Assessment of Supervised Machine Learning Models for their suitability in Flyrock Type Prediction induced by Mine Blasting

Padmavathi G [1], *Dayang Zulaika* Abang Hasbollah[2*], *Edy Tonnizam* Mohamad[2], *Roshni* A[3], *Ramesh* Bhatawdekar[4], and *Mohd Firdaus* Md Dan @ Azlan[5]
[1]Department of Computer Science, Avinashilingam Inst. for Home Science and Higher Education for Women, Coimbatore, Tamilnadu, India

[2]Centre of Tropical Geoengineering, Universiti Teknologi Malaysia
[3]Centre for Cyber Intelligence Avinashilingam Inst. for Home Science and Higher Education for Women, Coimbatore, Tamilnadu, India
[4]RMB Consultant, 2C 183, Kalpataru Hills Ph 2, Thane 400 604 India
[5]Sustainable Geostructure and Underground Exploration, Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn Malaysia, 86400 Batu Pahat, Johor, Malaysia

Abstract. Blasting is an essential operation in mining and construction for breaking hard rock, but it inherently risks the dangerous phenomenon of flyrock, which can cause injury to personnel and damage to nearby infrastructure. Consequently, the accurate prediction of flyrock type (e.g., fractured, mid-wall (MW), or fresh) during mine blasting is critical for safety in construction areas. This study addresses this need by implementing eight different Supervised Machine Learning (SML) models—including Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM)—to precisely forecast flyrock type based on real-time blasting parameters and rock mass properties. The models were trained and evaluated using a dataset comprising 152 blasting events recorded across three open-pit granite mines in Johor, Malaysia. The performance of the constructed SML models was rigorously assessed using standard validation metrics such as accuracy, precision, recall, and F1 Score. The results demonstrate the superior predictive capabilities of the ensemble models, with the Decision Tree, Random Forest, and AdaBoost models all achieving 100% accuracy in flyrock type prediction with zero prediction loss, thus providing robust tools for enhancing safety management in quarry and construction operations..

Keywords: *AdaBoost, Decision Tree, Flyrock Prediction, Mining, Random Forest, Supervised Learning*

*Correspondions author: dzulaika@utm.my

1 Introduction

For the vast majority of civil and mining engineering applications, breaking or moving hard rock with blasting is recognised as a standard procedure. Only a small percentage, up to 20–30%, of the explosive energy used in mine blasting is used to move and divide rock masses. The residual energy dissipates, producing harmful side effects like flyrock, air pressure buildup, and ground vibration.

Various AI techniques are developed for prediction of ground vibration, back-break, overbreak and fragmentation due to blasting. Based on point from where initiation of explosives, energy distribution plays crucial role in breaking rock. Geological conditions such as high in situ stress, crack formation, joints have influence on the blasting performance.

Flyrock is seen as a potentially lethal side effect. It has been suggested that the blast design parameters like controllable factors, must be used to regulate flyrock expanse in open-pit mines. These characteristics are the stemming length (ST), burden, and explosive charge per metre (CPM), as well as the powder factor (PF), burden (B) and hole diameter (d) [1-2]. In fact, the researchers in their work [3] claimed that the flyrock distance is influenced by the diameter of the hole and offered an empirical method for determining it. Similar to this approach, researchers have developed an empirical technique for forecasting flyrock distance that considers the ratio of stemming to burden (ST/B) [4]. Based on the correlation between ST/B and rock quality classification, the researchers established a new empirical formula to roughly calculate flyrock distance (RQD) [5]. The majority of the numerous studies that have examined empirical equations for calculating flyrock distance have used the parameters that can be controlled during blasting [7-8]. Several artificial intelligence techniques are applied for prediction of flyrock [9-10].

The parameters for evaluating the factors that influence the mine blasting components are based on the research on the investigation of flyrock distance that was described previously. But there are not many evidences to predict the flyrock type during mine blasting using the same parameters. A review of earlier research regarding the type of flyrock forecasting and range utilizing AI-based techniques (as described in Table 1) revealed that the controllable blasting parameters and a number of rock mass uncertainty parameters were used by researchers to forecast flyrock type and the distance. The majority of researchers only utilized one unknown parameter to make such predictions [11-15]. For the prediction of flyrock type and distance, many computational models with configurable parameters were also created. Nevertheless, not all mine blasting parameters are utilized to predict the type of flyrock rock based on flyrock distance. Hence, to identify the flyrock type in open-pit granite mines, this study examines the effects of geological parameters such the geological strength index (GSI), hole diameter (d), rock quality designation (RQD), stemming by burden ratio (ST/B), hole depth (HD), charge per meter (CPM), weathering index (WI) and power factor (PF) and they are considered to forecast the flyrock type prediction using SML algorithms. In the recent years, AI has gained recognition as a cutting-edge method for solving a variety of challenges in the real world. Numerous studies have used a variety of mechanisms, including ensemble learning methods (ELMs), such as the extreme gradient boosting (XGBoost) and random forest regression (RFR), to handle a variety of geotechnical difficulties. Many researchers have also developed a mixture of AI models to calculate flyrock distance and forecast the kind of flyrock in order to solve the limitations of empirical techniques as shown in Table 1. However, due to the differences in the characteristics of rock mass and explanatory power of the induced models, they do not adequately cover all parameters. Flyrock were classified with new system in opencast mines. On the other hand, fuzzy system was developed for prediction of flyrock.

