2 , was used as a model-performance adjustment factor to reflect the relative predictive capability of different indicator-specific models. The image-derived fine-particle content below 5 mm was included on the same relative basis: because it was obtained by image analysis rather than by sieving, its coefficient expresses the relative capability of the corresponding model within the same measurement chain, and the absolute value of the indicator is not interpreted as a sieving-equivalent fine fraction (Sections 2.3 and 4.4).

The final weight was calculated as

$$w_j^F = \frac{w_j^C R_j^2}{\sum_{k=1}^J w_k^C R_k^2} \quad (20)$$

where w_j^F is the model-performance-adjusted final weight of indicator j , w_j^C is its combined AHP–entropy weight, and R_j^2 is the mean five-fold cross-validated coefficient of determination of its selected model. Because all selected models yielded positive R_j^2 values, no further transformation was required. This adjustment does not represent statistical confidence, uncertainty estimation, or the probability of a correct prediction. Instead, it represents the relative predictive capability of the indicator-specific models evaluated through cross-validation. The coefficient is described in this section as a model-performance coefficient rather than as a reliability factor so that its restricted meaning is unambiguous: it expresses the relative predictive performance of the ten indicator-specific models under the adopted validation protocol, and it is not a confidence level, not a probability that a prediction is correct, and not a formal uncertainty estimate.

To verify that the final ranking does not depend on the particular choice of model-performance measure, a sensitivity analysis was performed in which the model-performance coefficient was replaced by seven alternatives: equal weighting of all indicators; R^2 squared; the square root of R^2 ; R^2 reduced by one and by two fold-level standard

deviations; R^2 capped at 0.85; and R^2 floored at 0.85. Across all seven variants, the Spearman rank correlation with the reference ranking of the 70 blast schemes was at least 0.9995, the largest shift in the rank of any individual scheme was two places out of seventy, and the largest change in the comprehensive score was 0.76 points on a 100-point scale. Peak particle velocity, mean fragment size, and flyrock distance were among the four highest-weighted indicators in every variant, whereas the fourth position alternated between D80 and toe height. Mean fragment size remained the second-highest-weighted indicator in seven of the eight cases. Because the ten selected models all achieve R^2 between 0.781 and 0.901, the model-performance coefficient operates over a narrow range and acts as a mild reallocation of weight rather than as a dominant driver of the final ranking. The complete results are provided in Supplementary Table S1.

The comprehensive score of blast scheme i was computed as

$$S_i = 100 \sum_{j=1}^J w_j^F z_{ij} \quad (21)$$

where a higher S_i indicates better overall blasting performance. In these equations, w_j^F represents the combined importance weight of indicator j obtained from AHP and entropy methods, while R_j^2 represents the cross-validated model-performance adjustment coefficient for the corresponding indicator. The normalized score S_i represents the overall performance level of blast scheme i after integrating multiple predicted responses. The constraint function C_i represents the engineering feasibility condition based on critical indicators such as D80 and PPV. Therefore, the proposed decision model integrates engineering preference, information contribution, and indicator-specific model performance into a unified blasting-scheme evaluation framework. The score-based grades are summarized in Table 7.

Table 7. Score-based grading criteria and critical-indicator constraints for blast-scheme assessment.

Decision Component	Item	Criterion	Interpretation
Score-based grading	Grade I	$90 \leq S_i \leq 100$	Excellent
Score-based grading	Grade II	$80 \leq S_i < 90$	Good
Score-based grading	Grade III	$60 \leq S_i < 80$	Moderate
Score-based grading	Grade IV	$S_i < 60$	Poor
Critical-indicator constraint	Characteristic fragment size, D80	$D80 \leq 340 \text{ mm}$	Required to pass the constraint check
Critical-indicator constraint	Peak particle velocity, PPV	$PPV \leq 15 \text{ cm/s}$	Required to pass the constraint check
Constraint status	Passed	Both critical limits are satisfied	Accepted for field implementation
Constraint status	Failed	Either critical limit is exceeded	Parameter adjustment required

Note: The score-based grade and critical-indicator constraint status were evaluated separately. Failure of the constraint check did not change the score-based grade but required parameter adjustment before field implementation.

The critical thresholds for D80 and PPV were defined according to the blast safety regulation GB 6722-2014 [26], the performance parameters of the loading equipment in use at the mine, and the operating records of the mine. The D80 limit of 340 mm corresponds to the upper bound of the acceptable fragmentation range for the loading equipment, above which secondary size reduction becomes necessary. The PPV limit of 15 cm/s follows the vibration-control requirement adopted for the operating conditions of the investigated mine. Both thresholds were used as engineering constraints for the studied site rather than universal criteria for all open-pit blasting conditions. Because these limits determine

whether a scheme is accepted or rejected, their influence on the final decision was examined by perturbation. The D80 limit was adjusted between 320 and 360 mm, the PPV limit was adjusted between 13.5 and 16.5 cm/s, and the criterion-level AHP weights were shifted by $\pm 10\%$ and by $\pm 20\%$. Across all nineteen perturbation cases, the Spearman rank correlation with the reference scheme ranking remained at least 0.9985, and at most one of the seventy blast schemes changed its final grade. The complete results are given in Supplementary Table S2.

3. Results

3.1. Feature Relationships and Target-Specific Inputs

All 70 blast records satisfied the completeness and outlier-screening criteria and were retained for analysis. The Spearman correlation matrices for the four blasting-performance dimensions are shown in Figure 6.

