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Evaluation of Blast-Induced Ground Vibration Using Machine Learning for Safe Construction of Hydropower Tunnels: A Case Study

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ABSTRACT

Large hydropower projects require extensive tunnel excavation, where the drill-and-blast method (DBM) is widely adopted for excavating hard rock formations. However, DBM generates blast-induced ground vibrations (BIGV), which may adversely affect surrounding rock masses and nearby structures. Peak Particle Velocity (PPV) is widely used to evaluate vibration intensity and assess structural safety. This study develops machine learning (ML)-based PPV prediction models for tunnel blasting at the Tapovan-Vishnugad Hydroelectric Power Project, Uttarakhand. A dataset comprising 332 field-monitored blasting events was used with a 70:30 training–testing split. Three tree-based regression algorithms, namely Decision Tree (CART), Random Forest (RF), and Extreme Gradient Boosting (XGB), were developed using six input parameters: tunnel cross-sectional area (a), rock mass quality index (Q), blasthole length (L), charge per delay (W), specific charge (SC), and monitoring distance (R). Model performance was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE), and compared with the conventional USBM empirical predictor. SHapley Additive exPlanations (SHAP) analysis was performed to evaluate parameter influence, while a parametric optimization framework was developed for safe charge estimation under varying blasting conditions.

The results show that ML models significantly outperform the empirical approach. Among the developed models, RF achieved the best performance with R^2 values of 0.98 and 0.90 for training and testing datasets, respectively, along with the lowest RMSE and MAE values. SHAP analysis indicated that the influence of input parameters follows the order: $R > W > Q > a > SC > L$. The proposed framework provides a reliable approach for estimating safe charge per delay for different geological conditions and supports safer tunnel blasting practices.

Keywords: Tunnel blasting; PPV prediction; Machine learning; Random forest; SHAP analysis.

1. INTRODUCTION

Hydropower is an important renewable energy source that converts the kinetic energy of flowing water into electricity using turbines and generators, making it a clean, reliable, and significant contributor to the world's power needs by utilizing the Earth's water cycle (CCI India, 2025) The development of large hydropower projects requires tunnelling for underground components such as headrace tunnels, desilting chambers, machine halls, penstock tunnels, and tailrace tunnels, etc. The excavation of tunnels can be done using the drill and blast method (DBM), tunnel boring machine (TBM) and road headers (Rana et al., 2022). Among these, DBM is the preferred technique for hard rock excavation in such projects because of its low capital investment, suitability under diverse geological conditions, adaptability to different shapes and sizes of tunnel openings, and comparatively easy access in remote mountainous terrains (Mandal & Singh, 2009; Verma et al., 2018). However, DBM also generates several adverse environmental impacts such as blast-induced ground vibration (BIGV), air overpressure, noise, heat, and fumes (Murmu et al., 2018). Among these, BIGV is particularly significant because it has the potential to damage the surrounding rock mass and nearby underground and surface structures (Chen et al., 2025; Fissha et al., 2024). Peak Particle Velocity (PPV) is a key parameter used to quantify BIGV and is widely adopted for safety standards (IS, 1973).

Traditionally, scaled distance-based empirical models have been used for *PPV* prediction (Ambraseys & Hendron, 1968; Duvall et al., 1926; IS, 1973; Nicholls et al., 1971). However, these models generally consider only the maximum charge per delay and the distance between the blast source and monitoring point, while neglecting several other geological and blasting-related parameters that significantly influence vibration propagation (Khandelwal, 2014; Rana et al., 2022). As a result, their prediction capability under complex tunneling conditions often remains limited. To overcome these limitations, machine learning (ML) techniques have increasingly been adopted for predicting blast-induced ground vibrations in both surface and underground excavations (Chen et al., 2025; Fissha et al., 2024; Khandelwal, 2014; Khandelwal & Singh, 2006; Ullah et al., 2025; Vishwakarma et al., 2024). Due to their ability to capture complex and nonlinear interactions among multiple influencing parameters, ML approaches have demonstrated superior prediction performance compared to conventional empirical methods. Various algorithms, including Artificial Neural Networks (ANN), Support Vector Regression (SVR), and ensemble learning methods, have been successfully applied for vibration prediction (Lawal et al., 2021; Ogunsola et al., 2025). Nevertheless, challenges related to model interpretability, dependence on data quality, and practical applicability under field conditions remain. In this regard, tree-based regression algorithms such as Decision Tree (CART), Random Forest (RF), and Extreme Gradient Boosting (XGB) provide an effective balance between prediction accuracy and interpretability. Furthermore, SHapley Additive exPlanations (SHAP) analysis (Ponce-Bobadilla et al., 2024) enables quantitative assessment of parameter influence, thereby improving the engineering transparency and applicability of ML-based models.

Accordingly, the present study is an attempt to develop a PPV prediction model using CART, RF, and XGB algorithms for tunnel excavation works associated with the TVHEP project. A total of 332 field-monitored blasting events were analysed for model development, with the dataset divided into 70% training and 30% testing subsets. Six influential input parameters, including tunnel cross-sectional area (*a*), maximum charge per delay (*W*), and rock mass quality index (*Q*), were considered in the analysis. Model performance was evaluated using regression error curves (REC) and statistical indices such as coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). In addition, SHAP analysis was performed for the best-performing model to quantify the contribution of individual input parameters to PPV prediction. Based on the findings, a blast design optimization framework is proposed for effective control of blast-induced ground vibrations during tunnel excavation, thereby minimizing the risk of construction suspension while ensuring structural safety, excavation efficiency, and sustainable tunneling practices.

2. PROJECT UNDER STUDY

Uttarakhand hosts several major hydropower projects due to its perennial river systems and favorable mountainous terrain. Among these, the Tapovan-Vishnugad Hydroelectric Project (TVHEP), located near Joshimath in Chamoli district, involves extensive tunnel excavation beneath nearby villages and residential areas (Fig. 1). During the construction phase, local inhabitants reported cracks and structural damage in residential buildings due to vibrations generated by tunnel blasting operations for the TVHEP project. As a result, excavation activities were temporarily suspended, causing significant delays in project execution and progress.