Therefore, this study focuses on prediction of flyrock rock type during mine blasting based on various geological parameters by considering the uncertainty components of rock

mass properties. Since the dataset is a labelled one, supervised machine learning methods are more appropriate to determine the prediction of flyrock type. In this study, eight SML prediction models are developed. They are Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), AdaBoost (AB), Multi-layer Perceptron (MLP) and Logistic Regression (LR).
Table 1 presents the various AI models to predict the flyrock based on blast design and other geological parameters.

The objective of the study is to identify the suitable prediction model to predict the flyrock type during mine blasting using supervised machine learning methods. It investigates; various prediction models that include Decision Tree, Random Forest, K-Nearest Neighbor, Gaussian Naïve Bayes, Support Vector Machine, AdaBoost, Multi-layer Perceptron and Logistic regression. To assess the efficacy of the eight different prediction models listed here to support flyrock prediction, performance evaluation metrics are applied to compare the robustness of the model. Based on the comparative analysis with high prediction results with no prediction loss, the desirable prediction models are suggested for flyrock type prediction using supervised machine learning methods.

The paper is organized as after the Section 1 introduction followed by, Section 2 that deals with the study site, Section 3 describes the dataset used in this study, Section 4 encompasses the proposed methodology to carry out the research and finally Section 5 concludes with future scope.

2 Study Site

Three surface quarries in Johor State were used for this investigation (Malaysia) [22]. These mines produce 20,000 to 40,000 tonnes per month. The drilling and blasting procedure is used to create aggregates. Between 400m and 1km are public roads and residential areas from these quarries. Additionally, a number of palm oil plantations, where plantation labourers work throughout the day, are located close to these mines. Therefore, engineers, mine operators, and neighbouring communities are very concerned about flyrock caused by blasting activities in these mines. The fact that the chosen quarries are in a tropical region means that weathering has drastically changed the rock mass, particularly its physico-mechanical properties [5]. Rock mass should be divided into distinct categories based on how much weathering has occurred. These categories include fresh, barely weathered, moderately or heavily weathered and completely weathered. Figure 1 shows granite quarry in Malaysia.

Figure 1. Granite quarry in Malaysia

Table 1 presents the various AI models to predict the flyrock based on blast design and other geological parameters.

Table 1. Various AI Models to Predict the Flyrock based on Blast Design and Geological Parameters

Ref.	**AI Models**	**Type of parameters for Prediction of flyrock**	
		Blast Design	**Geological/others**
[16]	Artificial Neural Network	ST, C, HD, BS, SpD, PF, N	RD
[2]	Fuzzy Inference System, Statistical Methods	SpD, B, HD, S, ST, C, PF	RD
[17]	Artificial Neural Network	ST, C, PF, B, S, HD,	RMR, BI
[7]	Artificial Neural Network	C, d, B, SpD, HD, ST, BS, PF	BI
[1]	Multivariate Regression Analysis	PF, d, B, ST, HD	Q
[4]	Artificial Neural Network – Genetic Algorithm	B, S, C, ST, SpD, HD, PF	RMR
[18]	ANN – Particle Swarm Optimization	d, HD, ST, SpD, B, S, PF, C, N	RD
[19]	Artificial Neural Network-Imperialist Competitive	ST, C, HD, BS, PF	RD
[5]	Multivariate Regression Analysis	B, S, CPM,	Q, σ_c , RQD
[8]	Multivariate Regression Analysis	B, C, S, ST, HD	RMR
[10]	Genetic-Gene Expression Programming	HD, PF, B, S, ST	
[9]	Empirical	BDF, EDF	
[20]	MVRA – Back Propagation Neural Network	B, S, CPM, PF	σ_c , RQD
[11]	Multiple Linear Regression - PSO	S, ST, B, PF	RD
[21]	ANN – Firefly Algorithm	B, PF, C, S, HD, ST	GSI
[12]	Rock Engineering System	D, B, PF, C, S/B, ST/B, HD	BI, RMR, VoD,
[13]	Least Squares – SVM and SVR	B/S, H/B, C, SpD, PF	RD
[15]	Logistic Regression	PF, B, S, ST,	RD
[14]	Multiple Discriminant Analysis	B/d, PF, S/B, ST/B, H/B	X_b
[12]	Fuzzy Rock Engineering System	B, d, B/d, PF, C, S/B, ST/B, H/B	RMR, BI, VoD

[22]	Harris Hawks Optimization-Multilayer Perception	d, ST/B, HD, CPM, PF	RQD, GSI, WI