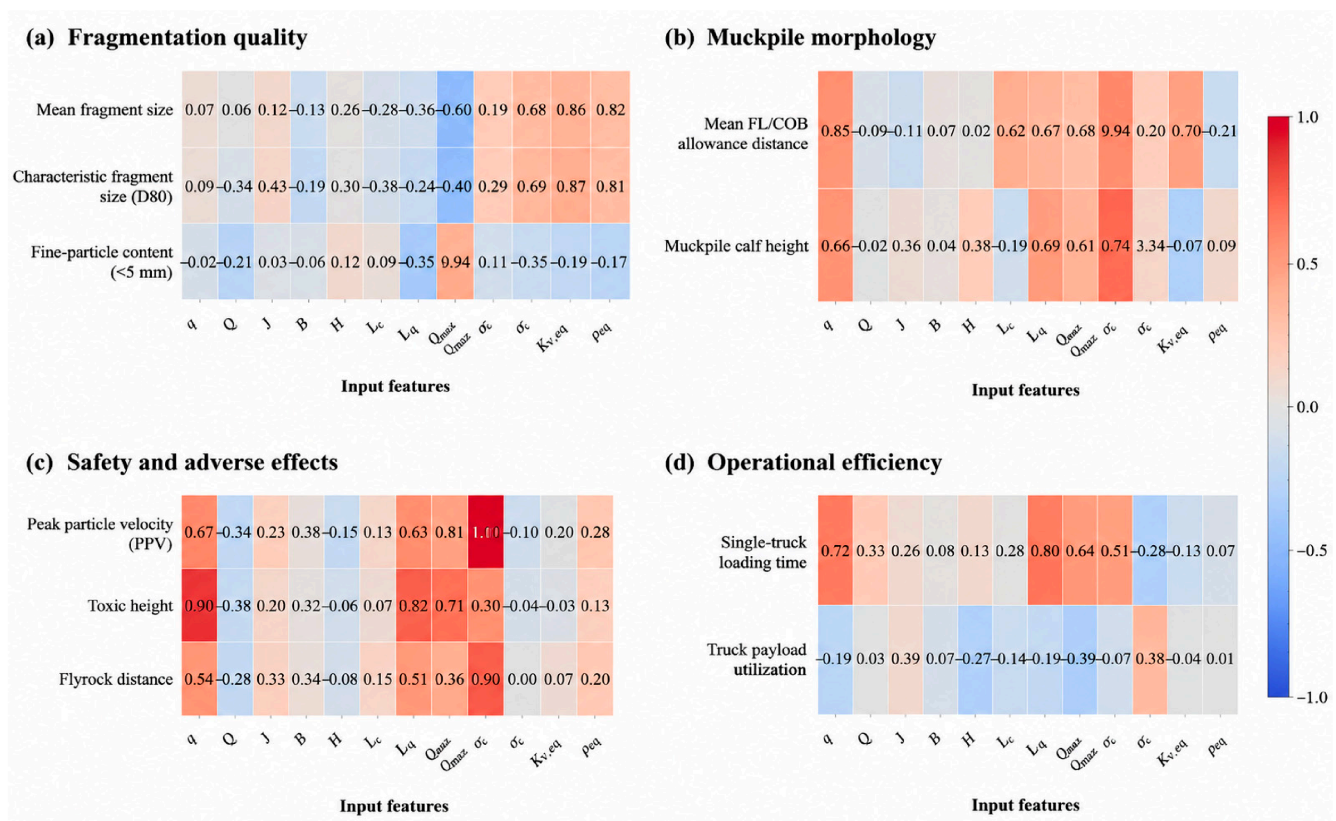


Figure 6. Spearman correlation matrices between the input features and output indicators. σ_c , uniaxial compressive strength; L_c , first-row-to-crest distance; L_s , stemming length; D , blasthole diameter; R_{sb} , spacing-to-burden ratio; H , blasthole depth; $K_{v,eq}$, equivalent integrity coefficient; ρ_{eq} , equivalent density; Q_{max} , maximum charge per delay; q , powder factor; L_q , charge length; and J , subdrilling depth.

The four dimensions exhibited distinct correlation structures. Fragmentation indicators were mainly associated with blasthole configuration, charge-related variables, and explosive-energy input. Muckpile morphology showed stronger associations with geometric variables, charge length, and maximum charge per delay. Safety and adverse-effect indicators were more closely related to charging intensity and rock-mass properties, whereas operational-efficiency indicators reflected the combined associations of energy input, muckpile geometry, and rock-mass properties affecting loading conditions.

The relevant feature combinations also varied among indicators within the same dimension. No single set of inputs consistently showed the strongest associations with all ten outputs. The correlation matrices are therefore reported as descriptive diagnostics of the indicator–response relationships in this dataset; they were not used to select model inputs. The indicator-specific input sets used for modeling were defined a priori from the governing physical mechanism of each response, as described in Section 2.5, and are listed with the model comparison in Table 8. These results indicate that no single input set is optimal for all ten prediction tasks, which supports the indicator-specific modeling strategy adopted in this study.

Table 8. Comparison of predictive performance among RF, XGBoost, LightGBM, and CatBoost models for different blasting-performance indicators.

Indicator	RF	XGBoost	LightGBM	CatBoost	Selected Model	Selected Input Features
Mean fragment size	0.8303	0.8551	0.7137	0.7260	XGBoost	$q; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Characteristic fragment size D80	0.7644	0.8168	0.7555	0.7922	XGBoost	$q; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Fine-particle content below 5 mm	0.7655	0.8164	0.7473	0.7522	XGBoost	$H; L_q; q; \rho_{eq}$
Mean muckpile advance distance	0.8246	0.7535	0.7878	0.7683	RF	$H; L_q; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Muckpile uplift height	0.7067	0.8209	0.7429	0.8483	CatBoost	$L_q; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
PPV	0.7992	0.7493	0.7379	0.8242	CatBoost	$J; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Toe height	0.8867	0.9012	0.8827	0.8532	XGBoost	$J; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Flyrock distance	0.8280	0.8602	0.8857	0.8676	LightGBM	$J; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Single-bucket loading time	0.7566	0.7812	0.7470	0.7333	XGBoost	$L_c; q; Q_{\max}; \sigma_c; K_{v,eq}; \rho_{eq}$
Truck payload utilization	0.8220	0.7945	0.7501	0.8038	RF	$R_{sb}; q; \sigma_c; K_{v,eq}; \rho_{eq}$

3.2. Prediction Performance and Model Selection

RF, XGBoost, LightGBM, and CatBoost were evaluated for each of the ten output indicators using the same five-fold cross-validation procedure. Model selection jointly considered R^2 , RMSE, MAE, and MAPE rather than relying on a single metric. The selected model was determined based on the combined evaluation of these metrics, with R^2 used as the primary indicator for summarizing predictive capability. The predictive performance of RF, XGBoost, LightGBM, and CatBoost for the ten blasting-performance indicators is summarized in Table 8, which reports the mean cross-validated R^2 together with the selected input features for each target, and in Table 9, which reports the corresponding RMSE, MAE, and MAPE for all four algorithms. Figure 7 summarizes the selected model for each indicator and its mean cross-validated R^2 .

As shown in Table 8, the selected algorithm varied among different blasting-performance indicators. XGBoost achieved the best performance for several fragmentation-related indicators, including mean fragment size, D80, and fine-particle content below 5 mm, whereas CatBoost and LightGBM showed better performance for specific indicators such as muckpile height and flyrock distance. These results indicate that no single algorithm consistently dominates all prediction tasks, suggesting the suitability of indicator-specific model selection.