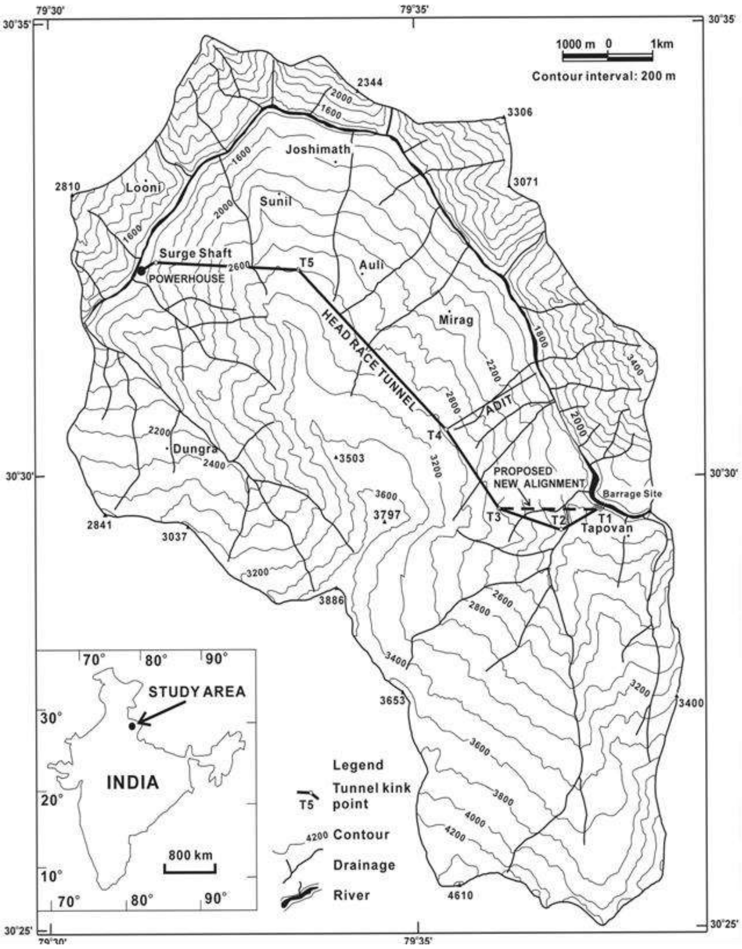

Figure 1 - Location of TVHEP site and tunnel alignments (Naithani & Murthy, 2006)

Subsequently, tunneling operations were resumed under strict conditions to ensure that blast-induced ground vibrations remained within the permissible PPV limits. Exceeding the prescribed vibration limits could again lead to suspension of the project and may cause structural damage. The inaccurate or less reliable PPV prediction may result in overly conservative blast designs adopted to control vibrations, which can reduce excavation efficiency and increase construction time. Therefore, precise prediction of PPV is essential to maintain vibration levels within permissible limits while avoiding unnecessarily conservative blast designs that may hinder excavation productivity and delay project completion.

3. METHODOLOGY

3.1 Details of Experimental Project Sites

The Tapovan–Vishnugad Hydroelectric Project (TVHEP) is a run-of-the-river scheme constructed across the Dhauliganga River in the Chamoli district of the Garhwal Himalaya (Figure 1), located about 280 km from Rishikesh along NH-58. The project lies on the left bank of the Dhauliganga-Alaknanda river system, with a barrage built across the Dhauliganga River and the tailrace tunnel discharging into the Alaknanda River. It comprises a 70 m wide barrage and a 12.3 km long headrace tunnel on the left bank that conveys water to an underground power-house, from where discharge is released into the Alaknanda River through a 510 m long tailrace tunnel. The underground powerhouse cavern measures 48.72 m×158.80 m×22.30 m, and the surge shaft has a diameter of 13.5 m and a depth of 145.20 m. Other underground structures include a butterfly valve house (42.35 m × 10.30 m × 17.70 m), a transformer cavern (148.15 m×18.30 m×27.50 m), and a 400-kVA switchyard (NTPC, 2006).

Geologically, the project site lies within the tectonically active Higher Himalayan region and is strongly influenced by the Main Central Thrust located about 2 km south of the powerhouse (Debnath, 2025). The rock mass is highly deformed, marked by intense folding, shearing, jointing, and medium- to high-grade metamorphism, with the tunnel alignment passing through gneiss, quartzite, augen gneiss, and mica schist. Frequent lithological variations and mixed-face conditions resulted in predominantly poor rock mass quality (Class IV-V), necessitating heavy support measures (Naithani and Murthy, 2006).

3.2 Dataset

Blasting investigations are conducted in different parts of the under-construction tunnels of the project sites described in Section 3.1 under varying excavation conditions. The tunnel cross-sectional area of each experimental tunnel was measured using survey equipment, and the tunnel face rock mass quality was evaluated using the Barton Q-System, as it is the most widely adopted rock mass classification system for underground excavations (Barton et al., 1974; Singh and Goel, 2011). The drill-and-blast parameters, such as blasthole length (L), maximum charge per delay (W), defined as the explosive weight designed to detonate within an 8 ms delay interval, and total explosive charge weight (TC) were recorded for every blast round.

Blast-induced ground vibrations were monitored in terms of PPV using Micromate seismographs manufactured by M/s Instantel Canada. To ensure reliable and accurate vibration measurements, only calibrated seismographs were used, and the geophones were properly coupled with the ground, following the standards recommended by the International Society of Explosives Engineers (ISEE, 2015). The distance from the blast face to the monitoring locations (R) for each round of blasting operations was determined using survey equipment, such as a Total Station.