Table 2. SML algorithms used for Prediction

Reference	**Prediction Algorithms**	**Observations**
[23] Manjula et.al (2016)	LR, GNB, SVM and RF	Determines the network intrusion detection using supervised machine learning models to detect and predict network traffic. Where RF algorithms outperforms 99% accuracy.
[24] Maisha et.al (2021)	KNN, SVM, DT, RF, GNB	Prediction of IoT attacks using supervised machine learning methods. Compared with other KNN model provides better results.
[25] Qasem et.al (2021)	LR, DT, Linear Quadratic Discriminant, NB, Ensemble	Port Scan attacks are detected using Supervised machine learning algorithms where LR model attains 99.4% accuracy.
[26] Ismail et.al (2022)	RF and XGBoost	Prediction of Distributed Denial of Service attacks using supervised learning approach and RF model performs better with 89% accuracy score.
[27] Sana et.al (2021)	RF, XGBoost, KNN, LR, SVM	Evaluated the performance of supervised models for multi-class intrusion detection systems and RF model provide 99.7% accuracy as best results.
[28] Sara et.al (2019)	NB, SVM, J48 Tree, RF	Detection and Prediction of attacks in SCADA Network using supervised
[29] Shereen et.al (2021)	Gaussian NB, Multinomial NB, Bernoulli NB	Compared the variations of Naïve Bayes model with other supervised models like KNN, SVM and MLP to detect cyber attacks in wireless sensor networks.

Based on the previous research works represented in Table 1 and Table 2, the prediction of flyrock type based on Mine Blasting has been using SML algorithms and the most desirable prediction model is selected.

Figure 2 exhibits different mechanism of flyrock namely face bursting, rifling and cratering under different conditions at the blasting face [6]. Weathered granite has difficult geological conditions due to variation in degree of weathering. Face burst occurs where explosives charge is in the proximity of geological discontinuities and explosives gases escape easily during blasting. Stemming plays an important role for keeping explosives gases for longer duration. On the other hand when stemming length is inadequate, rifling occurs.

There may be back break or weaker layer in stemming column which can dislodge in crater fashion resulting in cratering.

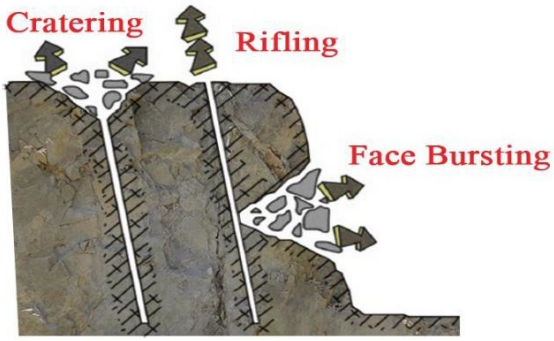


Figure 2. Mechanism of Flyrock [6]

3 Dataset

This study uses the observation of 152 blasting operations, and relevant information was gathered into a database. The flyrock distance is measured by the specified parameters RQD, HD, d, ST/B, CPM, PF, GSI and WI among the gathered data. The data is separated into two categories: (i) parameters of uncertainty, or the characteristics of the rock mass, and (ii) blast design controllable metrics [16 – 19].

Locating and determining the direction of the flyrock requires the use of a high-speed camera. By using GPS, the flyrock distance is then determined at the mining blast sites. When creating different blast patterns, controllable blasting factors including PF, ST/B, CPM, d and HD are taken into account. These included utilising a tape measure to measure d, B, and ST, figuring CPM using the length of each hole's explosive charge, and PF is calculated using the overall explosive charge and the volume of the subsequent blasting of the rock piles [20 – 22].

The blast design parameters are inconsistent between the three quarries due to the use of various drilling diameters. Three separate rock mass character traits load index, solubility, and moisture content employed to introduce WI. The granite that has totally broken down has the highest ratings for solubility and moisture content. The highest point load strength is found in fresh granite. From the blasting face, samples of worn granite were obtained. A ratio was calculated by contrasting each attribute with its corresponding highest value. The average of these three ratios was used to calculate WI for each blast.

In this experiment, in situ granite could be seen prior to blasting, and the GSI was computed after an excavator had thoroughly cleaned the blasting face. However, it must be emphasised that the input parameter used to predict flyrock was the average GSI value. Following the clearing of the blasting face, RQD was calculated using the scanline approach. The link between paired variables and histograms was utilised to depict the correlation matrices between the different variables. With the exception of the relationship between WI and PF, none of the variables have a normal distribution, and the majority have non- linear relationships. Furthermore, PF, GSI, and RQD are excellent candidates for the prediction models because to their favourable correlations. There may be bimodal skewed distributions for other variables. In order to apply them to the models, they might need to be normalised.

4 Proposed Methodology

A framework is devised to explore the suitability of various SML models to classify and predict the type of Flyrock during mine blasting. This study is basically conducted to assess the performance of the SML algorithms and the efficiency of the models in Flyrock prediction. In this proposed methodology, the framework is divided into different phases. Figure 3 presents the proposed framework to classify and predict the Flyrock using other geological parameters. Based on the acquired mining dataset taken for Flyrock prediction, data cleansing is applied to examine the excellence of the data. Data transformation is carried to convert the data type from one form to another form suitable for model development. Feature Scaling is a procedure to identify the maximum and minimum range of the data values to pre-allocate the memory size. Once, the raw data is converted into defined format suitable for model deployment to support flyrock prediction. The next consequent step is to develop a various supervised machine learning models for Flyrock prediction. Based on the learning rate, supervised machine learning models can automatically categorise and predict the flyrock. After developing robust models for flyrock prediction, the comparative analysis is done between SML models. The performances of the SML models are evaluated using recital valuation metrics to suggest the suitable SML prediction model to classify and predict the flyrock precisely.