XGBoost was selected for all three fragmentation indicators. The corresponding R^2 values were 0.8551 for mean fragment size, 0.8168 for characteristic fragment size D80, and 0.8164 for fine-particle content. For muckpile morphology, RF was selected for mean

muckpile advance distance ($R^2 = 0.8246$), whereas CatBoost was selected for muckpile uplift height ($R^2 = 0.8483$).

Table 9. Mean cross-validated RMSE, MAE, and MAPE of RF, XGBoost, LightGBM, and CatBoost for the ten blasting-performance indicators.

Indicator	Metric	RF	XGBoost	LightGBM	CatBoost
Mean fragment size	RMSE	18.8918	17.4538	24.5377	24.0018
Mean fragment size	MAE	15.6238	13.7957	20.2096	20.2361
Mean fragment size	MAPE (%)	7.14	6.39	9.33	9.35
Characteristic fragment size D80	RMSE	28.3956	25.0416	28.9275	26.6662
Characteristic fragment size D80	MAE	23.4104	20.4489	24.0732	22.2543
Characteristic fragment size D80	MAPE (%)	8.37	7.54	8.76	8.11
Fine-particle content below 5 mm	RMSE	0.2473	0.2189	0.2567	0.2542
Fine-particle content below 5 mm	MAE	0.1654	0.1304	0.1387	0.1732
Fine-particle content below 5 mm	MAPE (%)	27.05	21.58	19.95	28.69
Mean muckpile advance distance	RMSE	2.0971	2.4857	2.3063	2.4101
Mean muckpile advance distance	MAE	1.6929	1.9184	1.8348	1.9999
Mean muckpile advance distance	MAPE (%)	4.10	4.68	4.46	4.82
Muckpile uplift height	RMSE	46.4110	36.2620	43.4532	33.3796
Muckpile uplift height	MAE	21.1549	19.1290	17.8490	22.1652
Muckpile uplift height	MAPE (%)	13.27	14.43	11.11	16.35
PPV	RMSE	0.8867	0.9907	1.0130	0.8295
PPV	MAE	0.4638	0.6567	0.6712	0.5152
PPV	MAPE (%)	4.66	6.01	6.12	4.85
Toe height	RMSE	2.3014	2.1481	2.3409	2.6189
Toe height	MAE	1.5923	1.7391	1.9778	2.1263
Toe height	MAPE (%)	18.47	31.39	32.02	35.64
Flyrock distance	RMSE	7.1341	6.4318	5.8153	6.2576
Flyrock distance	MAE	5.3040	4.8848	4.3822	5.0870
Flyrock distance	MAPE (%)	6.11	5.62	5.07	5.70
Single-bucket loading time	RMSE	2.9974	2.8417	3.0557	3.1376
Single-bucket loading time	MAE	2.2786	2.1815	2.4485	2.5845
Single-bucket loading time	MAPE (%)	4.88	4.79	5.31	5.65
Truck payload utilization	RMSE	0.8858	0.9517	1.0496	0.9299
Truck payload utilization	MAE	0.6991	0.7466	0.8471	0.7281
Truck payload utilization	MAPE (%)	0.73	0.78	0.89	0.76

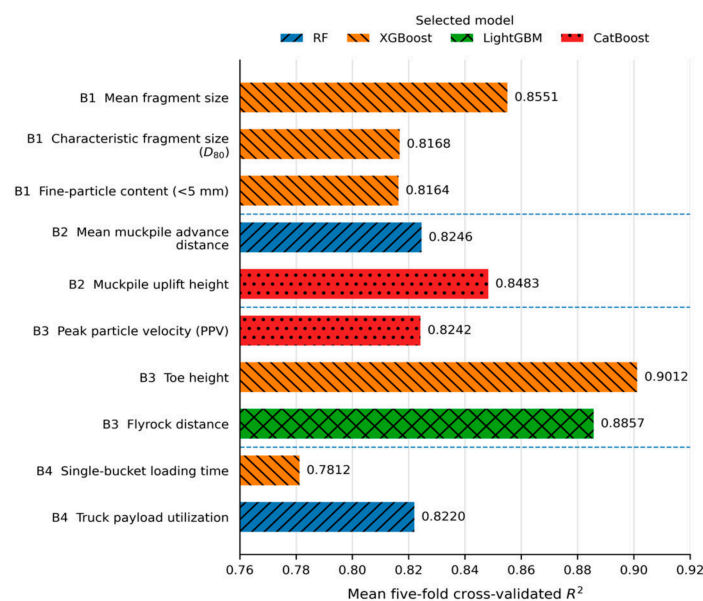


Figure 7. Selected ensemble-learning models and mean five-fold cross-validated R^2 values for the ten blasting-performance indicators. Hatch patterns identify the selected model for each indicator.

As shown in Table 8, the selected algorithm varied among different blasting-performance indicators. XGBoost achieved the best performance for several fragmentation-

related indicators, including mean fragment size, D80, and fine-particle content below 5 mm, whereas CatBoost and LightGBM showed better performance for specific indicators such as muckpile height and flyrock distance. These results indicate that no single algorithm consistently dominates all prediction tasks, suggesting the suitability of indicator-specific model selection.

XGBoost was selected for all three fragmentation indicators. The corresponding R^2 values were 0.8551 for mean fragment size, 0.8168 for characteristic fragment size D80, and 0.8164 for fine-particle content. For muckpile morphology, RF was selected for mean muckpile advance distance ($R^2 = 0.8246$), whereas CatBoost was selected for muckpile uplift height ($R^2 = 0.8483$).

Different models were selected for the three safety and adverse-effect indicators. CatBoost provided the selected PPV model with an R^2 of 0.8242. XGBoost achieved the highest value among the ten selected models for toe height ($R^2 = 0.9012$), while LightGBM was selected for flyrock distance ($R^2 = 0.8857$). For operational efficiency, XGBoost was selected for single-bucket loading time ($R^2 = 0.7812$), and RF was selected for truck payload utilization ($R^2 = 0.8220$).