After each blast round, tunnel advancement or blast pull (P) was measured using a total station, and specific charge (SC) was calculated as per equation (1).

$$SC = \frac{TC}{a*P} \tag{1}$$

where

TC= total explosive charge weight, kg,
a = Tunnel Cross-sectional area, m^2 and
p = tunnel advancement or blast pull, m.

During the field experiments, a total of 120 blast rounds were investigated, from which vibration events were recorded. Multiple monitoring points were used per blast round. The collected data were carefully screened to remove incomplete, inconsistent, and abnormal records to improve data reliability. Finally, 332 blast vibration datasets were compiled for further analysis. Table 1 presents the statistical summary of the dataset used in this study.

Table 1 - Summary of datasets recorded from project sites

Statistics	a, m²	Q	L, m	SC, kg/m³	W, kg	R, m	PPV, mm/s
Total count	332	332	332	332	332	332	332
Minimum	26.00	0.03	1.00	0.33	3.20	25.00	0.18
Maximum	67.80	14.90	4.00	3.15	44.00	400.00	38.90
Mean	42.86	2.73	2.20	1.45	16.97	145.07	7.04
Standard deviation	10.37	2.61	0.69	0.57	11.07	80.59	7.94

3.3 Software

In this study, the blast-induced ground vibration data were first processed and analyzed using Instantel's THOR software. Subsequently, the scaled distance empirical predictor was developed using Microsoft Excel. Finally, the machine learning models were implemented using python in Jupyter notebook.

3.4 ML Modelling

This study employs three tree-based regression algorithms, namely Decision Tree (CART) (Hasanipanah et al., 2017), Random Forest (RF) (Yan et al., 2024) and Extreme Gradient Boosting (XGB) (Ding et al., 2020) to predict blast-induced PPV during tunnel excavation. These models were selected due to their capability to effectively capture nonlinear relationships, multivariate interactions, and variability inherent in field blasting data.

The CART model operates by recursively partitioning the dataset into homogeneous subsets through binary splitting; to minimize the Mean Squared Error (MSE), the mathematical expression is given in equation (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{2}$$

where n: Total number of observations/data points; i: Index of each data point; γ_i: Actual (observed) value of the i^{th} data point; $\hat{y}_i$: Predicted value of the i^{th} data point.

Although CART models are simple and interpretable, they are susceptible to overfitting when dealing with highly variable datasets. To overcome this limitation, the RF algorithm was employed as an ensemble learning approach that combines multiple decision trees developed using bootstrapped samples and random feature selection, thereby improving prediction accuracy and generalization capability. Furthermore, XGB was utilized as an advanced gradient boosting technique in which trees are developed sequentially, with each new tree correcting the errors of the previous one while incorporating regularization to control model complexity and enhance robustness.

The complete dataset was imported into Jupyter Notebook, where six input parameters (*a, Q, L, SC*, *W*, and *R*) and *PPV* as the output parameter were assigned. The dataset was subsequently divided into training (70%) and testing (30%) subsets. To improve model stability and convergence, the training and testing datasets were transformed using logarithmic scaling followed by Min–Max normalization. Normalization parameters were computed using the training dataset and subsequently applied to the testing dataset to avoid data leakage. The transformed training dataset was then used to train the CART, RF, and XGB models.

To optimize model performance, the Particle Swarm Optimization (PSO) metaheuristic technique (Bui et al., 2019; Kennedy & Eberhart, n.d.) was adopted for tuning the hyperparameters of employed models. The PSO configuration consisted of C1 = 1, C2 = 1.5, inertia weight (w) = 0.7, 30 iterations, and a swarm size of 25 particles for the global best strategy. In addition, a 5-fold cross-validation approach (Trisnapradika et al., 2025) was implemented to enhance model robustness and reduce overfitting. In this method, the dataset was divided into five equal subsets, where four folds were used for training and the remaining one-fold for validation in each iteration, and the final performance was averaged over all folds.

After hyperparameter optimization, the optimal model configurations were retained and the models were retrained using the optimized parameters. The developed models were subsequently evaluated using both the training dataset and an independent testing dataset to assess their predictive performance under real-field conditions. Before evaluation, all predicted values were inverse-transformed to their original scale.

3.5 Performance Evaluation Criterion

Evaluation of the performance of the predictive models was carried out using statistical matrix, namely, the coefficient of determination (R^2), mean absolute error (MAE), and root mean squared error (RMSE). These metrics offer a comprehensive understanding of the model's accuracy and robustness (Khoshvaght et al., 2025). The range of R^2 value varies from 0 to 1, MAE and RMSE from 0 to ∞. A model is considered more effective when its R^2 value is closer to one, while the values for MAE and RMSE should be closer to zero. In addition to the statistical indicators, the regression error curve (REC) was also used, which enables a quick comparison of multiple models in a single plot, where steep and higher curves indicate better performance (Bi and Bennett 2003).

The area over curve (AOC) was also calculated; the lower value of *AOC* indicates better performance of ML models in predicting *PPV*. (Lower AOC values indicate smaller cumulative prediction errors and therefore better predictive capability.)

