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Ensemble Machine Learning Models for Blast-Induced Air Noise: A Review of Transformative Innovations in Minerals

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Abstract

The mining industry has increasingly integrated Machine Learning (ML) techniques to optimise performance, enhance decision-making processes, and ensure operational safety. This study reviews Machine Learning applications in mine blasting, focusing on predicting and mitigating blast-induced Air Overpressure (AOp) and related environmental impacts. Blasting, a key mineral extraction process, uses explosives to fragment rock, but only 20%-30% of the energy is effectively utilised, causing ground vibration, air overpressure, fly rock, and structural damage. Air overpressure, in particular, poses risks to nearby structures, highlighting the need for accurate prediction. Traditional empirical models like USBM, NAASRA, and Holmberg-Persson rely heavily on distance and maximum charge per delay, often failing to capture complex interactions. Advanced Machine Learning techniques, especially hybrid and ensemble models, have shown superior performance in 61% of case studies, with 72% in surface blasting and 45% in underground blasting, indicating a growing trend toward sophisticated approaches. Key parameters influencing air overpressure include burden, hole depth, stemming, spacing, and powder factor. Surface blasting predominantly depends on controllable parameters like blast design and geometry, while underground blasting is more influenced by geological and geotechnical factors. Despite the distinct challenges of underground blasting, research in this area remains limited. This study underscores the importance of enhancing Machine Learning model interpretability, integrating real-time monitoring, and training mining personnel on advanced technologies. By addressing existing gaps, the mining industry can improve blasting safety, operational efficiency, and environmental sustainability.

Major Findings: *Traditional blasting methods waste a majority of explosive energy (70-80%), causing environmental concerns like ground vibration and AOp. Machine learning offers a smarter alternative by integrating complex parameters (e.g., burden, stemming, powder factor) to optimise energy use and improve prediction accuracy. Hybrid and ensemble ML models outperform conventional methods in over 60% of studies, report improved results in both surface and underground blasting, especially with post-2023 advances focused on achieving higher R^2 values and better model reliability through feature selection. AI-driven strategies are essential for sustainable mining, using predictive analytics to enhance safety, reduce environmental impact, and improve operational efficiency in managing AOp.*

Keywords: *Air Overpressure, Blasting, Machine Learning, Mining Industry, R^2*

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1.0 Introduction

Mining is the process of extracting valuable minerals from the Earth's surface, including underwater reservoirs such as oceans. Minerals, with rare exceptions, are naturally occurring non-living substances distinguished by specific chemical compositions and unique physical or chemical structures. Coal, often categorised as a mineral, is an organic matter frequently debated in this context. An ore refers to a mineral rich in metals or a combination of metal-rich minerals and economically insignificant rock (gangue) that can be extracted for profit. A mineral deposit designates a naturally existing site containing valuable minerals, whereas an ore deposit signifies a mineral accumulation of sufficient size and concentration to justify extraction through mining. During blasting operations, only 20%-30% of the explosive energy is efficiently utilised for rock disintegration, with the remaining 70%-80% being wasted, leading to significant negative consequences such as fly rock, ground vibration, and AOp[1,2]. Additionally, the development of mining sites requires the establishment of essential infrastructure, including administrative buildings, power distribution networks, transportation routes, and industrial facilities, forming the foundation of strategic planning and site advancement[3,4]. Mining operations primarily focus on extracting and refining valuable minerals, encompassing activities such as loading, transporting, unloading, crushing, and sieving. The final phase, mine closure, plays a crucial role in rehabilitating the area to its original state before mining activities, addressing environmental consequences, and ensuring long-term sustainability[5,6]. Mining is broadly categorised into surface and subsurface methods, with surface mining employed for shallow mineral reserves and underground mining for deeper deposits. However, geological conditions, topography, and production demands contribute to the high costs associated with drilling and detonation, which can account for 15%-60% of the total mining expenses[7,8]. Figure 1 illustrates the article's structure and outlines

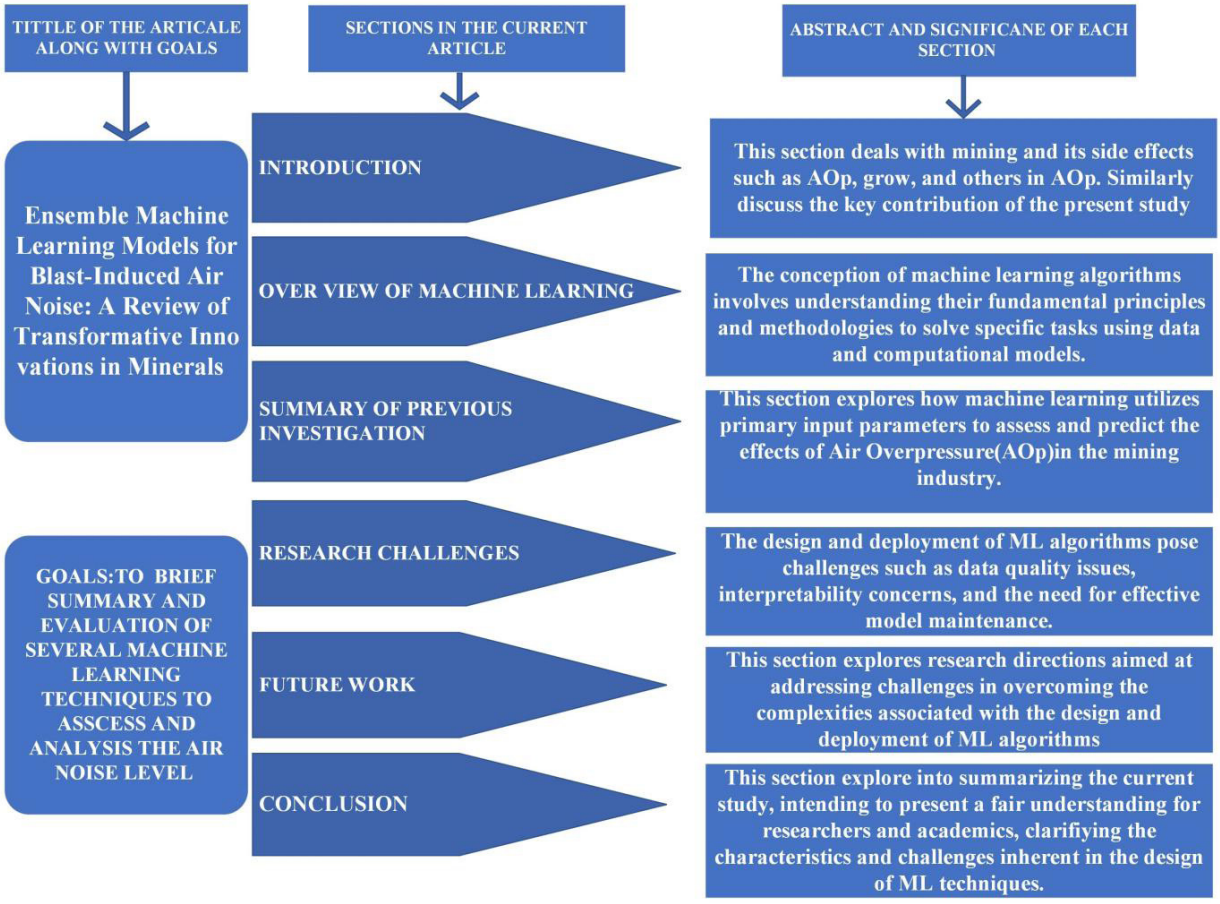


Figure 1. Article layout with section-wise explanation.

the purpose of each section in the study of machine learning models for predicting Air Overpressure. The consequences of blasting activities go beyond just physical damage, often triggering mental stress, discomfort, and anxiety among nearby residents and workers. In addition, the presence of dust clouds and scattered debris can visually degrade the environment, reducing its aesthetic value and negatively impacting the overall quality of life in the surrounding area. Over time, such activities may also result in significant ecological disturbances, including the fragmentation of habitats and changes in species distribution. These potential outcomes highlight the critical importance of thorough planning and the adoption of effective mitigation measures in blasting operations[9,10].

1.1 Introduction to Air Overpressure (AOp)

In civil engineering projects such as mining and tunnel construction, rock excavation is essential for various engineering objectives. Blasting, widely chosen for its cost-efficiency and adaptability, is a commonly used excavation technique in these projects. However, one of its undesired consequences is AOp or air blast, which results from the transient pressure waves generated by explosions. The propagation of these overpressure waves occurs through refraction along the horizontal plane, creating a significant shock wave that interacts with the surface, a phenomenon frequently discussed in academic literature. Acoustic Overpressure, characterised by its sound properties, is typically measured in decibels (dB) or Pascals (Pa)[11,12]. For the human auditory system to perceive a sound wave, its frequency must be at least 20 Hz. Sound intensity levels between 130 and 180 dB can shatter glass, while levels exceeding 180 dB may compromise structural integrity[13,14]. Windows in buildings can sustain vibrations or damage up to 130 dB, necessitating that AOp levels remain below 110 dB to protect nearby structures. Accurate prediction of AOp is crucial in defining blast safety zones, and in recent years, ML techniques have been extensively utilised for this purpose.

This study evaluates the application of ML methods in addressing challenges related to mine blasting. Findings indicate that ML techniques, particularly ensemble and hybrid approaches, outperform traditional methods in 61% of the examined case studies. A review of the historical background of ML applications in mining highlights a rising trend in adopting hybrid/ensemble or advanced techniques, with 72% of surface and 45% of subsurface blasting challenges being addressed using these models. The increasing reliance on statistical and graphical methodologies further supports this preference[13]. Additionally, ML models have been used to predict reductions in shock overpressure in atmospheric conditions following methane/air explosions when explosion events are detected at two different locations[15,16].

Rock fragmentation through blasting in mining operations focuses on optimising energy efficiency while mitigating negative impacts such as seismic vibrations, fly rock, air blast noise, and environmental hazards like dust emissions. As a result, mine management continuously seeks innovative techniques to enhance productivity while reducing excavation and operational costs. Air deck blasting is a widely adopted approach that improves blasting efficiency by modifying the transmission of explosive energy to a larger portion of the rock mass. While conventional tools have been used to study air deck blasting, there remains a pressing need for advanced numerical modelling to better understand this mechanism. The authors aim to provide valuable insights into this blasting technique and share their findings in forthcoming publications[17,18].

This investigation also employed Likert-scale surveys to evaluate the comfort levels of residents affected by air blasts. Various reporting units, including decibels, millibars, and Pounds per Square Inch (PSI), were analysed. Interviews were conducted with residents in multiple locations across the Midwest United States, incorporating both geographic and demographic considerations. The results were compared to those of survey participants residing outside the affected areas. Unlike noise pollution from airports and transportation systems, blast events are short-duration occurrences. For untrained individuals, including local regulators, perceived annoyance at 90 dB suggests that existing air blast limits of 133 dB may be excessively high, potentially necessitating stricter regulations. Some studies continue to reference the dBA scale when assessing noise-related annoyance levels[19,20].

The effectiveness of air deck blasting is largely due to the expansion of gaseous products, which interact dynamically with the borehole's bottom, stemming base, and shock waves within the air column. This study examines the techno-economic feasibility of air deck applications, including pre-splitting. Four tests

were conducted to analyse the effects of air decks in single-hole, multiple-hole, water-filled, and unstemmed borehole detonations. Single-hole tests with different deck configurations produced notable surface effects. The study also documents the implementation of Air Deck Pre-splitting (ADP) in an operational mining environment. In one case, a 9.2 meter air deck was used, with explosive charges occupying approximately 17% of the drill hole volume and 27% of the air deck. Across various rock formations, this method demonstrated favourable results, yielding cost reductions of 10% to 46%. The selection of air deck length is crucial and must be tailored to the rock type and blasting application. While exact values may vary, the optimal Air Deck Length (ADL) typically falls within the range of 0.1 to 0.35, leading to improved fragmentation, enhanced equipment efficiency, and overall economic benefits[21].

A review of prior research indicates that the intensity of an explosive spray at a tunnel entrance is influenced by factors such as tunnel section, length, portal distance, maximum charge per delay, and additional blast design parameters. This study introduces phonometric and iso-attenuation curves to illustrate airwave propagation beyond tunnels, offering solutions for distinct scenarios. A charge–distance curve is also proposed as a simplified approach to addressing this issue[22]. To assess noise levels and ground vibrations from blasting at the Ewekoro limestone quarry in Nigeria, vibro-monitoring equipment was used to systematically record these parameters over one month. Additionally, digital cameras captured images of residential structures in nearby villages. The results indicated that blast noise levels ranged from 82 to 89 dB, well within the Federal Environmental Protection Agency (FEPA) limit of 150 dB for noise and 5.0 mm/s for ground vibrations. Since managing air blasts is generally more feasible than controlling ground vibrations, priority should be given to air blast mitigation before addressing vibration amplitudes[23].