Across the ten prediction tasks, the selected models achieved cross-validated R^2 values of 0.7812–0.9012. XGBoost was retained for five indicators, RF and CatBoost for two indicators each, and LightGBM for one indicator. The variation in the model selection confirms that no single algorithm provided the best overall validation profile for all outputs. The resulting indicator-specific model set was therefore used in the subsequent SHAP analysis and model-performance adjustment. The value reported for the fine-particle content below 5 mm should be read in the light of its measurement basis: it is the output of the comparative, image-derived indicator defined in Section 2.3 and is not a sieving-equivalent fine fraction. The margin between the selected model and the best of the remaining three algorithms is small for every indicator: the difference in mean cross-validated R^2 ranges from 0.0145 for toe height to 0.0509 for fine-particle content below 5 mm, and for nine of the ten indicators, it is smaller than the fold-to-fold standard deviation of the cross-validated R^2 of the selected models, which is of the order of 0.05 (Section 2.8 and Supplementary Table S1). The leading algorithm should therefore be regarded as the most suitable member of a closely performing group rather than as decisively superior to the others, and Supplementary Table S5 reports these margins together with the metric values of Tables 8 and 9. Because the four algorithms perform within such a narrow band, and because the evaluation framework relies on the indicator-specific prediction rather than on the identity of the algorithm, the choice among them has only a marginal effect on the comprehensive evaluation. The values quoted here and in Tables 8 and 9 are selection-conditioned cross-validated estimates: they were obtained under the same five-fold partition that was also used to select the hyperparameter configuration and the algorithm for each output, and they are therefore conditional on that selection step rather than unbiased estimates of generalization performance.

3.3. SHAP Interpretation Results

SHAP analysis was applied to the indicator-specific models identified in Figure 7. To present the main response patterns without introducing ten repetitive plots, four representative indicators were selected, one from each performance dimension: mean fragment size, mean muckpile advance distance, peak particle velocity (PPV), and truck payload utilization. Their SHAP summary plots are shown in Figure 8.

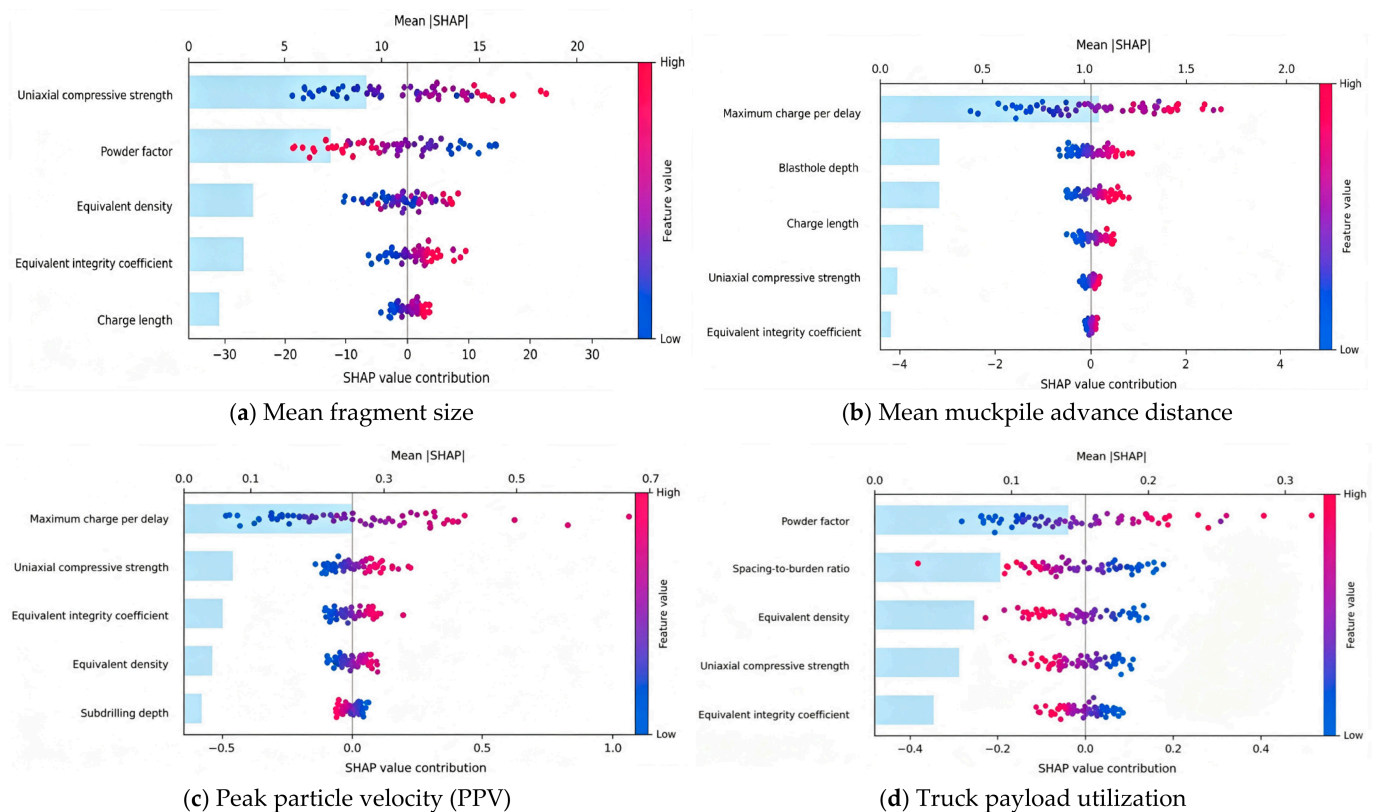


Figure 8. SHAP summary plots for representative blasting-performance indicators. Point color denotes the normalized feature value from low to high.

For mean fragment size, uniaxial compressive strength and powder factor produced the largest SHAP contributions. Higher compressive strength was predominantly associated with positive SHAP values, which indicates larger predicted fragments. By contrast, higher powder factor was mainly associated with negative contributions and, therefore, smaller predicted fragments. Equivalent density and integrity coefficient also contributed to the model output, although their effects were less pronounced.

Mean muckpile advance distance was primarily influenced by the maximum charge per delay, blasthole depth, and charge length. Higher values of the maximum charge per delay were generally associated with positive SHAP values, corresponding to greater predicted advance. The contributions of blasthole depth and charge length varied across the samples, which indicates a nonlinear dependence of horizontal muckpile displacement on the spatial distribution of explosive energy.

For PPV, the maximum charge per delay was the dominant feature. High values were concentrated on the positive side of the SHAP-axis, corresponding to higher predicted vibration velocity. Uniaxial compressive strength, equivalent integrity coefficient, and equivalent density also contributed to PPV predictions, which shows that vibration response varied with both charge intensity and rock-mass conditions.

Truck payload utilization was mainly associated with powder factor, spacing-to-burden ratio, and rock-mass properties. A higher powder factor generally produced positive contributions, whereas the spacing-to-burden ratio showed a more dispersed response across the samples. This pattern indicates that operational-efficiency predictions depended on both blast-induced fragmentation and the resulting material-placement conditions.