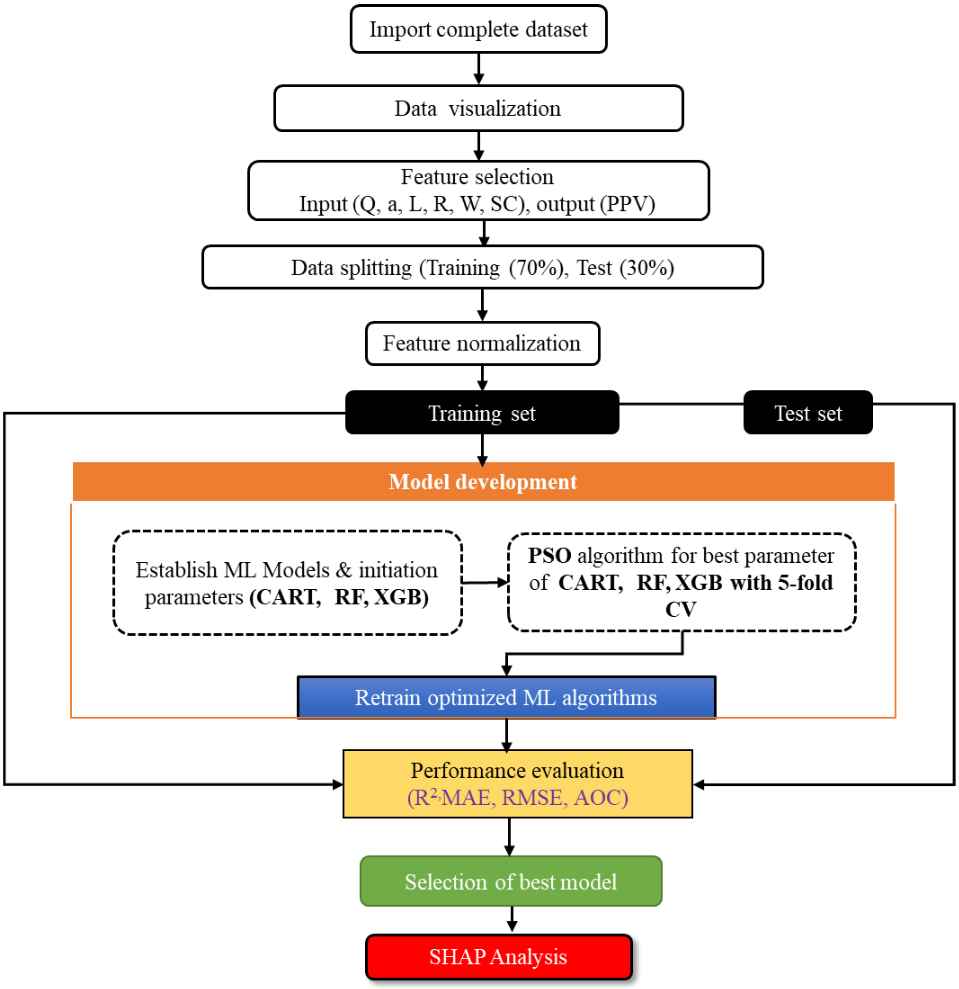

Figure 2 - Flowchart for PPV prediction modelling

4. DATA ANALYSIS AND DISCUSSION

The ML models developed as per the strategy outlined in Section 3.4 were evaluated for their predictive performance as per the criterion mentioned in Section 3.5. The results of the ML models for training (232 data points) and test (100 data points) phases are provided in Table 2. The results of ML models were also compared against the widely used empirical USBM predictor. The USBM predictor was selected because it is one of the most widely adopted empirical vibration prediction models in blasting engineering.

It can be observed from Table 2 that the RF model demonstrated the best predictive performance among all the developed models, achieving the highest R^2 values of 0.985 and 0.904 for the training and testing datasets, respectively, along with the lowest MAE (0.612 and 1.427 mm/s) and RMSE (1.036 and 2.131 mm/s) values. The small reduction in performance from training to testing indicates strong robustness and generalization capability of the RF model for predicting blast-induced PPV under varying field conditions. The XGB model also exhibited high prediction accuracy, with testing R^2, MAE, and RMSE values of 0.895, 1.576 mm/s, and 2.321 mm/s, respectively, performing slightly inferior to RF but better than CART. Although the CART model achieved a high training R^2 value of 0.96, its testing performance reduced to 0.83 with comparatively higher prediction errors, indicating lower generalization capability. In contrast, the USBM empirical model yielded significantly lower R^2 values (0.69–0.73) and substantially higher RMSE values (4.212–5.116 mm/s), highlighting the limitations of conventional empirical approaches in representing the complex nonlinear behavior of blast-induced vibrations. Furthermore, the scatter plots presented in Figure 3 show that RF predictions are more closely distributed around the 1:1 reference line, confirming its superior prediction accuracy.