The mining industry is closely linked to sustainable development, influencing environmental, economic, and social dimensions. This study explores the perspectives of researchers regarding the sustainability of the mining sector, emphasising the need to integrate sustainability principles throughout the entire mining life cycle. It outlines key sustainability requirements, necessary actions, and optimal strategies for each phase while reviewing relevant studies. Figure 2 demonstrates the

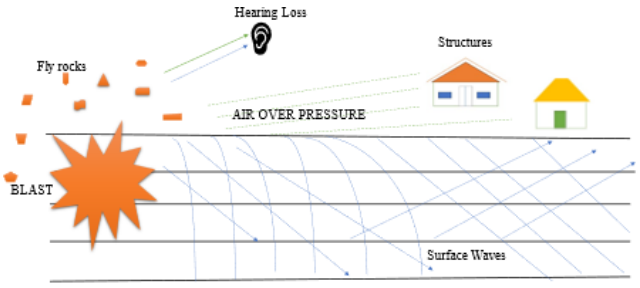


Figure 2. Effects of blasting operation.

main impacts caused by blasting, such as noise and vibration. Additionally, Tables 1 and 2 present an overview of machine learning algorithms and a list of shorthand input parameters, providing comprehensive information for analysis and comparison[24].

2.0 Directorate General of Mines Safety (DGMS) Rules for AOp

The Directorate General of Mines Safety (DGMS) regulates blast-induced AOp to ensure safety in mining areas. While specific AOp limits are not always explicitly stated, it is generally recommended to keep levels below 134 dB(L) to prevent structural damage and community disturbances. Compliance is ensured through monitoring and controlled blasting techniques.

Numerous efforts have been undertaken to regulate AOp levels due to their potential to cause harm. AOp, measured in decibels (dB) or pascals (Pa), represents the intensity of sound, with 20 Hz being the lower threshold of human auditory perception. Excessive AOp levels pose risks such as ear concussions and structural damage. While sporadic window breakage occurs at approximately 151 dB and general window breakage at 171 dB, structural damage can arise at AOp levels reaching 180 dB. Based on recommendations by Siskind *et al* referenced by the United States Bureau of Mines (USBM), a maximum AOp limit of 134 dB has been advised[25].

AOp is commonly associated with various types of damage resulting from its effects. When a blast occurs, whether from controlled demolition, mining activities, or military operations, it generates significant air pressure, which can impact nearby structures, communities, and ecosystems. Understanding these impacts is critical for enforcing safety measures, designing blast-resistant structures, and minimising adverse effects. Proper

Table 1. Machine learning algorithms and their abbreviations

S. No.	Models (techniques)	Abbreviations
1	KRR	Kernel Ridge Regression
2	KRVFL	Kernel Random Vector Functional Link
3	KRR (TKRR)	Transductive Kernel Ridge Regression
4	RVFL (edRVFL)	Ensemble Deep Random Vector Functional Link
5	ANN	Artificial Neural Network
6	RF	Random Forest
7	SVM	Support Vector Machine
8	MARS	Multivariate Adaptive Regression Splines
9	MVRA	Multivariate Linear Regression Analysis
10	ANFIS	Adaptive Neuro-Fuzzy Inference System
11	SFS	Stochastic Fractal Search
12	PSO	Particle Swarm Optimisation
13	GA	Genetic Algorithm
14	SVR	Support Vector Regression
15	GO	Grasshopper Optimizer
16	BFS	Boruta Algorithm
17	GP	Genetic Programming
18	PNN	Polynomial Neural Network
19	BSTSM	Boosted Smoothing Spline
20	CART	Classification And Regression Tree
21	KNN	K-Nearest Neighbors
22	BRR	Bayesian Ridge Regression
23	GP	Gaussian Process
24	MLP	Multilayer Perceptron Neural Network
25	BRNN	Bayesian Regularised Neural Networks
26	HYFIS	A Hybrid Neural Fuzzy Inference System
27	GMDH	Group Method of Data Handling
28	BART	Bayesian Additive Regression Trees
29	BRT	Boosted Regression Trees
30	CA	Cubist Algorithm
31	CIT	Conditional Inference Tree
32	PCA	Principal Component Analysis
33	MLR	Multiple Linear Regression
34	MCS	Monte Carlo Simulation
35	USBM	United States Bureau of Mines
36	RBF	Radial Basis
37	ICA	Imperialist Competitive Algorithm
38	GRNN	Generalised Regression Neural Network
39	RBFNN	Radial Basis Function Neural Network
40	GLMNET	Generalised Linear Modelling
41	MLPNN	Nonlinear Neural Network Modelling with Multilayer Perceptrons
42	PSO–SVR-L	Particle Swarm Optimisation-Support Vector Regression-Linear
43	PSO–SVR-Q	Particle Swarm Optimisation-Support Vector Regression-Quadratic
44	PSO– SVR-RBF	Particle Swarm Optimisation-Support Vector Regression-Radial Basis
45	FIS	Fuzzy Inference System
46	ICA	Imperialism Competitive Algorithm
47	CART	Classification And Regression Tree
48	GRNN	Generalised Regression Neural Network
49	RBFNN	Radial Basis Function Neural Network
50	MLPNN	Multilayer Perceptron Neural Networks
51	SA	Simulated Annealing

Table 2. List of the input parameters' acronyms

S. No.	Input Parameters	Abbreviations
1	HD	Hole Depth
2	St	Stemming
3	B	Burden
4	S	Spacing
5	MCD	Maximum Charge Per Delay
6	PF	Powder Factor
7	D	Distance
8	C	Charge
9	NOH	Number of Holes
10	DOH	Depth of Holes
11	DB	Distance from the Blast
12	BI	Blasting Index
13	Hd	Hole Diameter
14	RQD	Rock Quality Designation
15	M	Employ the Stemming Length
16	DBF	Distance of the Blast Face
17	MP	Monitoring Point
18	StL	Stemming Length
19	TC	Total Charge
20	MIC	Maximum Instantaneous Charge
21	NBH	Number of Blast Holes
22	DMS	Distance from the Monitoring Site
23	ECD	Explosive Charge per Delay
24	MD	Monitoring Distance
25	VD	Vertical Distance
26	LSt	Length of Stemming
27	BF	Blast-Face
28	SDT	Sequential Delay Time
29	BH	Blasting Holes
30	CWD	Charge Weight per Delay
31	LOD	Length of Delay
32	DA	Detonator Accuracy
33	CL	Charge Length
34	DI	Diameter
35	AOBH	The Angle of the Borehole
36	DOI	The Direction of Initiation
37	CWB	Charge Weight per Blast
38	BVCDC	Bare Versus Covered Detonating Cord
39	IS	Initiating System
40	BH	Bench Height
41	BI	Blasthole Inclination
42	MOE	Mass of Explosives
43	E	Energy (Heat of Explosion) in a Delay
44	V_t	Firing Velocity Down the Face
45	P	Number of Populations
46	N	Number of Variables
47	Pc	Crossover Probability
48	Pm	Mutation Probability
49	DBP	Distance of the Blast Points
50	JA	Joint Aperture
51	BS	Blasting Site
52	MS	Measuring Station
53	SD	Scaled Distance
54	DMS	Distance From the Monitoring Site
55	AEC	Amount of Explosive Charge
56	DBH	Depth of the Blast Holes
57	BP	Blasting Point
58	Bh	Bench Height
59	AH	Air Humidity
60	MOS	Monitoring Station
61	MECC	Maximum Explosive Charge Capacity
62	VD	Vertical Distance
63	SC	Specific Charge
64	WCD	Weight Charge Per Delay
65	TDI	Time Delay Interval
66	SUD	Sub-Drilling
67	WC	Weight Charge
68	SR	Stiffness Ratio
69	KEM	Kind of Explosive Material
70	NOR	Number of Rows
71	BDP	Blast Design Parameters
72	CW	Charge Weight
73	CD	Charge Density
74	BHDi	Blast-Hole Diameter
75	BHD	Blast-Hole Depth
76	WOE	Weight of the Explosive
77	EM	Explosive Material
78	TWC	Total Weight Charge
79	MCW	Maximum Charge Weight
80	DE	Depth
81	DIR	Delay Interval in Rows
82	BE	Blasting Engineers

Table3. Types of damages due to blasting in AOp

S. No.	Type of structural damage	AOp Value in dB(L)
1	General window breakage	171
2	Occasional window breakage	151
3	Long-term history of application as a safe project specification	140
4	Bureau of Mines recommendation following a study of large-scale surface mine blasting	134
5	Plaster cracks	180
6	Loose window sash rattles	176
7	Failure of badly installed window panes	140-145
8	Failure of correctly installed window panes over	168
9	All window panes fail	176

planning, coordination, and mitigation strategies are essential to ensure safe and effective blasting operations. Regulatory frameworks, including those established by DGMS, outline permissible AOp limits to safeguard surrounding environments[26,27]. Table 3 presents the DGMS regulations, specifying the permissible AOp values and limits for mining and excavation activities[26,27].

2.1 Typical Effects of Pressure on Buildings

2.1.1 Structures have Significant Values[28]

Aop Pressure effects on building structures, such as blast-induced air overpressure, can lead to varying levels of damage depending on intensity. Table 4 highlights the significant impact of pressure on building structures. High-pressure waves may cause windows to shatter, structural vibrations, or even cracks in walls. Continuous exposure to moderate pressure can weaken materials over time, while extreme cases might compromise structural integrity. Understanding these effects is vital for designing resilient buildings.

3.0 Statistical Empirical Predictor to Estimate the AOp

The measurement of air noise using statistical empirical predictors involves employing advanced statistical models to analyse and predict the complex patterns of airborne

Table 4. The effects of pressure on building structures can be substantial

S. No.	(dB-L)	Effect
1	120	Significantly compromised traditional structure
2	110	Common instances of window breakage
3	100	Safety regulations for personnel, GB6722, China
4	90	Instances of window breakage
5	80	Acceptable limit to mitigate damage to glass and plaster, USBM
6	70	Detachment of loose plaster flakes, USBM RI 8485, and regulatory standards
7	60	Vibration of windows and associated feelings of irritation

Table 5. Measurement of the air noise equations using statistical empirical predictor equations[29]

Prediction Model	Equations
USBM	$P = \beta_1 * \left(\frac{D}{Q^{0.33}} \right)^{\beta^2}$
NAASRA	$P = 140^3 \sqrt{\frac{Q}{200}}{d}$
Ollofso; Persson *et al.*	$P = 0.7 \times \frac{Q^{1/3}}{D} (mbar)$
Holmberg-Persson	$P = K \times 0.7 \times \frac{Q^{1/3}}{D} (mbar)$
Mckenzie	$P = 165 - 24 \log \left(\frac{D}{Q^{1/3}} \right) (dB)$

sound. These models provide a robust framework for assessing and understanding acoustic characteristics in various environments[29]. Table 5 presents the adopted statistical empirical predictors used to measure air noise.

Most studies have relied primarily on two input parameters: burden and distance, as identified in previous research. However, due to inherent errors and imperfect accuracy in these statistical empirical equations, machine learning techniques offer a promising alternative for improving predictive performance.

In this context, **P** represents the overpressure or air blast, **Q** denotes the mass of the explosive charge (kg), and **D** is the distance (m) from the charge to the monitoring point. Additionally, **H** and **β** are site-specific factors influencing the prediction.

The effects of blasting extend beyond immediate physical impacts, encompassing environmental consequences, structural implications, and potential socio-economic ramifications. Therefore, comprehensive studies and strategic mitigation approaches are essential to address and minimise these multifaceted repercussions.

4.0 Introduction to Machine Learning

In the twenty-first century, ML and Artificial Intelligence (AI) have emerged as invaluable, state-of-the-art tools within the global academic landscape. These technologies are transforming teaching and learning by shifting from traditional educational methods to a more technological approach. As a result, they bridge the gap between conventional classroom instruction and digital learning, advancing unidimensional learning patterns into multidimensional concepts. Figure 3 provides a detailed definition of machine learning.

Beyond education, ML has significant applications in industrial processes such as drilling and blasting. Compared to conventional methods, ML-driven techniques can reduce the quantity of explosives required for blasting by up to 89% and lower overall costs by approximately 23%[30] Figure 4 shows the seven key steps that make up the machine learning life cycle. These are listed below.

A subset of AI, machine learning enables machines to automatically generate predictions, improve performance based on historical data, and learn from it. This process involves training a collection of algorithms on large datasets to develop predictive models for specific tasks. ML algorithms are widely used to address diverse challenges, including association, forecasting, clustering, regression, and classification.

5.0 Machine Learning Life Cycle

Computer systems can now learn autonomously, thanks to ML without explicit programming. The implementation of a machine learning system can be understood through the machine learning lifecycle. Efficient development of the machine learning life cycle is a cycle that is followed in machine learning projects, with the main goal of handling a particular problem or task Compiling information and getting ready data, wrangling data, analyzing data, training the model, testing the model, and deployment are the seven main stages of the ML life cycle[31]. Figure 4 shows the seven key steps that make up the machine learning life cycle.