The SHAP results for the remaining indicators showed a consistent target-specific structure. Powder factor and uniaxial compressive strength were influential for D80; blasthole depth and charge length contributed strongly to fine-particle content; and uni-

axial compressive strength, first-row-to-crest distance, and powder factor were important for single-bucket loading time. Overall, the selected models relied on different combinations of rock-mass, geometric, and charge-related variables rather than on a common dominant feature.

The physical interpretation of these feature effects and their implications for blast design are discussed in Section 4.2.

3.4. Performance-Adjusted Weights and Comprehensive Evaluation

The AHP criterion weights assigned equal priority to fragmentation quality and safety and adverse effects, with weights of 0.3936 for both B_1 and B_3 . Operational efficiency (B_4) and muckpile morphology (B_2) received weights of 0.1375 and 0.0753, respectively. These criterion weights were combined with the entropy weights through multiplicative normalization and subsequently adjusted using the cross-validated R^2 values of the indicator-specific models.

After cross-validated performance adjustment, PPV received the largest final weight (0.2135), followed by mean fragment size (0.2062), flyrock distance (0.1463), and characteristic fragment size D80 (0.1432). Together, these four indicators accounted for 70.92% of the total weight, whereas the remaining six indicators accounted for 29.08%. The final weight distribution therefore retained fragmentation and safety-related responses as the principal components of the scheme-level evaluation. The image-derived fine-particle content below 5 mm received the smallest combined AHP–entropy weight of the ten indicators (0.0135) and was not used as a critical-indicator constraint, so the additional uncertainty associated with its image-based measurement basis has a negligible effect on the scheme ranking.

Applying the adjusted weights to the initial blast scheme produced a comprehensive score of 65.4. According to the score ranges defined in Table 7, this result corresponds to Grade III. The implementation decision was subsequently determined through the separate critical-indicator constraint check described in Section 2.8. The corresponding indicator-level results and constraint status are reported in Section 3.5.

3.5. Improved Blast Scheme and Field Application

A representative bench at the 415–400 m level was selected for field application. The initial scheme produced a comprehensive score of 65.4, corresponding to Grade III under the criteria in Table 7. However, its predicted characteristic fragment size D80 and PPV were 356.2 mm and 15.8 cm/s, respectively, exceeding the prescribed limits of 340 mm and 15 cm/s. The initial scheme therefore failed the critical-indicator constraint check, was withheld from field implementation, and was returned for parameter adjustment.

Based on the prediction and evaluation results, the blasthole pattern was reduced from 7.0×5.5 m to 5.5×4.5 m, and the powder factor was increased from 0.35 to 0.38 kg/m³. The spacing-to-burden ratio consequently changed from 1.27 to 1.22, while the remaining blast-design and rock-mass inputs were unchanged. This adjustment was performed by field engineers using model feedback rather than through a global mathematical optimization procedure. The initial and improved schemes are compared in Table 10.

The improved scheme increased the comprehensive score from 65.4 to 87.5. Under the grading criteria adopted in Table 7, the score-based grade improved from Grade III to Grade II. The predicted D80 decreased from 356.2 to 265.8 mm, which represents a reduction of 25.4%, while the predicted PPV decreased from 15.8 to 11.4 cm/s, which represents a reduction of 27.8%. Both indicators were below their prescribed limits after adjustment. The improved scheme therefore passed the critical-indicator constraint check and was accepted for field implementation.

Table 10. Input parameters, predicted critical indicators, and decision results for the initial and improved blast schemes.

Category	Parameter	Initial Scheme	Improved Scheme
Blast design	Blasthole diameter (mm)	152	152
Blast design	Blasthole depth (m)	16.2	16.2
Blast design	Subdrilling depth (m)	1.2	1.2
Blast design	First-row-to-crest distance (m)	2.5	2.5
Blast design	Stemming length (m)	4.0	4.0
Blast design	Charge length (m)	12.2	12.2
Blast design	Blasthole spacing $\times$ burden (m)	7.0 $\times$ 5.5	5.5 $\times$ 4.5
Blast design	Spacing-to-burden ratio	1.27	1.22
Blast design	Powder factor (kg/m ³)	0.35	0.38
Blast design	Maximum charge per delay (kg)	225	225
Rock mass	Uniaxial compressive strength (MPa)	26.5	26.5
Rock mass	Equivalent integrity coefficient	0.52	0.52
Rock mass	Equivalent density (t/m ³)	2.35	2.35
Prediction	Characteristic fragment size, D80 (mm)	356.2	265.8
Prediction	Peak particle velocity (cm/s)	15.8	11.4
Evaluation	Comprehensive score	65.4	87.5
Evaluation	Score-based grade	Grade III	Grade II
Decision	Critical-indicator constraint status	Failed	Passed
Decision	Engineering decision	Adjustment required	Accepted for field implementation

Note: The critical-indicator constraint check required $D80 \leq 340$ mm and $PPV \leq 15$ cm/s. Failure of the constraint check did not change the score-based grade but prevented field implementation until the blast parameters were adjusted.

The improved scheme was subsequently implemented in the field. Post-blast fragmentation, muckpile morphology, vibration, and operational-efficiency indicators were acquired using the monitoring procedures described in Section 2.3. Table 11 compares the predicted and measured values for all ten indicators. Relative error was calculated as the absolute difference between the predicted and measured values divided by the measured value.

Table 11. Predicted and measured blasting-performance indicators for the improved scheme.

Dimension	Indicator	Predicted Value	Measured Value	Relative Error (%)
Fragmentation quality	Mean fragment size (mm)	210.6	218.4	3.57
Fragmentation quality	Characteristic fragment size, D80 (mm)	265.8	275.2	3.41
Fragmentation quality	Fine-particle content below 5 mm (%)	0.58	0.61	4.92
Muckpile morphology	Mean muckpile advance distance (m)	38.5	39.6	2.78
Muckpile morphology	Muckpile uplift height (cm)	132.0	136.5	3.30
Safety and adverse effects	Peak particle velocity (cm/s)	11.4	11.8	3.39
Safety and adverse effects	Toe height (cm)	4.5	4.8	6.25
Safety and adverse effects	Flyrock distance (m)	92.5	95.0	2.63
Operational efficiency	Single-bucket loading time (s)	44.2	45.6	3.07
Operational efficiency	Truck payload utilization (%)	95.2	94.7	0.53

The relative errors ranged from 0.53% to 6.25%. Nine indicators had errors below 5%, while toe height showed the largest relative error; however, its absolute deviation was 0.3 cm. The measured D80 and PPV were 275.2 mm and 11.8 cm/s, respectively. Both values remained below their prescribed limits, which confirms that the improved scheme continued to satisfy the critical-indicator constraints during field implementation. Field observations also indicated a more uniform muckpile and uninterrupted loading operations. These results demonstrate agreement between the indicator-specific predictions and the measured performance of the improved scheme without treating the application case as an independent hold-out test set. For the image-derived fine-particle content below 5 mm, the comparison reported in this section is made on the same relative, image-based basis: the

predicted and the measured values are both outputs of the same image processing chain, so the relative error of this indicator characterizes the internal consistency of the image-derived quantity and does not constitute an absolute or sieving-equivalent validation of the fine fraction (Section 2.3).