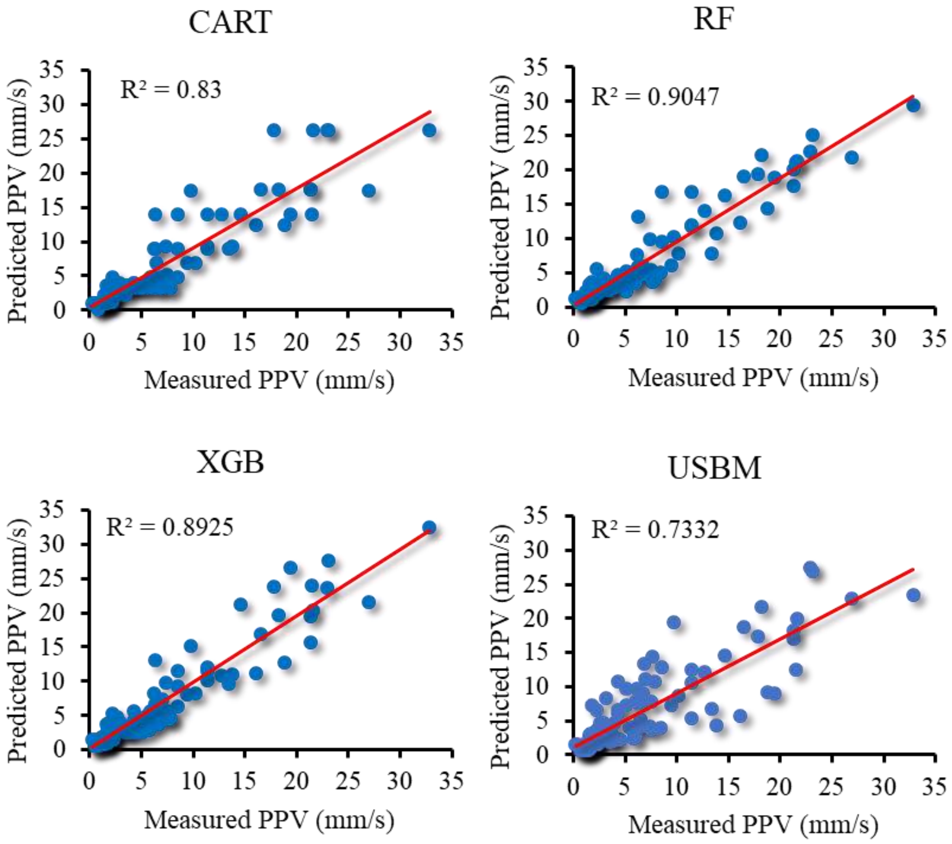

Figure 3 - Scatter plot for measured PPV vs predicted PPV on validation dataset

Table 2 - Summary of model performance results

Model	R^2		MAE		RMSE		AOC	
	Train	Test	Train	Test	Train	Test	Train	Test
CART	0.964	0.83	1.021	2.005	1.573	2.880	1.021	2.005
RF	0.985	0.904	0.612	1.427	1.036	2.131	0.613	1.428
XGB	0.981	0.895	0.745	1.576	1.136	2.321	0.745	1.575
USBM	0.692	0.733	3.841	4.584	4.212	5.116		

Figure 4 presents the Regression Error Characteristic (REC) curves for the developed ML models during the training and testing phases, where the x-axis represents the allowable prediction error (mm/s) and the y-axis denotes the proportion of predictions within the specified error threshold.

Models exhibiting steeper REC curves and lower Area Over Curve (AOC) values indicate superior predictive performance. Among the developed models, RF consistently exhibited the steepest REC curves and the lowest AOC values in both training and testing phases, demonstrating the highest prediction accuracy and strongest generalization capability. The XGB model showed comparable but slightly inferior performance, whereas CART displayed relatively flatter REC curves and higher AOC values, indicating lower predictive efficiency. Overall, the results obtained from Table 2, Figure 3 & 4 confirm that ensemble-based ML models, particularly RF, provide the most reliable and accurate prediction of blast-induced PPV for the present study.

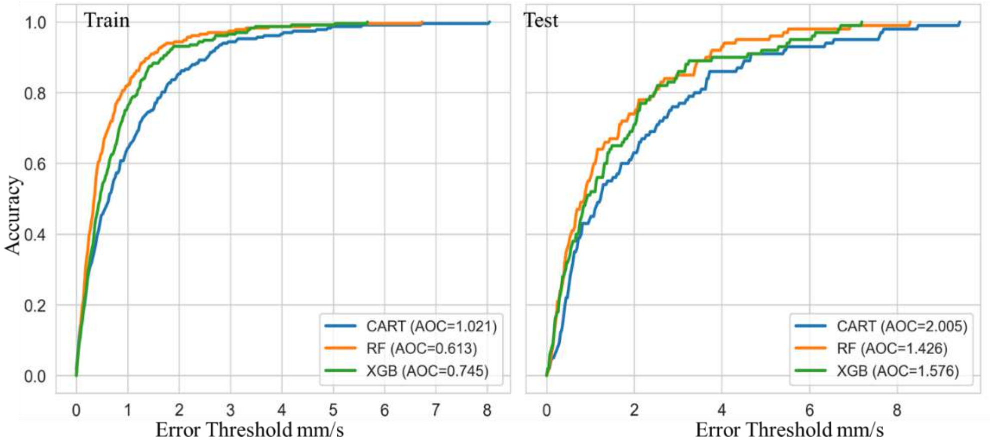

Figure 4 - Regression error curve for ML models for the training and testing phase

5. SHAP ANALYSIS

SHAP analysis was performed for the best-performing model, i.e., the Random Forest (RF) model, to improve model interpretability and assess the influence of input parameters on blast-induced vibration. The analysis considered all six input parameters (*Q, a, L, SC, W* and *R*) incorporated in the ML-based *PPV* prediction model developed in this study. The SHAP summary plot obtained from the analysis is presented in Figure 5, while the feature importance results are shown in Figure 6, illustrating the relative contribution of each parameter toward *PPV* prediction.

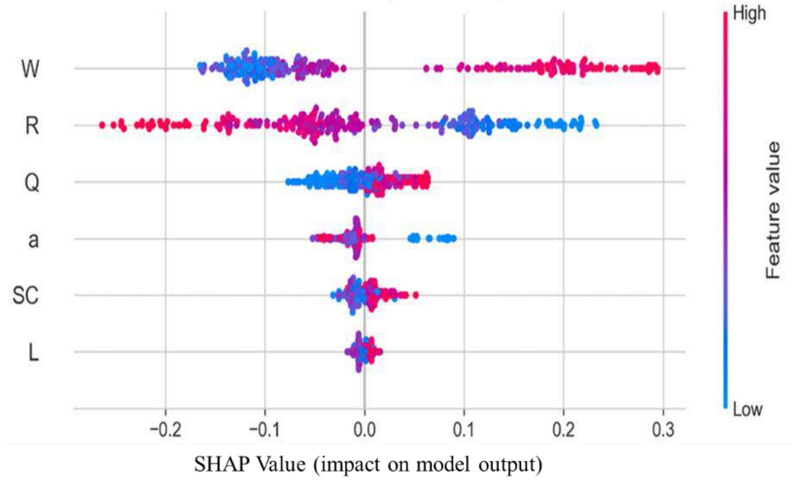

Figure 5 - SHAP analysis plot (RF)

Figures 5 and 6, obtained from the SHAP analysis, reveal that R (distance from the blast location) has the greatest influence on PPV prediction, with an increase in R reducing vibration levels due to the natural attenuation of stress waves through the rock mass. In contrast, higher *W* (maximum charge per delay) significantly increases *PPV* at the monitoring location. The *Q-value* (rock mass quality) also shows a considerable influence on vibration propagation characteristics, highlighting the importance of geological conditions in PPV prediction. Further, *a* (tunnel cross-sectional area) and *SC* (specific charge) exhibit moderate influence, indicating their role in the distribution of explosive energy during excavation. Further SHAP analysis reveals that the impact of the blasthole length (L) parameter is comparatively low, which may be associated with its relatively limited variability within the dataset and possible indirect interaction with other charge-related parameters.