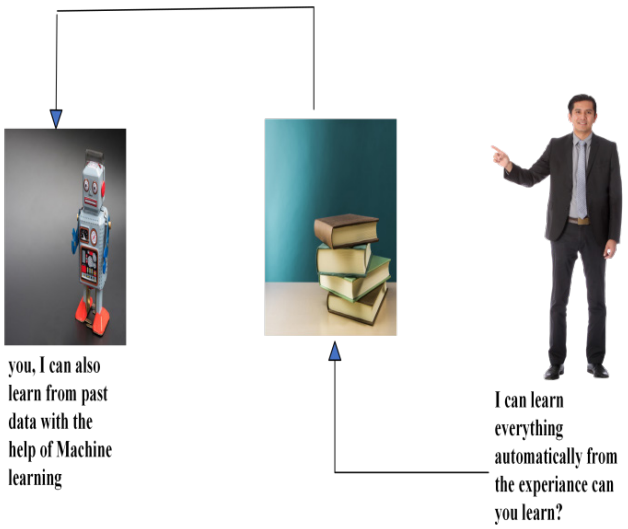


Figure 3. Description of machine learning.

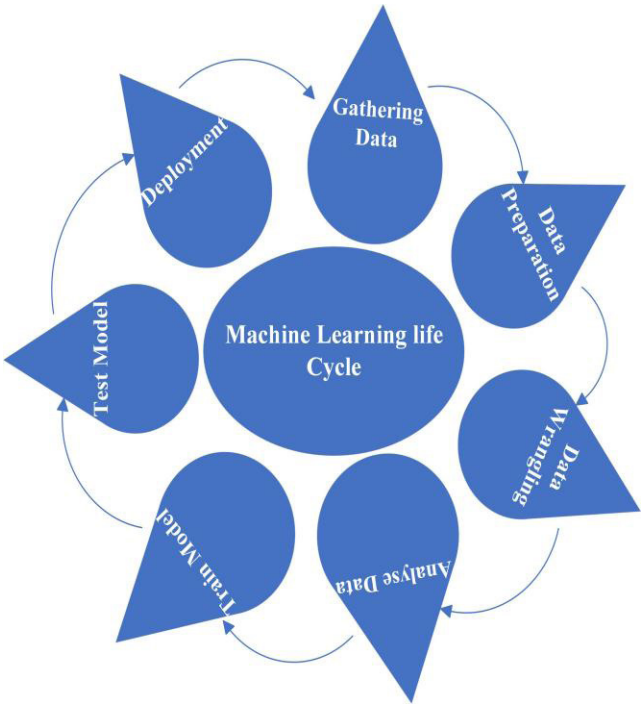


Figure 4. Machine learning life cycle.

5.1 Data gathering

Data gathering is the cornerstone of any research endeavour, regardless of its scope or field of study. This pivotal phase involves the systematic collection, measurement, and analysis of information about a specific subject or inquiry. By diligently gathering data, researchers lay the groundwork for insightful analysis and informed decision-making. Businesses, in particular, benefit greatly from this process, as they provide empirical evidence on which to base strategic decisions. Whether it is market research, customer feedback, or performance metrics, the data gathered during this phase serves as a valuable asset for guiding organisational strategies and initiatives. Ultimately, the thoroughness and accuracy of data-gathering efforts directly influence the quality and reliability of research outcomes, underscoring their indispensable role in the research process.

5.2 Step 1. Strategic Planning and Design

Successful data-gathering begins with strategic planning and design. Researchers meticulously outline their research objectives, formulate hypotheses or research questions, and select methodologies that align with their goals. This planning phase includes considerations, such as sampling techniques, survey design, and ethical guidelines, to ensure the integrity and validity of the data collected.

5.3 Step 2. Diverse Data Collection Methods

The selection of the data collection method is determined by the nature of the research. Researchers employ a variety of techniques, including surveys, interviews, observation experiments, and archival research, tailored to a specific research context. Each method offers unique insights and challenges, necessitating careful consideration during the selection.

5.4 Step 3. Sampling Strategies

Given the vast or inaccessible nature of the target populations, sampling strategies are employed to gather representative subsets of data. Techniques such as random sampling, stratified sampling, and convenience sampling are utilised to ensure that the data collected accurately reflects a broader population's characteristics.

5.5 Step 4. Precision in Measurement

Measurement lies at the heart of data gathering and requires precise tools and instruments to quantify the variables of interest. Researchers have developed surveys, tests, and observation protocols to ensure reliability (consistency) and validity (accuracy) in measurement. Pilot testing and refinement of measurement instruments are common practices for enhancing data quality.

5.6 Step 5. Analytical Rigor

Upon data collection, researchers engaged in rigorous analyses to derive meaningful insights. This involves data cleaning, coding, and application of appropriate statistical or qualitative analysis techniques. From descriptive statistics to advanced models, the analysis aims to uncover patterns, relationships, or trends relevant to the research objectives.

5.7 Step 6. Interpretation and Dissemination

The final stage of data gathering involves interpreting the findings within the research context and disseminating the results to relevant stakeholders. Researchers draw conclusions, discuss implications, and offer recommendations based on their analysis. Effective communication of results through research reports, academic publications, or presentations ensures broader dissemination of knowledge and informs decision-making processes. Ultimately, data gathering serves as the cornerstone of evidence-based decision-making across diverse domains, including business, academia, healthcare, and policymaking. This systematic approach fosters confidence in research outcomes, enabling stakeholders to make well-informed choices based on factual data.

5.8 Data Preparation

Data preparation is essential to the machine-learning process. The life cycle encompasses essential steps to refine raw data for accurate predictions and analysis. This multifaceted process, also referred to as data wrangling, data pre-processing, or data cleaning, entails compiling, merging, cleaning, and transforming raw data to ensure quality and suitability for machine learning projects. Following the initial data collection phase, data

preparation constitutes a later stage, where various tasks, such as cleaning, transforming, and engineering features, are undertaken to enhance the suitability of the data for analysis and model training. By meticulously preparing the data, practitioners can mitigate issues such as missing values, outliers, and inconsistencies, thereby optimising the performance and reliability of machine-learning models. Data preparation serves as a crucial precursor to model training, ensuring that the data is well-prepared and conducive to deriving meaningful insights and making accurate predictions.

5.9 Data Wrangling

A crucial step in the preparation of data, data wrangling, also called data munging, involves transforming and mapping unprocessed data into a format better suited for analysis and other downstream uses. Data wrangling's main goal is to improve the quality and utility by resolving problems like outliers, inconsistencies, and missing values. Data analysts frequently allocate a significant portion of their time to data wrangling as they form the backbone of the data preparation process. While analysis is undoubtedly important, the effectiveness of any analytical endeavour relies heavily on the quality and reliability of the data, underscoring the critical role of data wrangling in ensuring that the data are fit for analysis.

5.10 Analysis of Data

A thorough process of modifying, transforming, and visualising data is called data analysis, and it is used to extract insightful information that helps people, organisations, and governments make decisions. Through various analytical techniques, data analysts uncover patterns, trends, and correlations within datasets, enabling stakeholders to make informed choices and optimise outcomes. Data analysis serves as a powerful tool for leveraging data assets to drive innovation and success, identify market trends, improve operational efficiency, and inform policy decisions. By translating raw data into actionable insights, data analysis empowers organisations to adapt to changing environments, mitigate risks, and capitalise on opportunities in today's data-driven world.

5.11 Train Model

One of the most important stages of machine learning is model training, where the goal is to use labelled examples to determine the ideal values for weights and biases. In supervised learning, an algorithm meticulously scrutinises a plethora of labelled examples to minimise loss and constructs a model tailored to the specific task at hand. This iterative process, known as empirical risk minimisation, entails fine-tuning the model parameters to mitigate discrepancies between the predicted and actual outcomes, thus enhancing the model's predictive accuracy. Through an exhaustive analysis of the labelled data points, the algorithm iteratively refines its predictions, ultimately converging toward a model that accurately captures the underlying patterns within the data. This iterative learning process lies at the heart of supervised learning and facilitates the development of models capable of making reliable predictions across a wide array of applications.

5.12 Test Model

Model testing is an essential step in machine learning that assesses a fully trained model's performance. Testing the trained model's ability to generalise to new, unseen data involves exposing it to a testing dataset that is distinct from the training dataset. This procedure allows for a comprehensive evaluation of the model's efficacy and dependability, providing important information about both its strengths and weaknesses in terms of prediction. Researchers and practitioners can acquire a more profound comprehension of the model's advantages and disadvantages by closely examining its performance on unobserved data. This will facilitate their decision-making process when it comes to deployment and optimisation. In the end, model testing is essential to guaranteeing that machine-learning models are reliable and applicable in a variety of real-world situations.

5.13 Deployment

Model deployment in machine learning marks the transition from development to real-world application, as it entails integrating a trained model into an operational system. This process enables the model to receive input data and generate predictions or outputs, thereby making its predictive capabilities accessible within a production environment. The ultimate goal of model deployment is to seamlessly incorporate the model into existing systems or applications, allowing end-users or other systems to leverage its predictive power for decision-

making purposes. Throughout the deployment process, considerations such as scalability, reliability, and security are paramount to ensure smooth operation and mitigate potential risks. By successfully deploying a trained model, organisations can harness the advantages of machine learning to drive innovation, improve efficiency, and deliver valuable insights to stakeholders in a timely and actionable manner.

6.0 Categories of Machine Learning Techniques

There are four types of machine learning: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Different approaches are used in each category, each of which is adapted to particular data contexts and applications. While unsupervised learning identifies patterns in unlabeled data, supervised learning trains algorithms on labelled data to make predictions. When labelled data are hard to come by, semi-supervised learning makes use of both labelled and unlabeled data, which is frequently advantageous. Reinforcement learning focuses on decision-making through interactions with the environment, maximising cumulative rewards. These frameworks serve as the foundation for developing algorithms capable of learning and predicting data across a wide array of domains and challenges. Figure 5 shows types of Machine learning using examples.

6.1 Supervised Machine Learning

Supervised learning involves training machines using meticulously labelled data, allowing them to make predictions based on known input-output relationships. The training dataset consists of labelled data, where each input is mapped to a corresponding correct output. This structured learning approach is analogous to a student learning under the guidance of a teacher, ensuring that the model refines its accuracy over time. Supervised learning finds applications in various fields, including spam filtering, fraud detection, image classification, and risk assessment.

A significant advancement in supervised learning is the growing emphasis on explainability, particularly in critical sectors like finance, healthcare, and autonomous systems. Nadia Burkart and Marco F. Huber, in their report "A Survey on the Explainability of Supervised

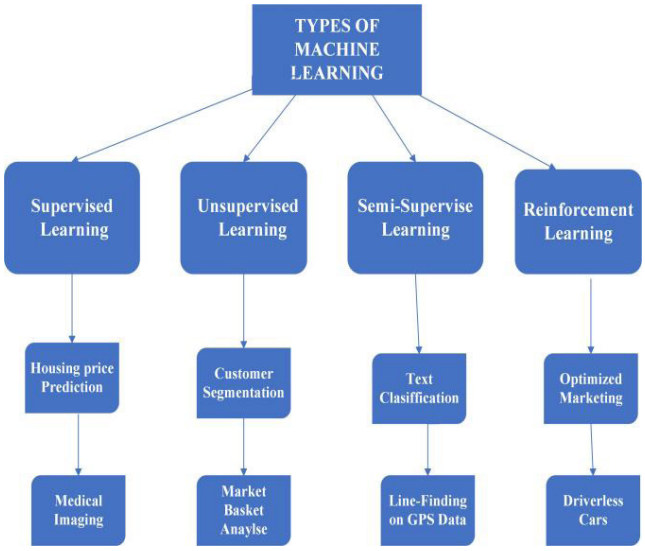


Figure 5. Various types of Machine learning, along with examples.

Machine Learning", provide a comprehensive examination of the need for transparency in ML models. They explore how explainable Supervised Machine Learning (SML) enhances model accountability, interpretability, and human understanding, particularly in high-stakes decision-making environments[32,33].

The study highlights a major challenge in human decision-making: our reliance on subconscious reasoning, which is difficult to encapsulate in ML classifiers. Often, human decision-making is articulated post-factum, through coherent narratives that may not directly translate into algorithmic logic. Burkart and Huber address this challenge by proposing methods to align ML model explanations with human interpretability, bridging the gap between opaque "black-box" models and transparent AI-driven decisions.

Their work categorises various explainable ML techniques, ranging from traditional rule-based models to advanced deep-learning interpretability frameworks. By reviewing both historical and cutting-edge approaches, they provide insights into how supervised ML models can become more accountable, auditable, and transparent, making their study a crucial contribution to the field of explainable AI.

6.2 Unsupervised Machine Learning

Unsupervised learning plays a crucial role in machine learning, particularly when labelled data is scarce or

expensive to obtain. Unlike supervised learning, which relies on labelled datasets, unsupervised learning allows models to uncover hidden patterns, structures, or relationships within unlabeled data. This ability makes it essential for applications such as clustering, anomaly detection, and dimensionality reduction.