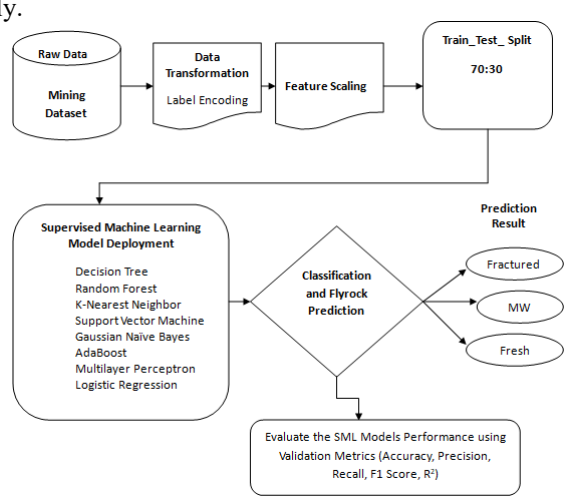


Figure 3. Overview of Proposed Framework for Flyrock Prediction during Mine Blasting

Unsupervised machine learning methods are used in security such as detection of malware in cell phones. However, in this study supervised learning methods are used which are described in the subsequent section.

4.1 Supervised Machine Learning (SML) Model Development to Predict Flyrock

Machine learning plays a vital role in every industry to automate the process effectively. The evolution of the mining sector can also be automated due to applications of artificial intelligence like Machine Learning (ML) and Deep Learning (DL) algorithms. Using ML algorithms, the dataset is loaded into the programming platform say Python Jupyter Notebook environment to automate the prediction process based on the data analysis. Since, the dataset is a labelled one, supervised machine learning can able to perform well on the target labelled data. In this research, nine different SML models are developed to detect and predict the Flyrock type based on other geological parameters during blasting Flyrock. The developed SML learning models are as follows,

- Decision Tree
- Random Forest

- K-Nearest Neighbor
- Support Vector Machine
- Gaussian Naïve Bayes
- AdaBoost
- Multilayer Perceptron
- Logistic Regression

4.1.1 Decision Tree (DT)

Decision trees will forecast the occurrences by ranking them according to the feature value. In this paradigm, each mode reflects a characteristic of an instance. Each branch stands for a value the node can adopt, and it should be noted. Based on the attribute selection measure (i.e) 'gini index' or 'entropy' can calculate the significant features as a parent node followed by the child nodes or sub nodes based on the estimated value of each geographical features of mining data. In this model, n=10 number of trees are prescribed.

4.1.2 Random Forest (RF)

Although the RF algorithm and DT algorithm share a similar operating principle, Ensemble Learning serves as its conceptual underpinning. In order to address a difficult problem, several models are combined, and this enhances the model's performance. In order to perk up the anticipated accuracy of the dataset, Random Forest averages the results of numerous decision trees applied to various dataset subsets. Instead of relying just on a single decision tree, the random forest predicts the outcome based on whose guesses received the most votes. Similar to DT model, RF model utilizes the attribute selection measure in forms of 'entropy' and 'gini index' to find the significant root node which facilitates the appropriate classification results. Finally, the optimum RF model was established with n estimators = 100 trees being considered.

4.1.3 K-Nearest Neighbor (K-NN)

Based on how strongly they relate to and correlate with other pieces of publically available data, data points are grouped using a non-parametric method. This approach is based on the assumption that adjacent comparable data points may be located. After that, it makes an effort to determine the separation between the data points, frequently using the Euclidean distance, and allocates a category based on the most well-liked category or average. Based on the Euclidean distance measure the K-NN will calculate each data point relevance to a particular group and exclude the different pattern with other groups. The Euclidean distance is calculated using the space of measure between the train data points and the new data points with k=5 neighbour points being employed to obtain the results.

4.1.4 Support Vector Machine (SVM)

A common application is to construct a hyperplane with the maximum possible partition among two groups of data points. The classifications of the data points on either side of the decision boundary are divided by a hyperplane called the decision boundary. To categorise n-dimensional space, the best line or decision boundary must be established before more data points can simply be added to that category in the future. To help create the hyperplane, SVM chooses the extreme vectors and points. Support vectors are used in these extreme situations,

to predict the data points. In this study, the probabilities of the feature data were utilised to boost the SVM model's ability to accurately forecast flyrock.

4.1.5 Gaussian Naïve Bayes (GNB)

It is based on Bayes Theorem. The formula for the probability of Y given condition X is provided by the Bayes rule. However, there might be more than one X variable in the real world. When data contains independent features, the Naive Bayes rule can be used in place of the Bayes rule. The Xs stand alone from one another. By replacing the parameters with the new input value for the variable, one can utilise the Gaussian probability density function to generate predictions. In order to facilitate flyrock prediction, the Gaussian function will offer a gauge for the likelihood of the new input value.. The following formula states the Bayes theorem,

$$P(A|B) = \frac{P(A).P(B|A)}{P(B)} \quad (1)$$

where,

P(A) = Probability of A, P(B) = Probability of B, P(A|B) = Probability of A given B and P(B|A) = Probability of B given A. In Gaussian distribution of data, the features likelihood are considered to be as,

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma y^2}} \exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma y^2}\right) \quad (2)$$

Where the variance is independent of Y (i.e., σi) or Xi (i.e., σk) or both (i.e., σ).