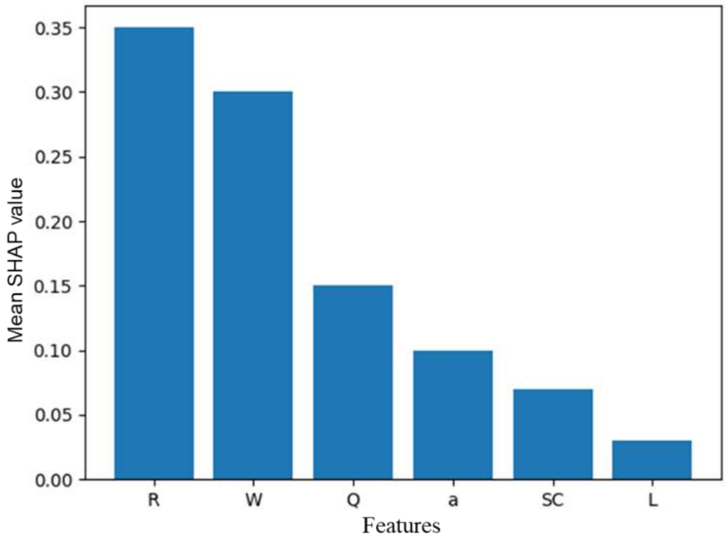

Figure 6 - SHAP feature importance analysis

6. BLAST DESIGN OPTIMIZATION

The developed machine learning framework for PPV prediction was further utilized for blast design optimization to maintain blast-induced ground vibrations within permissible limits and ensure safe and productive tunnel excavation at the TVHEP site. A parametric analysis was performed using the optimized Random Forest (RF) model to determine safe maximum charge per delay for different blasting scenarios.

Parametric analysis was carried out considering parameters as per the guiding principle of the tunnel blasting operations (Olofsson, 1988; NTNU, 1995; Ouchterlony et al., 2001; Murthy, 2003). In the parametric analysis, *Q*-values of 1, 4, and 10 were considered to represent poor, fair, and good rock mass conditions, respectively, along with tunnel cross-sectional areas (*a*) of 45 m² and 65 m². Corresponding to the 65 m² tunnel section, specific charge (*SC*) values of 1.0, 1.2, and 1.4 kg/m³ were adopted for *Q*-values of 1, 4, and 10, respectively, whereas for the 45 m² tunnel section, *SC* values of 1.1, 1.3, and 1.5 kg/m³ were considered for the corresponding *Q*-values. Higher *SC* values were adopted for the smaller tunnel cross-section because smaller tunnel cross-sections generally provide higher confinement and reduced free-face availability, which may increase transmission of explosive energy into the surrounding rock mass and consequently increase vibration intensity (Verma et al., 2018). Blasthole length (*L*) is decided based on the designed round length as per prevailing rock mass conditions and hence it was not considered as a major optimization parameter. Moreover, blasthole length is primarily governed by excavation cycle requirements and desired tunnel advance rather than vibration control criteria. The permissible *PPV* limit was fixed at 5 mm/s, and the corresponding safe maximum charge per delay (*W*) was estimated for different excavation conditions to maintain vibration levels within the allowable limit. Figure 7 presents the results of the parametric analysis for different blasting scenarios, showing the safe charge per delay required to control *PPV* within 5 mm/s at monitoring distances ranging from 50 to 200 m.

The results presented in Figure 7 indicate that tunnels with smaller cross-sectional areas and better-quality rock masses have lower safe charge per delay values as compared to weaker rock masses of the same cross-sectional area, because in hard rock masses, blast-induced vibrations are generally more intense and attenuate gradually than in weaker rock masses, which was also observed during the field investigations. Furthermore, smaller tunnel cross sections provide higher confinement, which further increases the intensity of blast-induced vibrations.

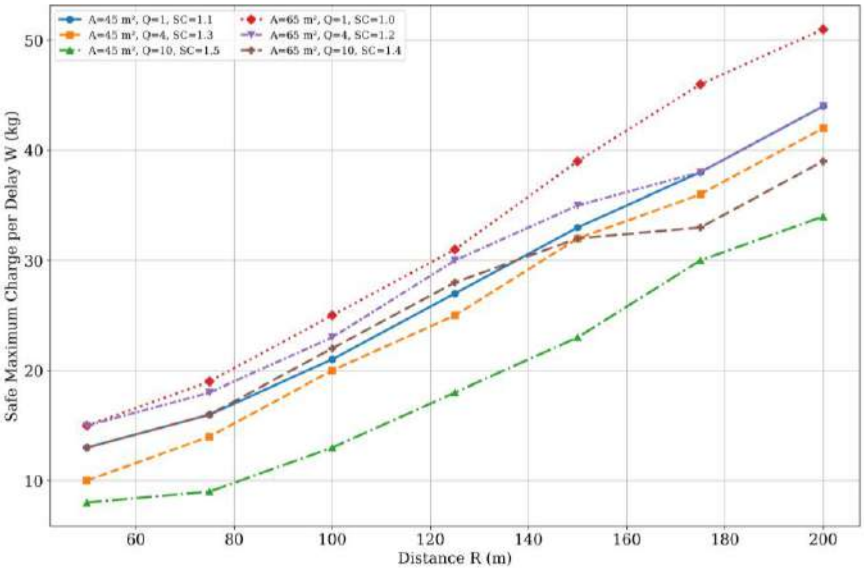

Figure 7 - Parametric analysis for optimization of maximum charge per delay in different blasting scenarios

7. LIMITATIONS OF THE STUDY

Although the proposed machine learning framework showed satisfactory performance in *PPV* prediction, certain limitations should be acknowledged. The dataset was collected from Himalayan hydropower tunnel projects dominated by metamorphic rock formations; therefore, the developed models may require recalibration for application in different geological conditions. In addition, the dataset size was relatively moderate, and larger datasets from diverse projects could further improve model generalization and reliability.