A key aspect of unsupervised learning is feature learning, which enables models to extract meaningful representations from raw data without human intervention. This approach is particularly advantageous because it leverages abundant unlabeled datasets and often results in the discovery of more effective features than those manually designed. By reducing reliance on domain expertise, unsupervised feature learning broadens the applicability of machine learning to diverse and complex data environments.

Deep learning has significantly advanced unsupervised feature learning, with its impact extending across various fields. While computer vision has been the primary beneficiary of these advancements, deep learning techniques are also proving highly effective for time-series data analysis. Traditional methods often treat time-series inputs as static data, but the most successful approaches incorporate modifications to deep learning architectures to better capture temporal dependencies.

Despite these advancements, challenges remain in applying deep learning to time-series data. One notable issue is that many studies still rely on pre-processed features, rather than allowing models to learn representations directly from raw data. Addressing these challenges requires continued innovation in unsupervised learning methodologies, feature extraction techniques, and model architecture design[34,35].

6.3 Semi-Supervised Machine Learning

Semi-Supervised Learning (SSL) is a category of machine learning that lies between supervised and unsupervised learning paradigms, utilising both labelled and unlabeled data during training. This approach is particularly valuable in scenarios where obtaining labelled data is expensive or time-consuming, while unlabeled data is abundant.

This survey provides a comprehensive overview of semi-supervised learning, covering its evolution from the early 2000s to recent advancements. A novel classification taxonomy has been introduced, categorising semi-supervised techniques based on their primary objectives: transductive learning (which makes predictions for specific unlabeled instances) and inductive learning (which generalises to unseen data). Additionally, it explores the diverse methods employed for leveraging unlabeled data, including wrapper techniques, unsupervised preprocessing, and intrinsically semi-supervised approaches.

Initially, research in SSL focused on wrapper techniques and modifications of traditional supervised algorithms such as Support Vector Machines (SVM). Over the past two decades, however, graph-based methods have gained prominence due to their ability to systematically capture similarities among unlabeled data points, making them one of the most intuitive approaches to SSL. Furthermore, the growing interest in deep generative models has led to their increasing application in semi-supervised learning, offering new perspectives on how models can effectively learn from limited labelled data[36,37].

6.4 Reinforcement

Reinforcement Learning (RL) is a machine learning paradigm driven by feedback, where an agent learns to interact with an environment by performing actions and observing their consequences. The agent is rewarded for desirable actions and penalised for unfavourable ones, enabling it to autonomously optimise decision-making over time. Unlike supervised learning, RL does not rely on labelled data but instead leverages trial-and-error mechanisms to refine its strategies.

Regression, on the other hand, is a supervised learning technique used for predicting continuous values. The core objective of regression algorithms is to determine an optimal fit line or curve that best represents the relationship between independent (predictor) and dependent (target) variables. Key performance metrics for regression models include variance, bias, and error, which are used to evaluate model effectiveness. Regression analysis is a widely used statistical approach that facilitates understanding of the relationships between variables, making it an essential tool for predictive modelling.

This study explores critical challenges in reinforcement learning, particularly the trade-off between exploration (discovering new strategies) and exploitation (leveraging known strategies for optimal performance). The theoretical foundation of RL is established through Markov Decision Processes (MDPs), which provide a structured framework for decision-making under uncertainty. Furthermore, the research investigates strategies for learning from

delayed reinforcement, constructing empirical models to accelerate learning, leveraging generalisation and hierarchy, and handling hidden states.

Despite the success of RL in solving smaller-scale problems, its application to complex, real-world challenges remain limited. The primary obstacle is not the inability of researchers to design learning techniques, but rather the difficulty in addressing arbitrary, large-scale problems within a generalisable framework. To overcome this, a shift from table-based learning approaches to bias-integrated learning methods is essential, allowing models to incorporate prior knowledge and achieve more efficient learning[38,39].

Figure 6 likely represents the various stages and sub-stages of a reinforcement learning workflow, with arrows indicating sequential dependencies and interconnections between different components. This visualisation can help conceptualise the decision-making process, illustrating how the RL agent progresses through iterative learning cycles.

7.0 Working Flow of Machine Learning

Machine learning follows a structured workflow that begins with data collection, where relevant data is gathered from various sources. Next, data preprocessing is performed to clean, normalise, and transform the data into a suitable format. Feature selection and engineering help identify the most important attributes for training the model. The chosen model is then trained using a training dataset, followed by evaluation using a separate test set to assess its performance. If necessary, hyperparameter tuning is applied to optimise the model. Finally, the trained model is deployed for real-world applications, where it continuously improves with new data.

7.1 Problem Understanding

The problem understanding in machine learning is a crucial first step that involves clearly defining the task, its objectives, and the challenges it presents. A thorough analysis of the available data is essential to uncover underlying patterns, relationships, and potential limitations that may impact model performance. By establishing well-defined goals, researchers and practitioners can identify the most appropriate machine-learning techniques and algorithms to tackle the problem effectively. Additionally, ensuring that the data is representative of real-world conditions enhances the reliability and applicability of the developed models. A well-structured problem-understanding phase not only guides subsequent steps such as data preprocessing, model selection, and evaluation but also lays the groundwork for building robust, interpretable, and actionable machine learning solutions.

7.2 Data Handling

Data handling in machine learning is a critical process that involves acquiring, preprocessing, and structuring data to enhance its quality and usability for analysis and model training. It begins with sourcing relevant and

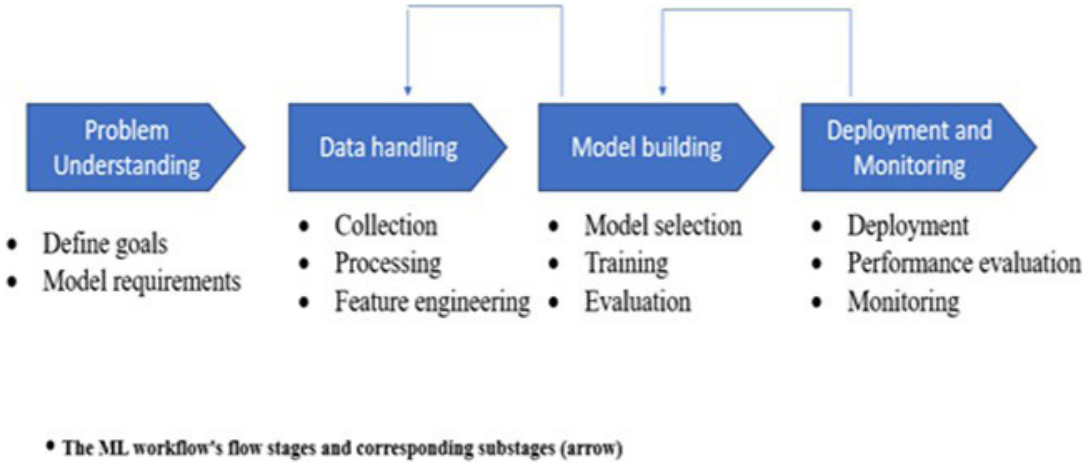


Figure 6. The workflow's stages and corresponding substages (Arrow).

representative data from databases, APIs, or files, ensuring comprehensive coverage of the problem domain.

Next, preprocessing steps such as cleaning, normalisation, and feature engineering are applied to refine the data, addressing issues like missing values, outliers, and inconsistencies to maintain integrity and reliability. Proper organisation and formatting further optimise data structures for computational efficiency and model performance. By meticulously managing data at every stage, practitioners establish a strong foundation for accurate predictions, meaningful insights, and well-informed decision-making, ultimately driving the success of machine learning applications.

7.3 Model Building

To ensure effective machine learning, the crucial initial step involves selecting an algorithm meticulously tailored to the specific task. This selection process considers factors such as the nature of the data, the complexity of the problem, and the desired outcome. Once chosen, the algorithm undergoes training using labelled data, which enables it to discern intricate relationships and patterns. This learning process empowers the algorithm to make informed predictions and classifications. During training, the model's parameters are optimised iteratively to minimise errors and maximise performance. Techniques like gradient descent or grid search may be employed during this optimisation phase, allowing for fine-tuning of the model's predictive capabilities. The result of this comprehensive model-building process is a robust predictive model. By harnessing the power of machine learning algorithms, this model delivers accurate and reliable predictions, ultimately enhancing decision-making across a wide spectrum of domains and applications.

7.4 Deployment and Monitoring

Deployment in machine learning signifies a pivotal shift from development to practical application, necessitating the integration of a trained model into a functional environment to facilitate real-time decisions and predictions. This crucial phase involves configuring the model to interface seamlessly with existing systems or applications, ensuring smooth operation within the production environment.

Once deployed, continuous monitoring is essential to maintain the model's performance and reliability over time. This monitoring entails ongoing evaluation of the model's predictive accuracy and effectiveness, allowing for the detection of any deviations or drift in its behaviour that could impact performance. By diligently tracking the model's performance, practitioners can swiftly identify and rectify issues, thereby ensuring that the deployed model remains robust and effective in achieving its intended objectives.

Ultimately, deployment and monitoring are integral components of the machine learning lifecycle. They ensure not only the successful implementation of machine learning solutions but also their sustained performance in real-world scenarios, thereby maximising their value across various applications. Table 6 portrays the summary of previous investigations in the field of AOp and provides insights into various methodologies, findings, and trends observed over time.

8.0 Summary of the Previous Investigation

In 2023, Zhang *et al.*[40] conducted a study utilising two extensive air noise datasets to evaluate the performance of their proposed Sa-WKRR model. This model was compared against nine other machine learning techniques, including Support Vector Machine (SVM), Random Forest (RF), ensemble deep RVFL (edRVFL), transductive Kernel Ridge Regression (TKRR), Kernelized Random Vector Functional Link (KRVFL), Artificial Neural Network (ANN), and Multivariate Adaptive Regression Splines (MARS). The study used seven input parameters: Hole Depth (HD), Stemming (St), Burden (B), Spacing (S), Mean Charge per delay (MC), Powder Factor (PF), and Distance (D) collected from the granite site in Hulu Langat. The dataset consisted of 76 data points, representing 70% of the total data. The Sa-WKRR model demonstrated remarkable accuracy, achieving R^2 values of 0.925 and 0.9991, as well as 0.9965 and 0.933 under different testing conditions. Additionally, the model yielded root mean square error (RMSE) values of 1.03/3.22 and 0.46/1.98, showcasing its superior predictive capability. Similarly, Chewu *et al.*[41] conducted a study in 2023 using 100 datasets and various machine learning algorithms, with a specific focus on the MVR application of ANN. Their model incorporated nine input parameters Spacing (S), Burden (B), Hole Depth (HD), Hole Diameter

Table 6. Summary of previous investigations in the field of AOp

S. No.	Author	Year	ML Models	Input Parameters	Dataset	R^2
1	Ruiuan Zhang *et al.*[1]	2023	KRR, KRVFL, SA-WKRVFL, TKRR, EDRVFL, ANN, RF, SVM, MARS	HD, ST, B, MC, S, D, PF	76	0.9965 AND 0.933
2	Charles Chewu *et al.*[41]	2023	ANN MVR	S, B, ST, PF, MC, M, HD, D, RQD	100	0.999 (ANN) 0.847 (MVR)
3	Brajendra Kumar *et al.*[42]	2023	SITE-SPECIFIC PREDICTION MODEL	DISTANCE BETWEEN THE BLASTING SITE AND MEASURING STATION, CHARGE PER DELAY, AND SCALED DISTANCE	100	0.7955
4	Yao Yevenyo Ziggah *et al.*[43]	2023	NCA WITH AI TO FORM NCA-SVM, NCA-BPNN, NCA-GRNN AND NCA-RBFNN. (PCA) AND AI (PCA-SVM, PCA-BPNN, PCA-GRNN AND PCA-RBFNN).	PF, StL, TC, MIC, NBH, HD, AND DMS	324	-
5	Jinbi Ye *et al.*[2]	2022	ANFIS-SFS, ANFIS-GA, & ANFIS-PSO	HD, PF, MC, T, B, S, RQD, D, NOH	64	0.986
6	Lihua Chen *et al.*[3]	2022	SVR-GO-BFS7	HD, B, RQD, ST, PF, S	1	0.983
7	Bhatawdekar Ramesh Murlidhar *et al.*[45]	2021	GP AND M5¢ MODELS	BI, DBP, JA, ST, PF, MC	125	0.8621
8	Hooman Harandizadeh *et al.*[12]	2021	HYBRID INTELLIGENT E ANFIS-PNN-GA MODELS	DI, MC, PF, ST	75	-
9	Hoang Nguyen *et al.*[46]	2021	GLMNET, SVM, MLPNN, RF, AND EMPIRICAL,	B, ST, D, S AND MC	180	(GLMNET) 0.916 (MLPNN) 0.597-0.860
10	Hoang Nguyen *et al.*[47]	2020	GA-BSTSM, SIX OTHER AL MODELS	W, R, T, RH, AP, WS, AND WD	121	0.971
11	Hoang Nguyen *et al.*[48]	2020	MLP NEURAL NET, BRNN, HYFIS	B, S, PF, N, D, Q, H, T, W	77	(MLP) 0.961
12	Wei Gao *et al.*[49]	2020	GMDH–GA	(RMR), PF, D, MC	84	0.988
13	Bhatawdekar Ramesh Murlidhar *et al.*[52]	2020	ANN, ANN-PSO, GA-ANN, FIS AND SVM	S, B, HD, HD, STL, AND NOR ARE BDP.	96	(FIS) 0.99.