4.1.6 AdaBoost (AB)

An ensemble modelling technique called adaptive boosting increases the model's accuracy relative to a collection of other models. The core idea of boosting techniques is that, after developing a model using the training dataset, a second model is generated to rectify any flaws in the first. Continuing this method until the mistakes are minimised and the dataset can be forecast appropriately. In this study, the adaboost classifier model performs sufficiently to classify and predict the flyrock with best efficacy rate.

4.1.7 Multilayer Perceptron (MLP)

It consists of densely packed layers that are properly linked, and it can convert any input dimension into any output dimension. A neural network with several layers is referred to as a multi-layer perception. A neural network is built by joining neurons so that some of their outputs are also their inputs. One neuron (or node) is present in each input layer of a multi-layer perceptron, one node is present in each output layer, and any number of nodes may be present on any number of hidden layers. Since, it is based on the neural network architecture the model perform flyrock prediction with significant outcome with minimum prediction loss.

4.1.8 Logistic Regression (LR)

It predicted how often a target variable would be. Given that the dependent variable is dichotomous in nature, there are only two feasible classes. It aims to precise the decision values between 0 and 1, either True or False, 0 or 1, or Yes or No, are potential outcomes. It offers strong assistance for predictive modelling, which determines the mathematical probability that a given incident falls into a given category. The sigmoid function acts as an activation function in logistic regression to predict the result as given,

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

where e is the natural logarithms' base. From this function, the logistic regression formula is derived as follows,

$$f(x) = \frac{e^{(b_0+b_1x)}}{1+e^{(b_0+b_1x)}} \quad (4)$$

Here, X is the input value, Y is the expected result, b0 is the bias or intercept term, and b1 is the coefficient for the input (X). In this study, this model performs well and forecast the flyrock with some prediction loss. Compared with other specified SML models, LR model results with 4 data points' prediction loss due to the multiclass data type in nature.

Table 3 shows the prediction criteria of type of Flyrock blasting using SML algorithms.

Table 3. SML algorithms Prediction Criteria of Type of Flyrock Blasting

SML Model	Prediction Criteria
Decision Tree	Based on Gini Index or Entropy
Random Forest	Based on Gini Index or Entropy
KNN	Measure of Euclidian Distance
SVM	Dimensionality of Hyperplane
Naïve Bayes	Based on Bayes Theorem
AdaBoost	Based on Ensemble Learning
MLP	Stimulates Back Propagation
Logistic Regression	Based on Sigmoid Function

5 Performance Evaluation

The developed SML models are validated to estimate the quality of results. Metrics notably accuracy, precision, recall, F1 Score, and R2 Score are used to assess the performance of SML models.

5.1 Accuracy

Focusing on incorrectly recognized real and forecast samples, harmonic mean could be calculated between precision and recall.

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (5)$$

5.2 Precision

Rate of precisely detected real samples considered as different from entire data (whether correctly or erroneously). The precision of the model indicates how well it classifies a sample as positive accurately.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (6)$$

5.3 Recall

The rate of correctly identified real samples also called original samples from entire samples. It rates a model's capacity to identify effective instances. As recall rises, more favorable samples are found.

$$Recall = \frac{\text{TP}}{\text{TP+FN}} \quad (7)$$

where, FP = False Positive, TP = True Positive, FN = False Negative and TN = True Negative.

5.4 F1_Score

It is characterised as the harmonic mean between recall and precision. Otherwise, termed as F-measure.

$$F1 = 2 * \frac{\text{Precision*Recall}}{\text{Precision+Recall}} \quad (8)$$

5.5 R2_Score

It is a crucial performance measurement factor for regression-based machine learning models. Otherwise termed as "coefficient of determination." The magnitude of the input independent variable determines how much variation in the output dependent characteristic may be expected. The ratio of the total deviation of the model's outputs is used to evaluate how well the model replicates the observed findings. It is a metric that provides how well a model fits a situation. Because of this, the R2 Score ranges from 0 to 1, with 1 being a perfect fit for regression.

$$R2 = 1 - SS_{res}/SS_{tot} \quad (9)$$

where,
SSres the residual error sum of squares.
SStot the total sum of the errors.

6 Experimental Results and Discussion

This section discusses the experimental results of SML model prediction of type of Flyrock during mine blasting are presented in Table 4.