The study considered six major input parameters; however, other influential factors, such as direction of monitoring from the blast location, delay sequencing, blasthole geometry, explosive characteristics, in-situ stress, discontinuity orientation, and groundwater conditions, were not included due to limited field data availability. Further, machine learning predictions are strongly dependent on the quality and consistency of field measurements, and some variability in blasting operations is unavoidable. Moreover, the proposed optimization framework is based on model predictions and should be used as a practical guideline rather than a substitute for detailed blast design and field trials. Also, the study does not incorporate uncertainty quantification or probabilistic modeling, which could further improve confidence in predictions. Future research should focus on integrating probabilistic approaches, such as Bayesian methods or Gaussian Process Regression, to address this aspect.

8. CONCLUSIONS

BIGV remains a critical concern in tunnel excavation due to its adverse impact on operational safety, structural integrity, and environmental sustainability. Therefore, accurately predicting PPV, a primary measure of ground vibration intensity, is pertinent for effective blast design and risk mitigation. In this study, with the objective of accurate prediction of PPV during excavation of Tunnels for the TVHEP hydropower project in Uttarakhand, three tree-based machine learning regression algorithms, namely CART, RF, and XGB, were employed using 332 datasets with six input parameters including tunnel cross section area (a), rock mass quality (Q), blasthole length (L), charge per delay (W), distance from the blast location (R) and specific charge (SC). For model robustness and enhanced accuracy, hyperparameters were tuned using the PSO metaheuristic approach with 5-fold cross-validation.

Performance comparison of the employed ML models shows that the RF has the highest prediction accuracy with R^2 of 0.98 and 0.90 during training and test phase, respectively, closely followed by XGB. Whereas the CART emerged as the weakest performer among the evaluated models. Further, all the ML models outperformed the USBM empirical model. Further, the SHAP analysis indicated that the R and W were the most influential parameters governing PPV prediction. Other parameters, including Q, SC, a, also showed significant contributions. In contrast, L length exhibited the least influence on PPV prediction. This may be attributed to the relatively limited variation in blasthole length within the collected dataset, as well as the fact that blast-induced vibrations are primarily governed by charge concentration rather than blasthole length itself.

Based on the best-performing RF model and SHAP analysis, a parametric optimization framework was developed to estimate safe maximum charge per delay under varying geological and excavation conditions while maintaining PPV within permissible limits. The proposed framework can assist in designing safer and more efficient blasting operations by balancing vibration control, excavation productivity, and structural safety. However, since the framework was developed using site-specific data from the TVHEP project, calibration with local geological and blasting conditions is recommended before application to other tunneling projects.

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References

Ambraseys NR, Hendron AJ (1968). Dynamic behaviour of rock masses. In: Rock Mechanics in Engineering Practice, K.G. Stagg & O.C. Zienkiewicz, Eds), John Wiley & Sons.

Barton N, Lien R, Lund J (1974). Engineering classifications of rock masses for the design of tunnel support. Rock Mech, 6:189-236.

Bi Jinbo, Kristin P Bennett (2003). Regression Error Characteristic Curves. In: Proc 20th Int Conf on Machine Learning (ICML 2003), August 21-24, Washington, DC, USA, pp. 43-50.

Bui XN, Jaroonpattanapong P, Nguyen H, Tran QH, Long NQ (2019). A novel hybrid model for predicting blast-induced ground vibration based on k-nearest neighbors and particle swarm optimization. Scientific Reports, 9(1). https://doi.org/10.1038/s41598-019-50262-5

IS (1973). Criteria for Safety and Design of Structures Subjected to Underground Blast. Bureau of Indian Standards, ISI Bull No 6922.

CCI India. (2025). Hydro Power – Introduction. Https://Www.Cciindia.Org/Hydro.Html.

Chen L, Fissha Y, Hasanipanah M, Ghodhbani R, Dehghani H, Khatti J (2025). Accurate prediction of blast-induced ground vibration intensity using optimized machine learning models. Defence Technology. https://doi.org/10.1016/j.dt.2025.06.019

Debnath S (2025). Geological risk management in tunnelling with focus on hydro tunnels: sectoral analysis supported by case references. International Journal of Research Publication and Reviews, 6(11):4079-4089. https://doi.org/10.55248/gengpi.06.1125.39134

Ding, Z, Nguyen H, Bui XN, Zhou J, Moayedi H (2020). Computational intelligence model for estimating intensity of blast-induced ground vibration in a mine based on imperialist competitive and extreme gradient boosting algorithms. Natural Resources Research, 29(2), 751–769. https://doi.org/10.1007/s11053-019-09548-8

Duvall WI, Fogelson DE, Eltschlager KK (1962). Review of criteria for estimating damage to residences from blasting vibrations office of surface mining reclamation and enforcement, United States Department of the Interior, Bureau of Mines.

Fissha Y, Khatti J, Ikeda H, Grover KS, Owada N, Toriya H, Adachi T, Kawamura Y (2024). Predicting ground vibration during rock blasting using relevance vector machine improved with dual kernels and metaheuristic algorithms. Scientific Reports, 14(1). https://doi.org/10.1038/s41598-024-70939-w.

Hasanipanah M, Faradonbeh RS, Amnieh HB, Armaghani DJ, Monjezi M (2017). Forecasting blast-induced ground vibration developing a CART model. Engineering with Computers, 33(2), 307–316. https://doi.org/10.1007/s00366-016-0475-9

ISEE (2015). International Society of Explosives Engineers. Blast Vibrations and Seismograph Section ISEE Field Practice Guidelines for Blasting Seismographs.