Table 6. *Continued*

S. No.	Author	Year	ML Models	Input Parameters	Dataset	R^2
14	Victor Amoako Temeng *et al.*[50]	2020	BPNN, GMDH, SVM	EMPLOY THE STEMMING LENGTH (M), THE NUMBER OF BLAST HOLES PER BLAST, THE MAXIMUM INSTANTANEOUS CHARGE (KG), AND THE DISTANCE BETWEEN THE MONITORING STATION AND BLASTING POINT (M)	171	-
15	Jaroonpattanapong P *et al.*[77]	2020	AI/ML	B, S, AND SDT FROM BH TO GENERATE AIR WAVEFRONTS TRANSMITTED OUT IN ALL DIRECTIONS	54	-
16	Xuan-Nam Bui *et al.*[51]	2019	ANN, BRT, BART, GP, RF, AND K-NN	W, R, B, S, STL, PF), BLAST-HOLE DEPTH, DELAY TIMES, AND BLAST-HOLE DIAMETER	97(113)	(ANN) 0.930
17	Qiancheng Fang *et al.*[15]	2019	GA–CA MODEL GP, CIT, HYFIS, PCA, K-NN	P, N, PC, AND PM	132	(GA-CA) 0.806
18	Hoang Nguyen *et al.*[53]	2019	ANNS-RF	W, R, H, P, B, S, AND T	114	(ANNs-RF)-0.985 (ANN)-0.960
19	H. Bakhshandeh Amnieh *et al.*[54]	2019	SA	HD, CW, B, S, STL, CD, AND DBF	70	-
20	Amir Mahdiyar *et al.*[55]	2018	MLR	D, ST, B, S, MC, PF, TC, AND DI	76	0.901
21	Amir Aminshokravi *et al.*[56]	2018	PSO, ANN, USBM	W, D, RMR	64	0.960
22	Danial Jahed Armaghani1 *et al.*[57]	2018	ANN AND GA-ANN	EM, TWC, MCW USED PER DELAY, BHD AND DE, DBF, PF, DIR, B, S, ST, AND SD, CAN BE CHANGED BY THE BE	97	(ANN)0.961 and (GA-ANN) 0.965
23	Mahdi Hasanipanah *et al.*[58]	2017	PSO–SVR-L, PSO–SVR-Q AND PSO–SVR-RBF.	MC AND DI	83	-
24	Mahdi Hasanipanah *et al.*[59]	2016	ANN, FUZZY SYSTEM, AND ANFIS	B, S, NBH, BHD BLAST-HOLE DEPTH, BHDI, SD, BH, STH AND WOE	77	(ANSFIS) 0.878, (FUZZY)0.797,(ANN) 0.650

Table 6. *Continued*

S. No.	Author	Year	ML Models	Input Parameters	Dataset	R^2
25	Danial Jahed Armaghani *et al.*[60]	2016	(ICA)-ANN, ANN	MCD AND DBF	70	(ICA)-ANN 0.886 (ANN)0.882
26	Danial Jahed Armaghani *et al.*[61]	2015	ICA-ANN	DI, MC, MP	95	-
27	Mohsen Hajihassani *et al.*[62]	2015	PSO-ANN	HD, MCD, B-TO-SPACING RATIO, STL, SUD, PF, AND NOH	88	(ANN) 1.714 (PSO)0.89
28	Danial Jahed Armaghani1 *et al.*[63]	2015	ANN, ANFIS	MCD AND DBF	166	0.947
29	M. Hajihassani *et al.*[64]	2014	PSO-BASED ANN, OPTIMUM MODEL	HD, PF, MC, ST, B, S, RQD, NOH	62	-
30	Manoj Khandelwal &P.K. Kankar[7]	2011	SVM MODEL	MCD AND D BETWEEN BF THE MP	75	-
31	P.Segarra *et al.*[72]	2010		HD, NOR, BH, BI, B, S BETWEEN BH, S, MOE DETONATED IN A DELAY(M), E, STL, PF, DR, DELAY BETWEEN ROWS, V_I, EXPLOSIVE TYPES, IN-HOLE AND SURFACE, IS	122	-
32	C.Kuzu *et al.*[73]	2008	EMPIRICAL EQUATION	CWD, LOD, DA, B &S STEMMING(AMOUNT) STEMMING (TYPE), CL AND DI, AOBH, DOI, CWB, CD, BVCDC, IS	1	-
33	G.R. Adhikari *et al.*[74]	2007	FIVE MICROPHONES &SEISMOGRAPHS	C, NOH, DOH, DB	125	-
34	Kenneth K *et al.*[75]	2005	MICROPHONE	-	-	-
35	Chengqing Wu *et al.*[76]	2005	NUMERICAL MODEL	-	-	-

(Hd), Stemming Length (StL), Powder Factor (PF) in m^3/kg, Mean Charge (MC), Rock Quality Designation (RQD), and the distance between the blast point and the monitoring point (DBP to DP). The model demonstrated high predictive accuracy, achieving an R^2 value of 0.847, a standard error of 0.02402, and an RMSE of 0.563716. The overall performance metrics were exceptional, reaching an accuracy of 0.999. Kumar *et al.*[42] initiated a research project in 2023 utilising a dataset of 100 samples to develop a site-specific air overpressure prediction model. Their study achieved an R^2 value of 0.7955 with a 95% Confidence Interval (CI). The developed model estimated AOp using the following equation: $AOp=162.82(D/Q^{0.33})-0.066$where AOp represents air overpressure, D is the distance between the Blast Source (BS) and the monitoring station (MS), and the model incorporated four key input parameters: blast source Distance (D), Charge Diameter (CD), Stemming Distance (SD), and powder factor (PF). These parameters were identified as critical in assessing and predicting the impact of explosive activities on the surrounding environment. Additionally, Ziggah *et al.*[43] explored dimensionality reduction of input data using the National Communication Authority (NCA) method in 2023. They applied NCA-reduced features to

various AI models, including SVM, Backpropagation Neural Network (BPNN), General Regression Neural Network (GRNN), and Radial Basis Function Neural Network (RBFNN). The resulting hybrid models NCA-SVM, NCA-BPNN, NCA-GRNN, and NCA-RBFNN were compared against standalone AI models (SVM, BPNN, GRNN, RBFNN) and AI models integrated with Principal Component Analysis (PCA) (PCA-SVM, PCA-BPNN, PCA-GRNN, PCA-RBFNN). The evaluation employed statistical metrics such as RMSE, scatter index (SI), correlation coefficient (R^2), Coefficient of Residual Mass (CRM), uncertainty at 95% confidence interval (U_{95}), and Bayesian Information Criterion (BIC). The study analyzed 324 datasets from various blast events, investigating the relationships between blast-induced noise and blast design parameters, including powder factor (PF in kg/m^3), stemming length (StL in m), total charge (TC in kg), maximum instantaneous charge (MIC in kg), Number of Blast Holes (NBH), Hole Depth (HD in m), and delay timing (DMS in ms). The results indicated that NCA integration significantly enhanced predictive performance. Among the hybrid models, NCA-BPNN achieved the best accuracy, with an R^2 of 0.912 and the lowest error values: RMSE (1.558 dB), SI (0.039), CRM (0.00), U_{95} (4.334), and BIC (78.4912). These findings highlight the potential of NCA in improving AI-based predictions of blast-induced air overpressure and noise. Figure 7 indicates the developed models for estimating AOp along with their corresponding R^2 values, demonstrating the effectiveness of various machine learning approaches in predictive analysis.

In 2022, Ye *et al.*[44] collaborated on 62 datasets and aimed to assess the effectiveness of a new hybrid evolutionary model that merges the Stochastic Fractal Search (SFS) algorithm with an integrated Adaptive Neuro-Fuzzy Inference System (ANFIS). In addition, ANFIS was integrated with a Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) to evaluate the acceptability and dependability of the ANFIS-SFS model. They used nine input parameters: DBH, PF, MC, St, B, S, RQD, NoH, and DBP, which represent a set of parameters and measurements commonly considered in blast design and explosive engineering. Together with a performance metric of R^2 value 1.223, this study produced a high accuracy (RMSE) value of 0.986. A study using a single dataset was conducted in 2022 by Chen *et al.*[3] using the SVR-GO-BFS7 model. This

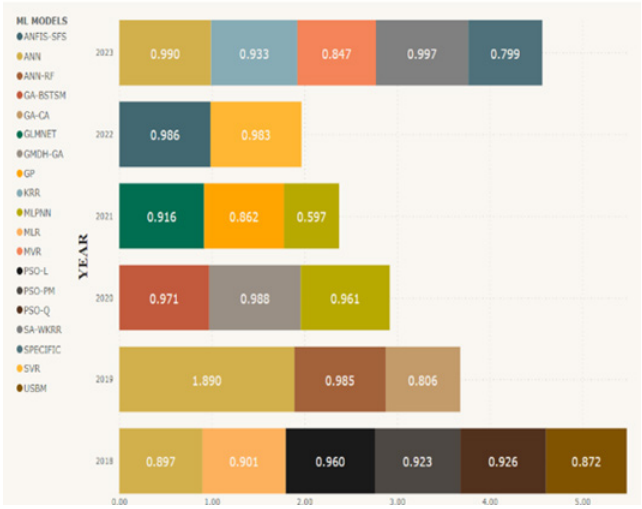


Figure 7. Developed models along with R^2 values to estimate AOp.

study utilised the GO algorithm to optimise SVR for forecasting the Aop caused by blasting. In addition, the BFS was employed as a novel input selection technique. The integration of these methods led to the development of a new algorithm named SVR-GA-BFS7 which used seven input parameters. There are primary explosive material used in the explosion was ANFO, a common industrial bulk explosive; the blast holes had diameters of 75, 89, and 115 mm, and granular gravel served as the stemming substance. The data collection process involved evaluating key blasting parameters such as RQD, burden (B), hole depth (HD), spacing (S), powder factor (PF), and stemming length (StL), considering both the bench height and RQD requirements. The study achieved an impressive R^2 value of 0.983 and an RMSE of 1.332, indicating high prediction accuracy. In 2021, Murlidhar *et al.*[45] conducted a study involving 125 datasets using the GP and M_5 models. The main goal of the current study was to create two distinct tree-based data mining algorithms, GP and M_5 decision trees, to precisely forecast blast-induced Aop in granite quarries. Furthermore, a multiple linear regression method was used to verify the accuracy of the GP and M_5 models. With six input parameters, StL, PF, BI, JA, MCD, and D of the BP, they were able to attain an accuracy of 0.8621. Furthermore, an RMSE value of 1.3997 was the performance metric obtained in this study. In 2021, Harandizadeh and Armaghani[12] collaborated on a study involving 75 datasets. They employed hybrid intelligence models, specifically ANFIS-PNN-GA

models, creating a novel hybrid intelligence method known as ANFIS-PNN-GA or ANFIS-PNN optimised by a biological algorithm (GA). From the FDM and the views of experts, four parameters, that is, the amount of explosive charge, PF, ST, and DBF, were identified as the most effective for Aop. The study yielded two sets of results: values (0.94, 0.72, and 0.84) and (0.92, 0.58, and 0.77) for different configurations. Additionally, the corresponding performance metrics were RMSE values (0.003, 0.03, and 0.021) and (0.005, 0.066, and 0.05). In 2021, Nguyen *et al.*[46] made valuable contributions to the field, as reflected in their work. The study employed a hybrid approach combining generalised linear modelling (GLMNET) with nonlinear neural network modelling utilising multilayer perceptrons (MLPNN). This integrated methodology, referred to as GLMNETs–MLPNN modelling, was applied to predict the AOp resulting from blasting activities in open-pit mines. Subsequently, six GLMNET models are developed.