Table 4. Comparison of SML Models for Type of Flyrock Prediction while Blasting

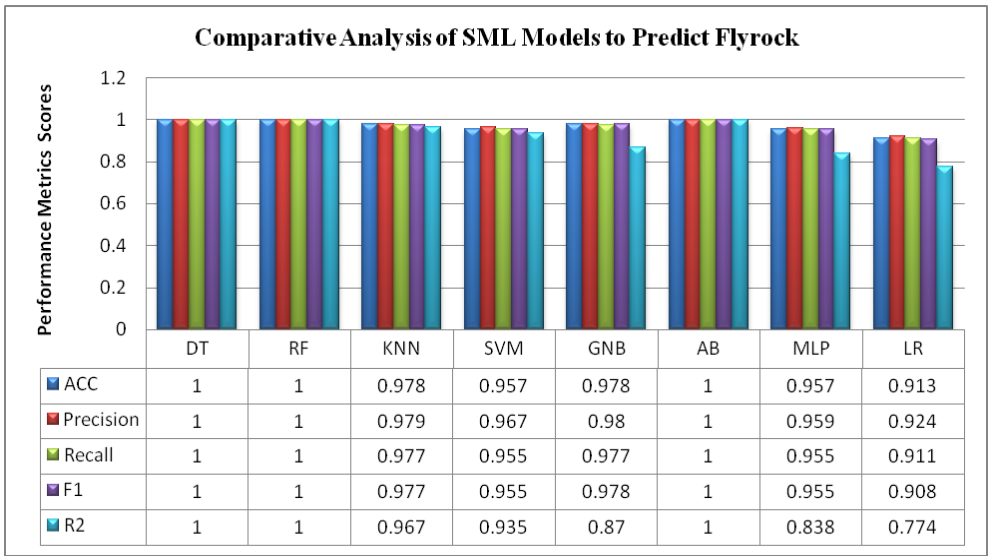
S.No.	SML Model	ACC	Precision	Recall	F1	R2	Prediction Loss
1.	**DT**	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**	**0**
2.	**RF**	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**	**0**
3.	KNN	0.978	0.979	0.977	0.977	0.967	1
4.	SVM	0.957	0.967	0.955	0.955	0.935	2
5.	GNB	0.978	0.980	0.977	0.978	0.870	1
6.	**AB**	**1.0**	**1.0**	**1.0**	**1.0**	**1.0**	**0**
7.	MLP	0.957	0.959	0.955	0.955	0.838	2
8.	LR	0.913	0.924	0.911	0.908	0.774	4

From Table 4, it clearly depicts that the assessment of SML models' performance using the metrics includes precision, recall, accuracy, F1 Score, R2 Score and as well as prediction

loss. It shows that Decision tree, Random Forest and AdaBoost model performs well with 100% accuracy rate attains in all parameters with 0 prediction loss in forecasting type of Flyrock data points. K-Nearest Neighbor model reveals that it provides 97.8% accuracy, 97.9% precision, 97.7% recall, 97.7% F1 Score, 96.7% R2 Score with 1 prediction data loss in forecasting the type of Flyrock. SVM model proves that it achieves 95.7% accuracy, 96.7% precision, 95.5% recall, 95.5% F1 Score, 93.5% R2 Score with 2 prediction data points loss in type of Flyrock prediction. Gaussian Naïve Bayes model attains 97.8% accuracy, 98% precision, 97.7% recall, 97.8% F1 Score, 87% R2 Score with 1 data point prediction loss in detecting the type of Flyrock. Multi-layer perceptron SML model thrives to predict the type of Flyrock during mine blasting scores 95.7% accuracy, 95.9% precision, 95.5% recall, 95.5% F1 Score, 83.8% recall score with 2 data points prediction loss. From logistic regression model, depicts that it forecast the type of Flyrock with 91.3% accuracy, 92.4% precision, 91.1% recall, 90.8% F1 Score, 77.4% recall score along with 4 data points prediction loss.

Based on the detailed comparative analysis of various SML models to predict the type of Flyrock during mine blasting it suggests that tree based models and boosting algorithms are pervasively providing higher accuracy with robust prediction rate. Figure 4 shows that Decision Tree, Random Forest and AdaBoost models are robust to forecast the Flyrock type by attaining 100% accuracy rate, K-Nearest Neighbor and Gaussian Naïve Bayes results 97.8% accuracy rate, Support Vector Machine and Multi-layer perceptron provides 95.7% accuracy rate and logistic regression marks 91.3% accuracy rate respectively.

Figure 5 depicts the performance of each prediction model includes Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), AdaBoost (AB), Multi-Layer Perceptron (MLP) and Logistic Regression (LR) to predict the flyrock type. Each prediction models are evaluated based on the measures such as accuracy, precision, recall, F1_Score and R2_Score to assess the robustness of the model and to arrive the best model for flyrock prediction.