4. Discussion

4.1. Indicator-Specific Model Performance

The comparison of four ensemble learning algorithms showed that model performance depended on the predicted blasting response. The selected models achieved cross-validated R^2 values of 0.7812–0.9012, but no algorithm ranked first for all ten indicators. This result supports an indicator-specific modeling strategy rather than the use of a single model for the complete evaluation system.

XGBoost was selected for the three fragmentation indicators, toe height, and single-bucket loading time. These outputs are influenced by interacting geometric, energy-related, and rock-mass variables and may include threshold-type responses. The residual-fitting and regularization mechanisms of XGBoost were therefore well suited to representing their nonlinear variation within the available dataset. Its selection for all three fragmentation indicators also indicates that mean fragment size, D_{80} , and fine-particle content shared some common predictive structure, despite requiring different feature subsets.

RF performed best for mean muckpile advance distance and truck payload utilization. Both indicators can be affected by local variations in muckpile shape, material placement, and loading conditions that are not fully represented by the measured inputs. Averaging across multiple randomized trees may have reduced sensitivity to these sample-level fluctuations. However, the selection of RF for these two targets should not be interpreted as evidence that the indicators follow the same physical mechanism; it only indicates that RF provided the most favorable cross-validation profile among the four evaluated algorithms.

CatBoost was selected for muckpile uplift height and PPV. These indicators may vary sharply with local charge distribution and rock-mass conditions. The ordered boosting procedure and constrained tree structure of CatBoost appeared to provide stable predictions for these responses under the limited sample size. LightGBM was selected only for flyrock distance, for which it achieved an R^2 of 0.8857. Its performance suggests that the leafwise growth strategy captured localized feature interactions relevant to flyrock prediction, although the advantage was not repeated for the other indicators.

The highest cross-validated R^2 was obtained for toe height, whereas single-bucket loading time had the lowest value. Toe height was measured as a direct post-blast geometric response, while loading time also depended on operational factors such as excavator movement, material handling, and short-term site conditions. These unmeasured influences may partly explain the lower predictability of loading time. Nevertheless, its R^2 of 0.7812 remained sufficient for inclusion in the evaluation framework, with its contribution subsequently moderated through the model-performance adjustment.

Overall, the model comparison indicates that algorithm selection should be performed at the indicator level when a blasting-evaluation system contains outputs with different physical origins and measurement characteristics. The present results demonstrate relative performance within the studied dataset and cross-validation procedure; they do not establish the universal superiority of any algorithm across other mines or geological conditions.

4.2. Physical Interpretation of Key Influencing Factors

The SHAP results indicate that blast performance was governed by the combined effects of explosive-energy input, blasthole geometry, and rock-mass properties. Their relative importance varied among indicators, which confirms that fragmentation, muckpile

displacement, vibration, flyrock, and loading efficiency should not be interpreted using a single control variable.

Powder factor was influential for the fragmentation and operational-efficiency indicators. Within the sampled range, a higher powder factor was generally associated with smaller predicted fragment sizes and higher truck payload utilization. Increasing explosive energy per unit rock volume can promote crack propagation and reduce coarse fragments, thereby improving material diggability and loading consistency. This relationship should not be interpreted as supporting unrestricted increases in powder factor, because excessive energy may increase vibration, flyrock, fines generation, and explosive consumption. Its engineering value therefore lies in identifying a suitable range rather than maximizing the parameter.

Uniaxial compressive strength was strongly associated with mean fragment size, D_{80} , toe height, PPV, and loading time. Stronger rock requires more energy for crack initiation and propagation, and a larger proportion of the explosive energy may remain in stress-wave transmission rather than effective fragmentation. Consequently, high-strength zones were generally associated with coarser fragmentation and less favorable excavation conditions. The contribution of equivalent integrity coefficient and equivalent density further shows that intact strength alone was insufficient to characterize blast response. More competent and denser rock masses can alter stress-wave propagation, energy attenuation, and the development of blast-induced fractures.

The maximum charge per delay was the dominant variable for PPV and an important contributor to muckpile displacement and flyrock distance. A larger instantaneous charge releases more energy during each delay interval, increasing the amplitude of the stress wave transmitted through the rock mass. The same increase in released energy can enhance the horizontal displacement of the muckpile but may also increase vibration and material projection. This dual effect explains why maximum charge per delay must be considered jointly with safety constraints rather than optimized solely for muckpile movement.

Blasthole depth and charge length were particularly relevant to fine-particle content and muckpile morphology. These parameters determine the vertical distribution of explosive energy and the proportion of the rock column directly coupled with the charge. Inadequate energy coverage may leave poorly fragmented material near the collar or toe, whereas excessive local energy concentration may increase fines and vertical heave. Their dispersed SHAP distributions suggest that these effects were nonlinear and depended on interactions with stemming, subdrilling, and rock-mass conditions.

The spacing-to-burden ratio and first-row-to-crest distance represented the influence of blasthole layout and free-surface conditions. The spacing-to-burden ratio affected truck payload utilization, which indicates that the uniformity of burden breakage and muckpile formation influenced subsequent loading performance. The first-row-to-crest distance contributed to loading time, probably because an unsuitable free-face distance can produce either insufficient forward breakage or excessive displacement, both of which reduce muckpile accessibility.

Overall, the SHAP patterns were consistent with established blasting principles: explosive-energy variables were associated with the intensity and distribution of energy release, geometric variables reflected confinement and free-surface conditions, and rock-mass variables were related to fracture resistance and wave-propagation characteristics. However, SHAP values describe statistical associations learned from the available data and do not establish causal relationships. The identified effects should therefore be interpreted within the parameter ranges and geological conditions represented by the investigated dataset.