The predictions are then aggregated using a bootstrap process to form new predictors. Subsequently, an optimal MLPNN model was constructed based on these aggregated predictors. To demonstrate the enhanced performance of the proposed GLMNET–MLPNN model, conventional models, including GLMNET, support vector machine, MLPNN, random forest, and empirical models, were also considered and developed using the same dataset, and a total of 180 blasts were gathered, encompassing AOp measurements along with blasting parameters. Earlier research findings suggest that crucial blasting parameters, including S, ECD, PF, St, B, and MD, exert significant effects on the AOp during blasting. The results indicated that combining the predictions of six generalised linear models (GLMNET models) through bootstrap aggregation and utilising a nonlinear model (MLPNN) significantly improved the accuracy of predicting AOp. This enhanced predictive model demonstrated a Root-Mean-Squared Error (RMSE) of 2.266, a determination coefficient R^2 of 0.916, and a Mean Squared Error (MAE) of 1.718. In contrast, the standalone models exhibited poorer performance, yielding RMSE values ranging from 2.981 to 4.686, R^2 values ranging from 0.597 to 0.860, and MAE values ranging from 3.156 to 1.990. Nguyen *et al.*[47] introduced the GA-BSTSM model in 2020. To assess the effectiveness of the suggested GA-BSTSM model, they developed an empirical model and six other artificial intelligence models for predicting Aop based on the same dataset. The models include CART, KNN, ANN, BRR, SVR, and GP. This study utilised 121 datasets and evaluated the performance of these models based on seven input parameters: W, R, T, RH, AP, WS, and WD. The results demonstrated an R^2 value of 0.971 and an RMSE value of 1.726 for the GA-BSTSM model. In 2020, Hoang Nguyen *et al.*[48] explored 77 datasets. In this study, three types of neural networks were developed: HYFIS, BRNN, and MLPNN to predict AOp. This study used eight input parameters. To assess the accuracy of the AOp prediction models proposed in this study, 146 blasts were gathered from the Deo Nai open-pit coal mine. These explosions were characterised by typical parameters associated with explosion design, including AOp, B, S, PF, number of borehole rows per blast (N), Air-blast Overpressure MD, CPD, Bh, StL, and AH. Notably, the impact of AH on AOp was highlighted, achieving a coefficient of determination value of R^2 96.1% and a loss of including a mean-square error (RMSE)value of 2.319. In 2020, Gao *et al.*[49] presented a study involving GMDH–GA models and suggested a novel hybrid approach by combining the Group Method of Data Handling (GMDH) with GA. In other words, GA was utilised for the optimisation of the GMDH. For this study's modelling, 84 sets of data from the Shur River Dam were gathered. The models demonstrated a high level of accuracy, achieving an R^2 value of 0.988. In this study, we developed an approach to predict AOp, with one output parameter and four input parameters in the database that was created. This database includes PF, BP, MSD, MC, and RMR data. In 2020, Victor Amoako Temeng *et al.*[50] analysed 171 datasets using BPNN, GMDH, and SVM and proposed a new class of advanced artificial neural networks known as Brain-Inspired Emotional Neural Networks (BIENN) to predict AOp. The proposed BI-ENN approach was compared with two classical AOp predictors (generalised predictor and McKenzie formula) and three established AI methods: BPNN, GMDH, and SVM. The authors' current decision was to choose and employ the StL, number of blast holes per blast, MIC (kg), and D between the MOS and BP as the input parameters. The results revealed an R^2 of 0.8249 and an RMSE of 1.0941. In 2020, Bui *et al.*[51] introduced datasets tagged 97. This study compared and applied seven AI techniques to predict blast-induced AOp. The seven techniques are ANN, BRT, Bayesian additive regression trees, GP, Gaussian processes, random forests, and k-nearest neighbours. Additionally, an

empirical method was employed for comparison with the AI models. These models were evaluated using seven input parameters, yielding an R^2 value of 0.930 and an RMSE value of 7.514. In 2020, Qiancheng Fang *et al.*[15] introduced a dataset of 132. They applied the Genetic Algorithm-Cubist Algorithm (GA–CA) model and evaluated it using various techniques, including Genetic Programming (GP), Classification and Regression Trees (CIT), Hybrid Fuzzy Inference System (HYFIS), Principal Component Analysis (PCA), and k-nearest neighbours (k-NN). The parameters of the GA, including the number of populations (p), the number of variables (n), crossover probability (Pc), and mutation probability (Pm) The model achieved an R^2 value of 0.806 and an RMSE (Mean Square Error) value of 3.884. In 2020, Murlidhar *et al.*[52] and colleagues explored various machine learning models, including ANN, ANN-PSO, GA-ANN, FIS, and SVM, using inputs such as S, B, HD, HD, STL, NOR, and BDP. Their study encompassed 96 datasets, achieving a remarkable accuracy of R^2 value 0.99, with the FIS model. In 2019, Nguyen *et al.*[53] researched a robust artificial intelligence system, named ANNs-RF, designed for predicting blast-induced AOp by leveraging ANNs and Random Forest (RF). The development process involved the creation of five ANN models that were subsequently combined using the RF algorithm. Additionally, empirical techniques, ANN models, and RF models were developed for prediction and comparison with the ANNs-RF model. This study utilised data from 114 blasting events at the Nui Beo open-pit coal mine in Vietnam with input variables for predicting AOp, including MECC, MD, VD, PF, B, S, and StL. The findings revealed that the proposed ANNs-RF model outperformed the other models, exhibiting superior performance on the testing dataset with an RMSE of 0.847, R^2 of 0.985, MAE of 0.620, and a total ranking of 40. In contrast, the best-performing ANN model showed slightly lower metrics, with an RMSE of 1.184, R^2 of 0.960, MAE of 0.809, and a total ranking of 39. The RF model performed with an RMSE of 1.550, R^2 of 0.939, MAE of 1.222, and a total ranking of 22. The empirical model demonstrated the lowest accuracy levels on the testing dataset, with an RMSE of 5.704, an R^2 of 0.429, and an MAE of 5.316. Writing samples to get you started. In 2019, H. Bakhshandeh Amnieh *et al.*[54] introduced a machine learning model, SA, designed to process 70 datasets using input parameters, such as HD, CW, B, S, STL, CD, and DBF.

In 2018, Mahdiyar *et al.*[55] presented a dataset comprising 76 datasets. In this study, to address the blast-induced AOp problem, the authors utilised both Multiple Linear Regression (MLR) and Monte Carlo simulation techniques. The established equation was employed as the basis for the Monte Carlo simulation. The Monte Carlo simulation incorporated eight variables: HD, St, B, S, MCD, PF, TC, and DBF. The model demonstrated an R^2 value of 0.901 and a Mean Square Error (RMSE) value of 3.379. In 2018, Shokravi *et al.*[56] presented a study that involved 80 datasets. They employed Particle Swarm Optimisation (PSO), ANN, and the United States Bureau of Mines (USBM) models. The models were based on three input parameters, which are within the engineers' power to alter the blast design or controllable parameters, such as SC, WCD W, B, S, TDI, SUD, WC, SR, and KEM. The results showed an R^2 of 0.960 and a (Mean Square Error) of 4.33. In 2018, Armaghani *et al.*[57] developed ANN and GA-ANN models to analyse various parameters affecting blasting operations. These parameters include EM, TWC, MC, BHD, D, DBF, Pf, DIR, B, S, St, and SD. These models were designed to accommodate the changes made by blasting engineers. With a dataset comprising 97 samples, the R^2 values obtained were 0.961 for ANN and 0.965 for GA-ANN, indicating a high predictive accuracy for both models. Figure 8 represents the Machine learning models applied between 2019 and 2023 for the assessment of Air Overpressure (AOp) levels.

In 2017, Hasanipanah *et al.*[58] conducted a study using 83 datasets. This study introduces a novel hybrid model for predicting blast-induced AOp by combining PSO with Support Vector Regression (SVR). The PSO–SVR model incorporates Linear (L), Quadratic (Q), and Radial Basis (RBF) kernel functions, denoted as PSO-SVR-L, PSO-SVR-Q, and PSO, respectively. This study also utilised and developed an MLR model to assess the accuracy of the proposed PSOSVR models. In the examined case, monitoring was conducted, and the values of two influential parameters affecting the blast-induced AOp, namely MCD and DBF, were measured. These parameters were then chosen as input variables to develop predictive models. In 2016, Hasanipanah *et al.*[59] explored the utilisation of ANN, fuzzy system, and Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting parameters such as burden, spacing, number of blast-holes, blast-hole depth, blast-hole diameter, sub-drilling, bench height, stemming height, as well as the

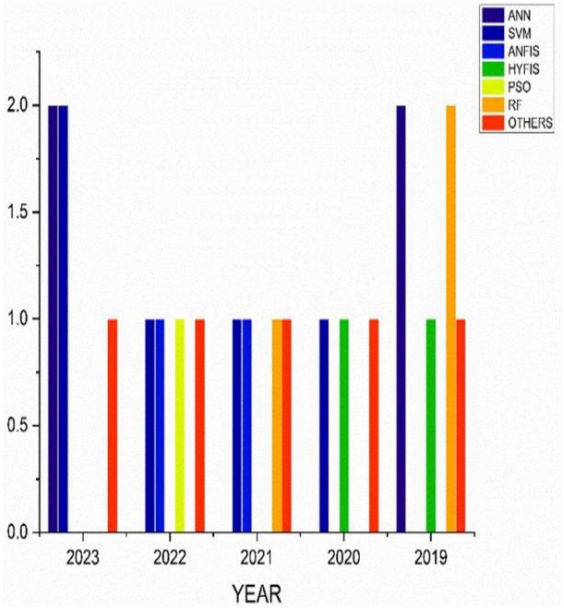


Figure 8. Applied ML models from 2019 to 2023 to assess the AOp levels.

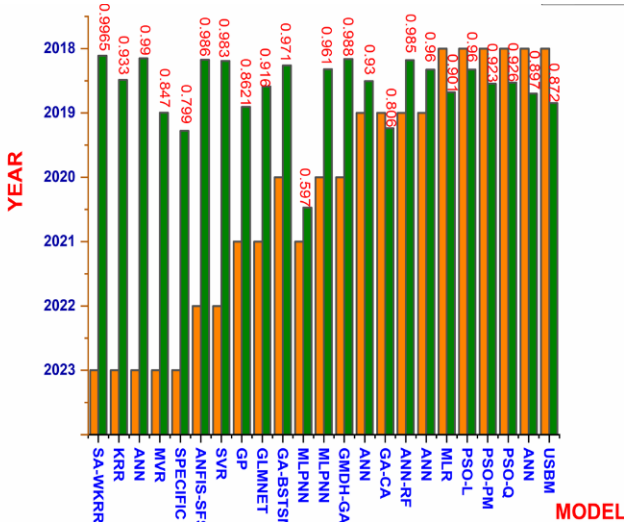


Figure 9. All ML models, along with R^2 values from 2018 to 2023.

type and weight of explosive materials. Their analysis involved 77 datasets, yielding R^2 values of 0.878 for the ANSFIS, 0.797 for the fuzzy system, and 0.650 for the ANN. In 2016, Armaghani[60] utilised ICA-ANN and ANN models to predict the AOp in blasting operations. Their analysis focused on input parameters, such as the maximum charge per delay and the distance from the blast face, using a dataset comprising 70 samples. The study revealed correlation coefficient R^2 values of 0.886 for the ICA-ANN and 0.882 for the ANN, indicating a strong predictive capability of the models for estimating the AOp in blasting practices. The below Figure 9 indicates that all ML models developed from 2018 to 2023 are presented along with their corresponding R^2 values.

A study comprising 95 datasets was conducted in 2015 by Armaghani *et al.*[61] The input layer included two factors that had the greatest effects on AOp: The DBF and the MC. Four input parameters were used to create the ICA-ANN model, which was trained using measurements of the most important parameters of AOp, such as the MCD and the separation between the BF and MP. An additional empirical equation was created to predict the AOp based on the generalised predictor equation and measured data from the granite quarry site. Conventional ANN models were created, and their outcomes were compared with findings for comparative analysis. The findings showed that compared to other methods, the suggested ICA-ANN model can predict blast-induced AOp more accurately. In 2015, Hajihassani *et al.*[62] presented machine learning models, PSO-ANN, which utilised input parameters such as HD, MCD, B-TO-SPACING RATIO, STL, SUD, PF, and NOH, applied to 88 datasets. The achieved values were 1.714 and 0.89 for ANN and PSO, respectively. In 2015, Danial Jahed Armaghani, Mohsen Hajihassani, Masoud Monjezi, Edy Tonnizam Mohamad, Aminaton Marto, and Mohammad Reza Moghaddam[63] employed ANN and ANFIS models to analyse the relationship between maximum charge per delay and distance from the blast-face. Using a dataset comprising 166 samples, the study yielded an impressive R^2 value of 0.947, indicating the strong predictive capability of the models for this analysis. In 2014, Hajihassani *et al.*[64] employed a dataset comprising 62 quarry blasting records for the analysis. The input parameters for the PSO-based ANN model included nine input parameters: HD, PF, MCD, StL, B, S, RQD, and NOH, and two sets of SF were obtained for two distinct distances in front of the blast face. The accuracy of the suggested PSO-based ANN model was evaluated by comparing the AOp values with the results derived from the empirical formulas. In 2017, Hasanipanah *et al.*[65] conducted a study using 83 datasets. This study introduces a novel hybrid model for predicting blast-induced AOp by combining Particle Swarm Optimisation (PSO) with Support Vector Regression (SVR). The PSO–SVR model incorporates linear (L), quadratic (Q), and radial basis (RBF) kernel functions, denoted as

PSO-SVR-L, PSO-SVR-Q, and PSO, respectively. This study also utilised and developed an MLR model to assess the accuracy of the proposed PSO and SVR models. In the examined case, monitoring was conducted, and the values of two influential parameters affecting the blast-induced AOp, namely MCD and DBF, were measured. These parameters were then chosen as input variables to develop predictive models. In 2016, Hasanipanah[66] and ANFIS for predicting parameters such as burden, spacing, number of blast-holes, blast-hole depth, blast-hole diameter, sub-drilling, bench height, stemming height, as well as the type and weight of explosive materials. Their analysis involved 77 datasets, yielding R^2 values of 0.878 for the ANSFIS, 0.797 for the fuzzy system, and 0.650 for the ANN. In 2016, Armaghani[67] utilised ICA-ANN and ANN models to predict the AOp in blasting operations. Their analysis focused on input parameters, such as the maximum charge per delay and the distance from the blast face, using a dataset comprising 70 samples. The study revealed correlation coefficient R^2 values of 0.886 for the ICA-ANN and 0.882 for the ANN, indicating a strong predictive capability of the models for estimating the AOp in blasting practices. A study comprising 95 datasets was conducted in 2015 by Armaghani *et al.*[68] The input layer included two factors that had the greatest effects on AOp: the DBF and the MC. Four input parameters were used to create the ICA-ANN model, which was trained using measurements of the most important parameters of AOp, such as the MCD and the separation between the BF and MP. An additional empirical equation was created to predict the AOp based on the generalised predictor equation and measured data from the granite quarry site. Conventional ANN models were created, and their outcomes were compared with ICAANN findings for comparative analysis. The findings showed that compared to other methods, the suggested ICA-ANN model can predict blast-induced AOp more accurately.