Kennedy J, Eberhart R (Eds). Particle swarm optimization. In: Proc ICNN'95 - Int Conf on Neural Networks, 1942–1948. https://doi.org/10.1109/ICNN.1995.488968

Khandelwal M (2014). Evaluation of safe explosive charge in surface mines using artificial neural network. In: Proc 6th Int Conf on Agents and Artificial Intelligence, ICAART 2014, 1, 366–371. https://doi.org/10.5220/0004761703660371

Khandelwal M, Singh TN (2006). Prediction of blast-induced ground vibrations and frequency in opencast mine: A neural network approach. Journal of Sound and Vibration, 289(4-5), 711-725. https://doi.org/10.1016/j.jsv.2005.02.044

Khoshvaght H, Permala RR, Razmjou A, Khiadani M (2025). A critical review on selecting performance evaluation metrics for supervised machine learning models in wastewater quality prediction. J Environ Chem Eng 13(6), 119675. https://doi.org/10.1016/j.jece.2025.119675

Lawal AI, Kwon S, Kim GY (2021). Prediction of the Blast-Induced Ground Vibration in Tunnel Blasting using ANN, Moth-Flame Optimized ANN, and Gene Expression Programming. Acta Geophysica, 69(1), 161–174. https://doi.org/10.1007/s11600-020-00532-y

Mandal SK, Singh MM (2009). Evaluating Extent and Causes of Overbreak in Tunnels. Tunnelling and Underground Space Technology, 24(1), 22–36. https://doi.org/10.1016/J.TUST.2008.01.007

Murmu S, Maheshwari P, Verma HK (2018). Empirical and Probabilistic Analysis of Blast-Induced Ground Vibrations. International Journal of Rock Mechanics and Mining Sciences, 103, 267–274. https://doi.org/10.1016/j.ijrmms.2018.01.038

Murthy VMSR (2003). Development of predictive models for blast-induced rock mass damage in tunnels and mines, Project Report No. MHRD (27)/1999-2000/111/ME, ISM Dhanbad 214 p.

Naithani AK, Murthy KSK (2006). Geological and Geotechnical Investigations of Tapovan-Vishnugad Hydroelectric Project, Chamoli District, Uttarakhand, India. Journal of Nepal Geological Society (Vol. 34).

Nicholls HR, Johnson CF, Duvall WI (1971). Blasting Vibrations and Their Effects on Structures. USBM, Bull 656.

NTNU (1995). Project Report 2A-95: Tunnelling – Blast Design, NTNU, Department of Civil and Transport Engineering, Trondheim.

NTPC (2006). Detailed Project Report, Tapovan Vishnugaad Hydro-electric Project Vol. 4, Part-II, NTPC Ltd., New Delhi, India, 262 p.

Ogunsola NO, Shin C, Lawal AI, Kim YK, Cho S (2025). Blasting-induced ground vibration modeling in tunnel excavation: A comparative study of ANN, hybrid ANNs, and empirical models. Rock Mech Rock Engg, 58(3), 2711–2737. https://doi.org/10.1007/s00603-024-04299-2

Olofsson SO (1988). Applied Explosives Technology for Construction and Mining, Applex, Arla, Sweden, 303 p.

Ouchterlony F, Olsson M, Bergqvist I 2001. Towards new Swedish recommendations for cautious perimeter blasting, EXPLO 2001, Hunter Valley, NSW, Australia, pp. 169 -181.

Ponce-Bobadilla AV, Schmitt V, Maier CS, Mensing S, Stodtmann S (2024). Practical guide to SHAP analysis: Explaining supervised machine learning model predictions. Drug Development. Clinical and Translational Science, 17(11). https://doi.org/10.1111/cts.70056

Rana A, Bhagat NK, Jadaun GP, Rukhaiyar S, Pain A, Singh PK (2020). Predicting blast-induced ground vibrations in some Indian tunnels: A comparison of decision tree, artificial neural network, and multivariate regression methods. Mining, Metallurgy and Exploration, 37(4), 1039-1053. https://doi.org/10.1007/s42461-020-00205-w

Rana A, Bhagat NK, Singh A, Singh PK (2022). Predicting blast-induced pull using regression tree. Arabian Journal of Geosciences, 15:173; 1-10. https://doi.org/10.1007/s12517-022-09452-1

Singh B, Goel RK (2011). Engineering Rock Mass Classifications: Tunnelling, Foundations and Landslides, BH Elsevier, USA, 365 p.

Trisnapradika GA, Akrom M, Rustad S, Dipojono HK, Maezono R, Kasai H (2025). A machine learning approach for forecasting the efficacy of pyridazine corrosion inhibitors. Theoretical Chemistry Accounts, 144(8):1-24. https://doi.org/10.1007/s00214-024-03165-2

Ullah S, Ren G, Ge Y, Fissha Y, Kinyua EM, Zhang L (2025). Machine learning-based prediction of blast-induced ground vibration in open-pit mining. J Vib Eng Technol, 13:293, 1-14. https://doi.org/10.1007/s42417-025-01855-0

Verma HK, Samadhiya NK, Singh M, Goel RK, Singh PK (2018). Blast-induced rock mass damage around tunnels. Tunn Undergr Space Technol, Elsevier, 71:149-158. https://doi.org/10.1016/j.tust.2017.08.019

Vishwakarma AK, Himanshu VK, Dey K (2024). Prediction of ground vibration at surface for ring blasting in sublevel stoping through empirical approach, k-nearest neighbor, and random forest model. Mining, Metallurgy and Exploration, 41(3), 1567–1584. https://doi.org/10.1007/s42461-024-00976-6

Yan Y, Guo J, Bao S, Fei H (2024). Prediction of peak particle velocity using hybrid random forest approach. Scientific Reports, 14:30793, 1-27. https://doi.org/10.1038/s41598-024-81218-z