4.3. Performance-Adjusted Evaluation and Engineering Implications

Conventional combination weighting accounts for expert-assigned importance and the information contained in the observed indicator variation. However, when the indicator values used for decision-making are generated by different prediction models, their predictive performance also differs. Directly applying the base weights may therefore allow a comparatively less predictable indicator to exert an excessive influence on the comprehensive score. In the proposed method, the cross-validated R^2 of each selected model was introduced as a relative model-performance coefficient before final normalization.

The model-performance adjustment should not be interpreted as a statistical confidence level or probability of correctness. Instead, it provides a dimensionless measure of the relative predictive performance of the ten indicator-specific models under the same five-fold cross-validation procedure. Indicators with lower cross-validated performance retain their contributions to the evaluation but receive a proportionally reduced influence. This treatment links model evaluation with scheme-level decision-making without removing the engineering priorities represented by the AHP and entropy weights.

After adjustment, PPV, mean fragment size, flyrock distance, and D80 received the four largest final weights. This distribution reflects the combined effects of engineering importance, sample-level information, and predictive performance. A high final weight therefore does not indicate that an indicator is controlled by a single dominant physical mechanism; rather, it means that the indicator was simultaneously important to the evaluation system, informative within the available data, and predicted with comparatively favorable cross-validated accuracy.

The field application illustrates the practical role of the two-level decision framework by identifying the schemes requiring adjustment and balancing multiple blasting objectives under engineering constraints. The field implementation reported in Section 3.5 is an application case of the framework rather than an independent external validation: the improved scheme was designed with the assistance of the same indicator-specific models, so the post-blast measurements confirm engineering feasibility under the studied conditions rather than out-of-sample predictive transferability.

The combination of score-based grading and a separate critical-indicator constraint check is particularly important for blasting decisions. An aggregate score may allow favorable performance in one dimension to compensate numerically for an unacceptable quality or safety response in another. The separate constraints on D80 and PPV prevent unacceptable fragmentation or vibration responses from being concealed by the aggregate score and leading directly to field implementation. Accordingly, the framework should be regarded as a decision-support procedure rather than a purely score-maximizing method.

The parameter changes in the application case were selected by field engineers with reference to the model predictions and SHAP results. They were not obtained through global or multi-objective mathematical optimization. The current framework therefore supports the comparison and iterative improvement of candidate schemes, while final parameter selection remains subject to engineering constraints, construction feasibility, and safety requirements.

4.4. Limitations and Applicability

Several limitations should be considered when interpreting the results and applying the proposed framework to other mining conditions.

First, the dataset consisted of 70 production blasts collected from a single open-pit mine. Although these blasts represented actual production conditions, including the geological environment and blast-design practices of the investigated mine, the dataset only covered the parameter ranges and operational conditions represented at this site. Therefore,

the developed models should be regarded as site-specific rather than universally transferable. Differences in geological conditions, blast-design strategies, equipment operation, and monitoring environments may influence model performance when applied to other mining sites. Furthermore, explicit separation of spatial and geological domains between the training and validation subsets was not implemented because all samples originated from the same mine. Further validation using larger multi-site datasets, newly collected production blasts, and external cases is required, with model recalibration when necessary. The available records do not carry bench or location labels, so an explicit spatially blocked partition could not be constructed, and the possibility that the reported accuracy is somewhat optimistic because neighboring blasts share geological and operational conditions cannot be formally excluded; the numerical check reported in Section 2.5 indicates, however, that the records are not near-duplicates of one another. The nearest-neighbor calculation reported in Section 2.5 only shows that the records are not near-duplicates of one another; it does not establish the spatial or geological independence of the training and validation folds. Because bench and location labels were not retained, spatial autocorrelation between the folds cannot be tested retrospectively, and this dependence therefore remains an unresolved limitation rather than a limitation that the numerical check has removed.

Second, model evaluation was conducted using five-fold cross-validation without an independent hold-out test set or nested cross-validation. Therefore, the reported performance metrics represent cross-validated estimates within the investigated dataset rather than independently verified generalization performance under completely unseen conditions. The field application demonstrated the practical applicability of the framework for blast-scheme comparison and parameter adjustment under the studied conditions; however, it should not be interpreted as an independent validation of model generalization because the improved scheme was developed with assistance from the proposed framework. Additional validation using newly collected blasts, different benches, or external mining sites is required to further assess model transferability. In addition, the hyperparameter search and the reporting of the performance metrics used the same five-fold partition, so the reported values are conditioned on the model-selection step and the absolute level of the metrics may be optimistic to an unquantified degree, although the comparison among the four algorithms is not affected in the same way because they were evaluated on identical folds. The consequence for the decision framework is limited, because the cross-validated R^2 is used in Equation (20) only as a relative coefficient among the ten indicator-specific models, and the scheme ranking was shown to be insensitive to its formulation (Supplementary Table S1). Nested cross-validation with repeated outer partitions and a grouped validation based on retained bench and location labels are the two methodological extensions that would be required to establish unbiased and spatially independent performance estimates. The absence of the nested protocol in the present study is a design choice and a limitation rather than a computational or data-size constraint, because nested cross-validation is applicable to a dataset of this size; the single-partition protocol was retained so that all four algorithms are compared on identical folds, and the reported values are correspondingly described as selection-conditioned cross-validated estimates rather than as unbiased estimates of generalization performance.

Third, the feature-selection and interpretation procedures have several limitations. Spearman correlation analysis was used as a descriptive diagnostic of the indicator–response relationships rather than as an input-selection mechanism; the input sets were defined a priori from the governing physical mechanisms of the responses (Section 2.5). Correlation analysis alone cannot fully capture the nonlinear interactions or multicollinearity among blasting parameters. The multicollinearity assessment reported in Section 2.5 (Tables S3 and S4) showed that the maximum VIF within the indicator-specific

input subsets ranged from 9.54 to 13.00, so dependencies among the retained variables remain partly present; although the correlated inputs describe distinct design and rock-mass quantities and were therefore retained, they may still influence the relative contribution of correlated features in the SHAP interpretation. Future studies with larger datasets should incorporate variable-aggregation or regularization strategies and more advanced nonlinear feature-selection approaches to improve feature robustness and interpretability.