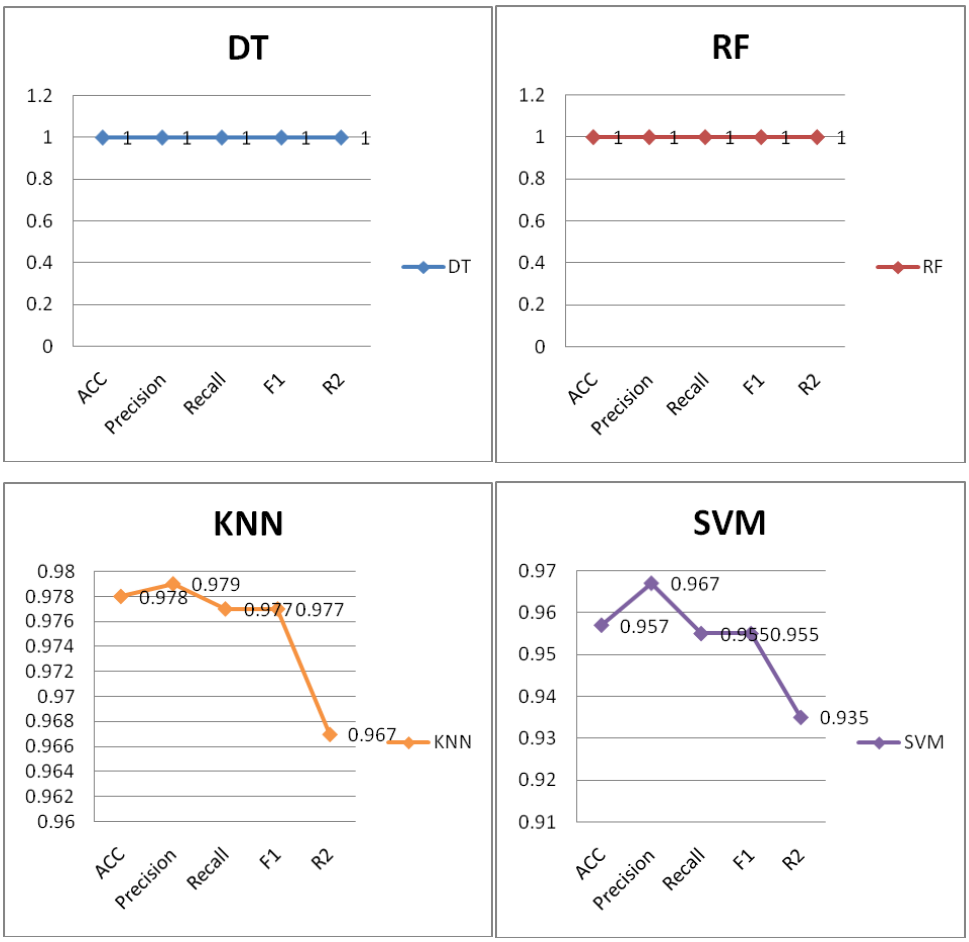


	DT	RF	KNN	SVM	GNB	AB	MLP	LR
ACC	1	1	0.978	0.957	0.978	1	0.957	0.913
Precision	1	1	0.979	0.967	0.98	1	0.959	0.924
Recall	1	1	0.977	0.955	0.977	1	0.955	0.911
F1	1	1	0.977	0.955	0.978	1	0.955	0.908
R2	1	1	0.967	0.935	0.87	1	0.838	0.774

Figure 4. Comparison of SML Models Performance to Predict the Flyrock

Figure 5 depicts the performance of each prediction model includes Decision Tree (DT), Random Forest (RF), K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), Gaussian Naïve Bayes (GNB), AdaBoost (AB), Multi-Layer Perceptron (MLP) and Logistic Regression (LR) to predict the flyrock type. Each prediction models are evaluated based on

the measures such as accuracy, precision, recall, F1_Score and R2_Score to assess the robustness of the model and to arrive the best model for flyrock prediction.