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In 2010, Segarra[72] employed a dataset consisting of 122 records from 40 blasts, encompassing 15 input parameters. These parameters included Hd, NOR, BH, blast hole inclination, B, S between BH, mass of explosive detonated in a delay (M), energy (heat of explosion) in a delay (E), StL, PF, delay within rows, delay between rows, firing velocity down the face (VI), explosive types, and in-hole and surface initiation systems. The model was developed using blast data and air blast measurements from 122 records of 40 blasts, including a single shot conducted in low-to very-low-strength rocks. The initiation velocity ranged from 67 to 383 m/s, while the explosive mass in a delay varied from 21.3 to 284 kg. Linear-type microphones were used to measure the air blast around the blasted blocks at distances ranging from 45 to 394 m. The peak overpressures were measured within a range of 482-6 Pa with a relative expanded uncertainty of 13.1%. The model demonstrated statistical significance,

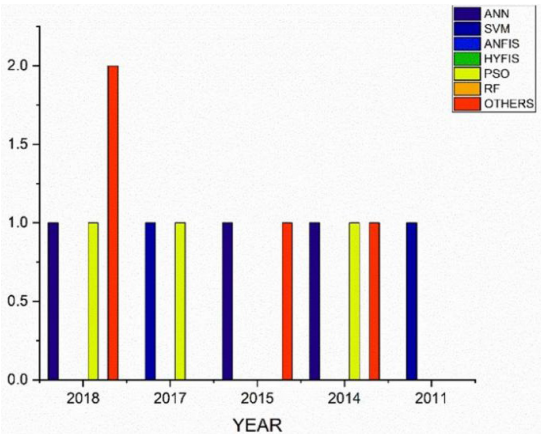


Figure 10. Applied ML models from 2011 to 2018 to assess the AOp levels.

accounting for 87% of the variation in the logarithm of the overpressure. Interestingly, substituting the explosive energy for the explosive mass did not affect the fit quality. The accuracy of overpressure prediction was determined to be 32%. The below Figure 11 depicts ML models that have been featured in a significant number of published papers, highlighting their widespread application and research interest across various domains. Similarly. Figure 12 exhibits the Chronological application of various ML models in AOp prediction.

The empirical equation introduced by Kuzu *et al.* in 2009[73] is designed exclusively for a singular dataset characterised by 13 input parameters. These parameters include the CWD, LOD, DA, B, and S, stemming amount and type, charge length and diameter, angle of BH, DOI, CWB, CD, bare versus covered detonating cord, and IS (electric or non-electric). Adhikari *et al.*[74] used 125 datasets, including five seismographs and microphones, with four input parameters: TC (kg), NOH, DH, and DFB in 2007. Seismographs of the same make and model and five microphones were compared to determine whether the measurements of the air overpressure from a source at various distances were accurate. While the readings from the four microphones were identical, the fifth had some differences. The impact of the mounting height on air overpressure measurements was also investigated using the same five microphones and seismographs. A microphone was used in 2005 by Eltschlager[75], a Mining/ Explosives Engineer at Pittsburgh, Pennsylvania's Office of Surface Mining Reclamation and Enforcement. In this study, measurements of the Air Overpressure were conducted at various height intervals and subsequently compared. The study utilised blasting seismographs that adhered to the ISEE (International Society of Explosives Engineers) "Performance Standards for Blasting Seismographs." These seismographs were used to monitor blasting activities at construction sites, quarries, and coal mines. Representative spectral and amplitude ranges were obtained by taking measurements in both near and far fields. Comparative analysis demonstrated that the air overpressure measurements were barely affected by the height of the microphone. The air overpressure readings for blasts of the coal mine, quarry, and construction types were compared at microphone height intervals ranging from 0 to 5 feet. The comparative analysis revealed that the microphone height had little effect on the air overpressure measurements based on waveforms, amplitudes, and spectral energy.

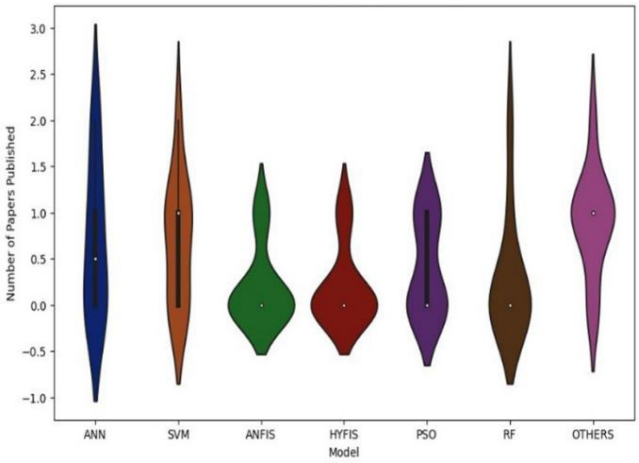


Figure 11. ML models show a significant number of published papers

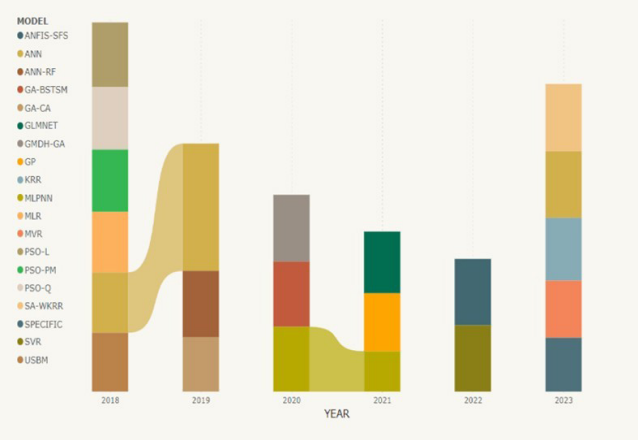


Figure 12. Various ML models utilized over the years to predict AOp

Wu *et al.*[76] developed a numerical model in 2005. As waves travel differently through geomaterials and air, the ground shock typically reaches a structural foundation before the air blast pressure. However, depending on how far away the explosion centre is from the structure, ground shock and air blast may act on it simultaneously. Therefore, both ground shock and air blast pressure should be considered in a precise analysis of the response of the structure and damage resulting from a nearby surface explosion. However, the current procedures often only consider the air blast pressure. Numerous empirical relationships exist for forecasting air blast pressure, yet the majority focus solely on predicting the peak pressure

levels. The main goal of this study was to establish readily applicable simultaneous forces of ground shock and air blast for use in structural response analysis. The time delay between the arrival of the air blast pressure and ground shock at the structure was calculated. Utilising these empirical formulas can improve the accuracy of estimating explosive loads when modelling the response and damage of structures to surface explosions. Empirical formulas were employed to ascertain the time gap between the air blast pressure and the arrival of the ground shock at the structure. Utilising these formulas provides a more accurate method for estimating explosive loads when modelling the response and damage of structures to surface explosions. In 2021, Jaroonpattanapong *et al.*[77] employed Machine Learning AI/ML techniques with input parameters B, S, and SDT to generate air wavefronts transmitted in all directions from the BH. They utilised 54 datasets for the analysis. Raina *et al.*[78] examination of the human reaction to blasting in four mining regions throughout India indicates that the response is not solely political, as often assumed. The findings reveal that regardless of the individuals surveyed, a fundamental concern for the safety of property emerged as the primary response. Proposing a methodology to consider human response criteria becomes essential when contemplating blasting within 400 m of inhabited areas, assuming that a completely negative reaction from residents would result in complaints. However, the significance of Air Overpressure has received less attention. The vastness of the literature and the diverse range of topics discussed make it impractical to incorporate the entire relevant literature into this paper.

In 2000, Wharton *et al.*[79] examined the air blast generated by explosives in the commercial sector, characterised by detonation velocities (VoDs) ranging from 2000 to 8200 m/s. Two distinct methods for calculating the TNT equivalent (TNTe) yielded highly comparable results, consistently ranking the explosives in the same order. The average TNTe values also demonstrated reasonable agreement with those obtained from the ballistic mortar experiments. However, there is an indication that as the explosive energy decreases, the impact of the loss of confinement becomes more pronounced, especially when the explosive is tested in an airburst configuration. Michael Sharp *et al.*[80] 1998 To determine air overpressures about the distance from shallow subsurface detonated charges and to establish parameters for predicting blast effects beyond the boundary of the ordnance disposal facility. This concern is addressed by establishing conservative operational parameters, such as charge size, and allowing for permissible weather conditions. These measures are designed to ensure that blast effects do not threaten the integrity of these structures. Employing conservative parameters is crucial not only to prevent actual damage but also to minimise claims of perceived damage arising from public awareness of blasting activities. In 1995, blasting generated airborne energy known as air blast overpressure or impulsive sound[81]. An air blast dissipates as distance increases, experiencing a reduction in energy amplitude or "loudness" from the blast site to the monitoring location. Although there are fewer variations, air blast regulations are just as inconsistent as those governing the ground vibrations. Recommendations for the U.S. Bureau of Mines' RI 8485[91]. were precisely followed by federal regulations regarding air blasts from surface coal mining (OSM). Four recommended limits, ranging from 105 to 134 dB, are contingent on the method used to measure and analyse the air blast. Air blast regulations are not uniform or consistent when it comes to non-coal blasting. The Wisconsin Rules of 1987, which regulate vibration and air blasts, have already been mentioned. They also adopted RI 8485 criteria for general blasting situations. Most states do not have set air-blast limits. In 1993, Clerico and Patrucco[82] presented initial findings from their research study conducted at the Centro per la Sicurezza del Lavoro Minerario e di Scavo, a research centre specialising in safety within mining and underground operations. Operating under the auspices of the Dipartimento Georisorse e Territorio at the Politecnico di Torino, the centre aimed to develop a straightforward technique for predicting the blast peak sound pressure levels. This technique can be applied to mitigate noise levels in communities and guide the formulation of noise control strategies and residential area plans. The predictive method depends on comprehending the primary noise propagation characteristics of the area and specific parameters such as the explosive charge, millisecond delays, depth, and stemming. Given the infrequency of wind speeds exceeding 1 m/s and the focus on reducing community noise, this study disregarded the impact of meteorological conditions. The examination of an air blast, viewed from a simplified acoustical perspective, is crucial because of its potential to cause

significant annoyance in the community. Sudden peak sound pressure levels can be measured at levels more than 60 dB higher than the background noise. In March 1987, Rosenthal and Morlock[83] were likely involved in a joint attempt, such as a collaboration on a project or the release of a publication. The consultant is an expert in blasting vibrations before hiring them to handle air-blast monitoring programs. Though this measure may seem unnecessary, A recent proposed local air blast ordinance was formulated based on the study of a professional engineer who not only seemed unaware of the differences between "sound" and "air blast" but also appeared to lack a full understanding of the contrast between an impulsive event and a steady state. He made an effort to apply noise study metrics, such as dBA, Leq, and d'. He also grounded his conclusions on determines obtained from a single location in a mountainous area, resulting in only two events. If a potential consultant is about to monitor a shot, exhibits any of the aforementioned tendencies, or uses a "sound level decibel meter," it should be immediately assumed that he lacks the necessary experience or competence in blast vibration monitoring and control. Take great care when choosing a consultant. By Kopp and Siskind[84] 1986 At a surface coal mine in southern Indiana, 52 production blasts were monitored and instrumented. Seismograph arrays were deployed to capture the time-past events of both vibrations and air blasts. The gathered data underwent analysis to pinpoint peak values for both vibration and air blast, alongside evaluating the frequency content. Different delay intervals were utilised within and between the rows of blast holes. The air blast was influenced by the trace velocity along the free face, making it advisable to choose a trace velocity determined by the delay interval and distance between holes in an echelon, which is slower than the speed of sound in the air. Opting for delays resulting in a trace velocity at 80 per cent of the speed of sound, as opposed to supersonic velocity, led to a reduction of approximately 6 dB in the air blast. For each row or level, it is recommended to have intervals between holes longer than one millisecond per foot spacing to prevent air blast wavefronts from each hole, reinforcing each other. Careful consideration in selecting delay intervals was emphasised to avoid alignment of air blast frequencies with the natural frequencies of the midwalls in adjacent structures, typically ranging from approximately 11 to 25 Hz. Delay intervals shorter than 40 ms are generally considered unproblematic.