Fourth, the image-derived fine-particle content below 5 mm ($F < 5$) has inherent measurement limitations. UAV orthophotos combined with WipFrag analysis provide an efficient approach for fragmentation characterization; however, fine-particle identification may be affected by image resolution, particle overlap, surface exposure conditions, and segmentation performance. Particles close to 5 mm occupy only a few pixels at the ground sampling distance of the survey, so this indicator should be considered an image-based comparative measure rather than an absolute or gravimetrically validated measurement of fine-particle content. Because $F < 5$ enters both the prediction stage and the weighting framework, its influence was limited in two ways: it received the smallest combined AHP–entropy weight of the ten indicators (0.0135), and it was not treated as a critical-indicator constraint. Independent physical sieving or weighing validation of this indicator would further improve fine-particle quantification and is recommended for future work. The ground sampling distance of the survey imagery was approximately 2.1–2.6 cm per pixel for the flights at 75–90 m and 0.6 cm per pixel for the lowest-altitude passes (Section 2.3), so a 5 mm particle is represented by less than one pixel and the 5 mm class lies beneath the resolution limit of the imagery; the reported value is therefore an extrapolation of the fitted particle-size distribution rather than a direct measurement of individual fine particles. Independent sieving or physical weighing validation could not be carried out within the present study, and no such validation is claimed. In the absence of sieving-based calibration, the absolute value of $F < 5$ should not be compared with fine-fraction values obtained by sieving or weighing, and the indicator should be used only as a relative index of fine-fragment variation among schemes surveyed and processed with the same chain. This limitation applies wherever $F < 5$ is used in this work, including its use as a prediction target in Section 3.2 and its use in the weighting procedure of Section 2.8, and it is therefore restated in the corresponding results and in the Abstract and Conclusions.

Fifth, the critical-indicator thresholds used for blast-scheme acceptance were defined according to the operational requirements and safety-control objectives of the investigated mine. Therefore, the D80 and PPV thresholds should be considered site-specific engineering constraints rather than universal criteria. Variations in production objectives, geological conditions, or safety regulations may require recalibration of the acceptance criteria when the framework is transferred to other mining environments.

Sixth, although representative ensemble learning algorithms, including RF, XGBoost, LightGBM, and CatBoost, were compared in this study, other machine learning approaches such as neural networks and support vector regression were not evaluated. Larger datasets may enable evaluation of a broader range of algorithms to further investigate model selection and generalizability.

Finally, the performance-adjusted weighting strategy integrates the predictive performance of indicator-specific models into multi-indicator decision-making, but the cross-validated R^2 coefficient used in this study only reflects relative model performance under the adopted validation strategy. It does not represent statistical confidence, prediction uncertainty, or the probability of obtaining a correct prediction for an individual blast. In addition, the sensitivity of the scheme rankings to the AHP–entropy weighting scheme, indicator weights, and grading thresholds requires further investigation. Incorporating uncertainty-aware evaluation methods, such as prediction intervals or probabilistic forecast-

ing approaches, may further improve the robustness of scheme ranking under alternative weighting assumptions and data partitions. The cross-validated R^2 that enters the weighting procedure is a relative model-performance coefficient only. The expressions “reliability” and “reliability-weighted” are therefore used in this restricted sense wherever they appear in this work, and the coefficient should not be interpreted as a confidence level, as the probability that a prediction is correct, or as a formal uncertainty estimate.

5. Conclusions

This study developed a multi-source sensing and interpretable ensemble learning framework for the performance-adjusted evaluation of open-pit blasting performance. Data from 70 production blasts were organized into 12 input variables and 10 sensing-derived performance indicators covering fragmentation quality, muckpile morphology, safety and adverse effects, and operational efficiency. RF, XGBoost, LightGBM, and CatBoost were compared separately for each indicator using five-fold cross-validation.

The selected models achieved cross-validated R^2 values of 0.7812–0.9012. No single algorithm performed best for all indicators, which suggests the suitability of indicator-specific model selection. SHAP analysis further showed that the models relied on different combinations of explosive-energy, blasthole-geometry, and rock-mass variables. Powder factor and uniaxial compressive strength showed strong contributions to fragmentation-related predictions, whereas maximum charge per delay was a dominant contributor to PPV and muckpile displacement predictions.

The cross-validated R^2 of each selected model was incorporated into the AHP–entropy weighting process as a relative model-performance adjustment coefficient. After adjustment, PPV, mean fragment size, flyrock distance, and D80 accounted for 70.92% of the total weight. The combined use of score-based grading and a separate critical-indicator constraint check prevented favorable performance in one dimension from compensating for unacceptable fragmentation or vibration responses.

In field application, the initial scheme was classified as Grade III but failed the critical-indicator constraint check because its predicted D80 and PPV values were 356.2 mm and 15.8 cm/s, respectively, exceeding the prescribed limits of 340 mm and 15 cm/s. After the blasthole pattern was reduced from 7.0×5.5 m to 5.5×4.5 m and the powder factor was increased from 0.35 to 0.38 kg/m³, the comprehensive score increased from 65.4 to 87.5, corresponding to Grade II, and the improved scheme passed the critical-indicator constraint check. The predicted D80 and PPV decreased to 265.8 mm and 11.4 cm/s, respectively. After field implementation, the measured D80 and PPV were 275.2 mm and 11.8 cm/s, respectively, and the relative errors between the predicted and measured values of all ten indicators ranged from 0.53% to 6.25%. These results demonstrate the practical applicability of the proposed framework for site-specific blast-scheme comparison and iterative parameter adjustment. Therefore, the framework should be regarded as site-specific within the represented geological and operational conditions, and its broader transferability requires further assessment using larger multi-site datasets. Because all records originate from a single mine, the framework is presented as a site-specific decision-support procedure, and the field implementation is an application case of the framework rather than an independent external validation. The image-derived fine-particle content below 5 mm is likewise a comparative image-based index whose absolute value should not be interpreted as a sieving-equivalent fine fraction. Because the performance values that enter the scheme-level evaluation were obtained under the same five-fold partition that was used to select the hyperparameters and the algorithm, they are selection-conditioned cross-validated estimates rather than unbiased estimates of generalization performance, and the site-specific scope stated here should be read together with that condition.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/app16199650/s1>. Table S1: Sensitivity of the comprehensive scheme ranking and score to the choice of model-performance coefficient; Table S2: Sensitivity of the final scheme grading to the critical-indicator limits and to the criterion-level AHP weights; Table S3: Variance inflation factors of the 12 candidate input features; Table S4: Maximum variance inflation factor within each indicator-specific input subset; Table S5: Model-selection margins of the selected models and their relation to the fold-to-fold variability of the cross-validated R^2 . Supplementary Tables S1, S2 and S5 are provided with the submission in full, and every numerical statement that summarizes the sensitivity analyses in Sections 2.8 and 4.4 can be verified directly from those tables.

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