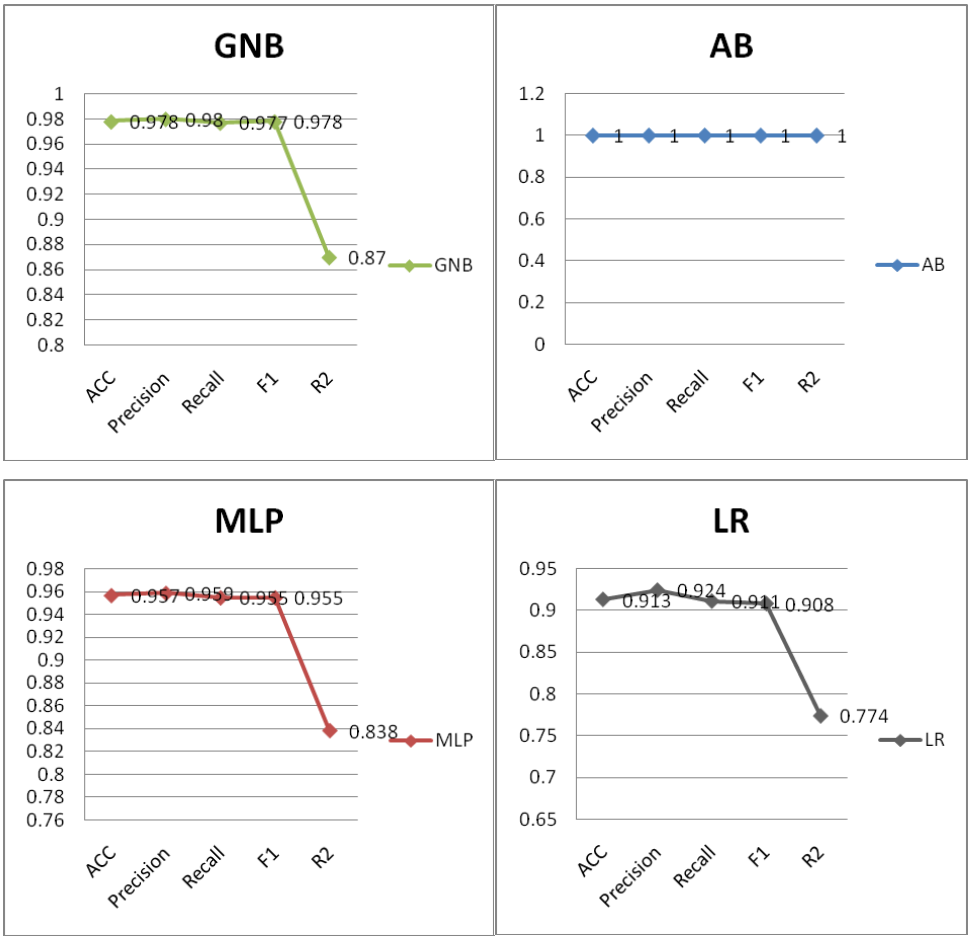


Figure 5. Experimental Results of SML Models Performance Measures to Predict the Flyrock

Figure 6 shows the comparison of SML models prediction loss indicates that DT, RF, AB models does not contain any data points loss during prediction of Flyrock. Whereas, KNN and GNB models results in 1 data points loss while Flyrock prediction. Moreover, SVM and MLP models contain 2 data points prediction loss in Flyrock prediction. Other than DT, RF, KNN, GNB, SVM, MLP models LR model contains 4 data points loss during Flyrock prediction. Therefore, LR model contains high amount of data point's loss compared with other SML models.

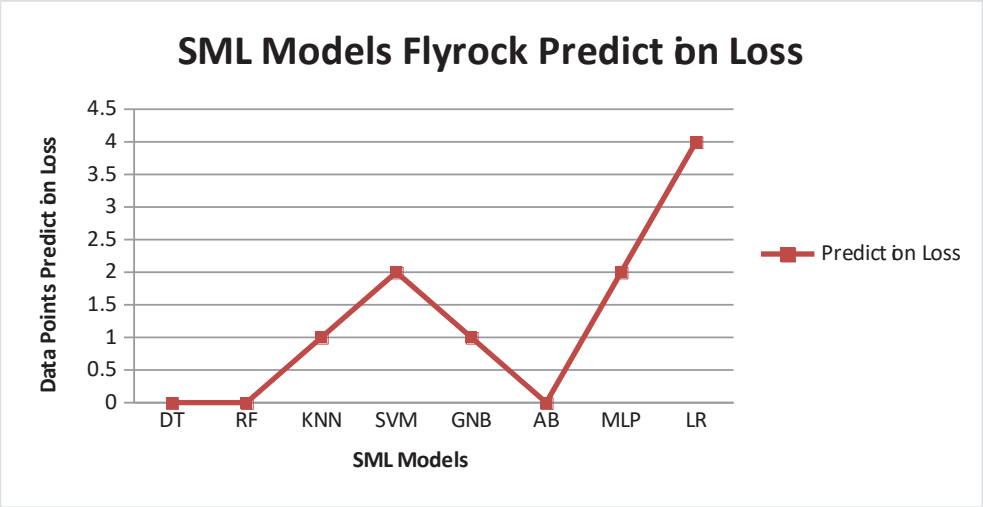


Figure 6. Comparision of SML Models Flyrock Prediction Loss

7 Limitations and Future Studies

The limitation of the proposed study, does not apply large dataset for robust prediction analysis. Also it does not involve any feature engineering method to identify the significant geological parameter that thrives for robust prediction. In future, a real time dataset has been collected which is in unlabelled form with raw features the experimental analysis of the unlabelled data can be done with unsupervised machine learning models along with feature engineering. Deep Neural Network models can be applied to support big data and also helps to predict the significant geological parameters that influence the mine blasting explosion.

8 Conclusion

Flyrock is a catastrophic condition that occurs during mine blasting activities in open-pit mines. Prediction of flyrock type is essential to calculate the type of flyrock generated while blasting the mines by analyzing various geological parameters. Geological parameter plays a vital role in prediction of flyrock type to overcome the hazardous event in a mining environment. Artificial Intelligence helps to automate the process of flyrock prediction depends on geological factors of mining activities. In this research study, eight SML models are developed to predict the flyrock type based on geological features of mining. The developed prediction model includes DT, RF, KNN, SVM, GNB, AB, MLP and LR. The SML models performances are validated using various performance evaluation metrics as mentioned above. Considering the outcomes of the generated models, the performance of DT, RF and AB models provide robust results for prediction of flyrock type attains 100% precision, recall, accuracy, F1_score, R2_score and 0% prediction loss. The predictive models are performed by taken all eight input geological parameters based on rock mass properties. The developed models will be a very good automation framework for mining industries to test the results in prior with real time study. The proposed models are well produce the significant results with high efficacy rate compared with previous research work in this area. Hence, in future the developed models are applied with mining big data as a hybrid deep learning framework to enhance the complexity of the framework in an effective way.

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