It is normal to experience an air blast and ground vibrations after blasting. However, there are two unique issues with steep-slope contour mines in Ap Palachia that have an impact on the air blast's creation and spread, and, to a lesser extent, ground vibration. For prediction and design control, the industry requires technical data on rock fragmentation caused by blasting, including the creation and propagation of blast-produced vibrations and noise. This indicates that the air blast amplitude drops by 6 dB for each doubling of the distance between the blast and the receiver. Although there exists a range of attenuations from 3.1 to 10 dB due to variations in both source spectra and propagation conditions, the majority of mining values clustered around 5 dB per doubling of distance. Given the prevalence of lower frequencies in mining air blast values, a-5 dB reduction is deemed typical. Two comprehensive summaries of air blast measurements on steep-slope contour mines were conducted to facilitate comparisons with summaries from other mining methods. Measurements from shots 154 to 196 were taken in rolling terrain and steep-slope contour mines located in Ohio and Virginia. These findings were previously documented by the Bureau of Mines (RI 8485). For this study, shots beyond 196 were specifically tracked, with gaps representing mines outside the contour mining area. In this study, shots 154-329 were used for the analysis. In 1984, Virgil J. Stachura, D. E., Siskind, and A.J. Engler[85] conducted a study that compared broadband research instrumentation with commercially available impulse precision sound level meters. The investigation included the measurement of various parameters, including mean square, peak, fast, slow, impulse, A and C weighting, C-weighted Sound Exposure Level (CSEL), and "linear" (flat) response. These measurements were gathered through field assessments and the analysis of broadband FM tape recordings capturing production blasts in areas and contour coal mines, limestone quarries, and iron mines. In addition, the frequency responses of 14 different commercial systems were evaluated. The Bureau has been engaged in research on instrumentation and air blast issues since 1939. The focus of this research was poorly confined or uncontrolled blasts, which can be measured using common commercial sound measurement equipment. These blasts are predominantly composed of acoustic energy within the audible range (20-20 kHz). In a separate study conducted in 1973, Siskind and Summers utilised instruments with varying frequency responses to

survey the air blast noise from traditional quarry blasting. In 1980, a collaborative study by Siskind *et al.*[86] examined sonic booms and human reactions to brief overpressures. This study combined insights from direct measurements of air blast-induced structural responses, damage assessments, and instrument characteristic analyses. The study identified specific safe air blast levels: 134 dBL (0.1 Hz), 133 dBL (2 Hz), 129 dBL (6 Hz), and 105 dB C-slow. These levels, along with their corresponding measurement techniques, were deemed equivalent in gauging structural responses. Thus, any of these methods could be employed as criteria for determining safe levels and offering practicality for various industries. Among these methods, the 0.1-Hz high-pass linear approach accurately gauges the total air blast energy. However, for a singular air blast measuring system, a 2-Hz linear peak response emerged as the optimal compromise. The study highlighted that the primary contributor to human annoyance and reactions to air blasts likely stems from wall rattling and subsequent secondary noise[87,88]. The significance of controlling noise and its effects on the environment while blasting away unnecessary materials. There is a way to lower noise levels and improve operational efficiency by adding time delays between the explosive charges. To avoid complaints and maintain good relations with surrounding communities, the noise produced by the rock drill must be addressed. It is common knowledge that noise levels (Leq) in living rooms range from 40 to 45 dB(A) and in bedrooms from 30-35 dB(A). These would be comparable to outside dwelling levels of 50-55 dB(A) during the day and 40-45 dB(A) at night, when windows are open. Although such levels might be deemed 'acceptable' in the sense that they would not likely disrupt restful sleep or casual conversation, it is important to keep in mind that opinions regarding noise levels are influenced by a variety of factors. Although guidelines exist for determining Leq for the measurement period, there is a dearth of general information, none of which is especially pertinent to noise from opencast mining regarding the application of short-term measurements to obtain Lcq values over extended periods. Amin S *et. al*[89] in 2024 Machine learning serves a wide array of functions, including social media analysis, healthcare, diagnosing Coronavirus Disease, advertising, credit approval, employment, education, and criminal justice. Surveillance systems based on Social Media (SM), when integrated with Machine Learning (ML) and Deep Learning (DL) techniques, have demonstrated promise in detecting epidemic outbreaks at an early stage. This review examines the present status of SM-based surveillance methods designed for the early detection of epidemic outbreaks, while also exploring the contribution of ML and DL to augment their efficacy. Machine-learning models uncover patterns within data and accumulate knowledge, thereby progressively enhancing their performance. Within supervised machine learning, the central focus is on classification, which aims to ascertain a suitable category or class for a given entity by analysing its features or parameters. Supervised classifiers employ techniques to capture the interplay between data, posing numerous challenges for machine learning. Figure 13 below conveys the representation of each model and its R^2 value with a unique colour to help visually distinguish and compare their performance effectively.

This process involves leveraging extensive datasets to train algorithms that subsequently utilise these correlations and patterns to make predictions or decisions on new data. Common machine-learning techniques include RF, DT, SVM, and LR[90]. This paper focuses on the diagnosis of Corona Virus Disease 2019. Initially, the document outlines the diagnostic procedure employing machine learning, covering key stages such as medical data collection, image preprocessing, feature extraction, and image classification. Following this, we delve into a detailed examination of seven methodologies: transfer learning, ensemble learning, unsupervised learning, semi-supervised learning, convolutional neural networks, graph neural networks, and explainable deep neural

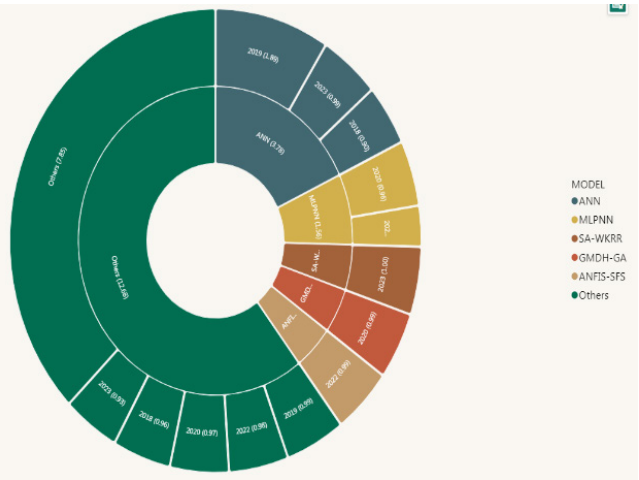


Figure 13. Representation of each model and R^2 value with one unique color.

networks, among others. We also conduct a comparative analysis of the benefits and drawbacks of these diagnostic approaches. AI technologies not only contribute to achieving more accurate predictions in areas like advertising, credit approval, employment, education, and criminal justice but also empower decision-making in these domains with significant implications. AI has found applications across diverse fields, including scholarship recipient selection, mortgage approvals, and economic capital allocation. Furthermore, studies focusing on risk factors incorporating fairness principles and addressing underlying challenges have been undertaken[91]. Figure 14 describes an overview of different machine learning models employed during the specified year. Figure 15 demonstrates a Year-wise summary of the data, including an analysis of all models developed, providing insights into their performances and trends over time.

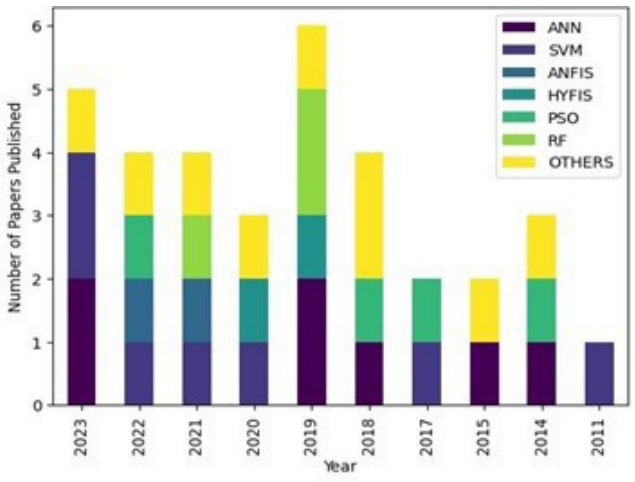


Figure 14. The diverse array of ML models in the specified year.

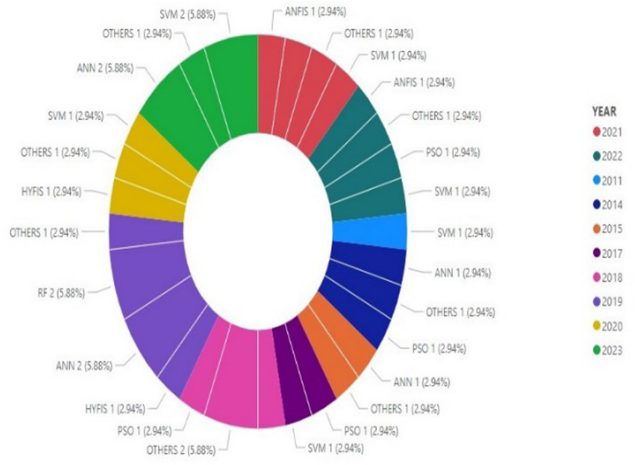


Figure 15. Year-wise summary of the data along with an analysis of all models.

9.0 Future Work

The authors of the previous study utilised 15 input parameters, including row count, hole diameter (d), bench height (H), burden (B), blast hole inclination, distance between blast holes (S), explosive mass that detonates gradually (M), explosion energy (E), stemming length (T), powder factor, interval between rows, interval within rows, velocity of firing down the face (VI), explosive categories, and systems of surface and in-hole initiation. Additionally, factors such as bench width, bench spacing, number of blast holes, joint gaps, joint openings, acceleration down the face, acceleration up the face, distance from the bench gap, and the number of benches were also considered.

This study explores the application of machine learning techniques for blast-induced air overpressure prediction, employing various models such as ANN, Support Vector Machines (SVM), Hybrid Fuzzy Inference Systems (HYFIS), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Multiple Variable Regression (MVR), and Brute Force Search (BFS). Furthermore, deep learning approaches, including Convolutional Neural Networks (CNN) and multi-objective optimisation using ANN combined with Genetic Algorithm (GA) optimisation methods, were investigated to enhance predictive accuracy.

10.0 Research Challenges

Gathering a dataset for mining operations is a challenging task due to the complexities involved in accessing and compiling relevant information from various sources, including sensors, machinery logs, and geological surveys. The remote and harsh environments of mining sites further complicate data collection, making the process even more demanding.

One major challenge in machine learning for blast-induced AOp prediction is overfitting, which occurs when a model learns noise or irrelevant patterns from the training data, resulting in poor performance on new, unseen data. To mitigate this risk, cross-validation is employed, where the dataset is iteratively split into

training and testing subsets to evaluate the model's generalisation ability.

The training phase involves using historical data to teach a machine learning model how to predict AOp, while the testing phase assesses its accuracy and reliability on unseen data. This process ensures that the model can perform well in real-world scenarios. Additionally, training and testing on air overpressure data involve simulating blast effects to evaluate potential damage, refine blast designs, enhance structural resilience, and develop safety protocols to mitigate risks associated with explosive operations.

11.0 Conclusion

The integration of Machine Learning (ML) techniques in mining operations has significantly enhanced blasting optimization, prediction accuracy, and environmental impact assessment. This study highlights the increasing adoption of advanced ML methods in addressing blast-induced air overpressure and other critical challenges. Over the past decade, 61% of research efforts have demonstrated that hybrid and ensemble ML models outperform traditional empirical approaches in both surface and underground blasting. While surface blasting optimization has progressed due to advancements in blast design and controllable parameters, underground blasting remains a challenging frontier due to complex operational conditions and limited research.

ML techniques offer a transformative approach to mining operations, providing data-driven solutions to predict, monitor, and mitigate blasting impacts more accurately. However, maximizing their potential requires (i) increased awareness of technological advancements, (ii) stronger collaboration between research institutions and mining companies, and (iii) enhanced training programs for mining personnel. By addressing these aspects, the mining industry can improve safety, optimize operational efficiency, and minimize environmental risks. The inevitable shift towards automated mining will further solidify ML's role as a key enabler of sustainable and precise blasting practices, ensuring the long-term prosperity of the sector.

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