（様式２）

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論 文 名：EVALUATION OF EFFECTS OF ROCK MASS CONDITIONS AND BLASTING DESIGN ON THE FLYING BEHAVIOR OF BLAST-INDUCED FRAGMENTED ROCKS AND DEVELOPMENT OF FLYROCK PREDICTION MODEL BY USING MACHINE LEARNING（岩盤条件および発破規格が起砕岩石の飛翔特性に及ぼす影響評価ならびに機械学習を用いた飛石予測モデルの開発）

区　　分：甲

# 論　文　内　容　の　要　旨

Mine blasting can crush large amounts of rocks, making it an important method in mining operations from the perspective of efficient mineral resource extraction. However, mine blasting poses serious safety risks related to flyrocks, which may undermine the safety and productivity of mining operations. Flyrocks are a problem in which crushed materials generated by blasting travel farther than expected, and cause direct damage to nearby infrastructure and endangering workers and residents. Predicting and controlling the flyrock distance is essential for enhancing the overall safety of mining operations. Prediction of flyrocks is difficult by using conventional methods because various factors such as blasting design and rock heterogeneity are intricately related. Therefore, the application of machine learning (ML), which is good at analyzing complex data and is used in various fields due to its high applicability, could be a solution. Machine learning can learn patterns and relationships between parameters by accumulating past data, and it is possible to predict flyrocks in mine blasting based on conditions. The purpose of this study is to develop a flyrock prediction model using machine learning to enable mines to perform safe blasting. The findings from this research work are included in the following chapters:

**Chapter 1**: This chapter reviews relevant literature on rock blasting and explores fundamental principles of rock mechanics, including fracture mechanics, energy dissipation, and ejection velocities, to provide context for the research. Past studies on flyrock hazards are examined, emphasizing the limitations of traditional predictive models in capturing the complexity of blasting scenarios. The advantages of machine learning methods in improving prediction accuracy are discussed, including an overview of techniques like regression and classification models. Finally, the chapter frames the problem statement, emphasizing the necessity of accurate predictive models, and sets forth the research objectives: predicting initial velocity, elevation angle, flyrock range and blast safety classification using machine learning approaches.

**Chapter 2**: This chapter encompassed the survey of past research on flyrock accidents, and it pointed out the limitations of conventional prediction models in that they cannot capture the behavior of flyrocks caused by mine blasting in complex rock conditions. Since flyrocks are a high-speed phenomenon that occurs shortly after blasting, the measurement method of initial velocity and flight angle using a high-speed camera was described. It is indicated that a larger median block size ($Xb_{50}$), a parameter characterizing the initial rock mass condition, correlates with reduced initial velocities of ejected rock fragments. However, higher powder factors or increased charge volumes were observed to increase ejection velocities, even in scenarios involving large $Xb_{50}$ values. Smaller fragments exhibited greater acceleration, a behavior indicative of over-blasting. Additionally, the highest velocities occurred at lower elevation angles (specifically between 25° and 45°). A good correlation between the cumulative 50% particle size ($Xb_{50}$) of rock blocks before blasting and the cumulative 50% particle size ($Xp_{50}$) of crushed material was found, and clarified that the crack state of the rock has a significant effect on the particle size of the crushed material as higher crack densities yield lower median fragment sizes. In addition, it is summarized the test results by focusing on the difference between $Xb_{50}$ and $Xp_{50}$ as an index of the rock crushing effect of blasting. It is shown that the higher the uniaxial compressive strength, the more the crushing effect depends on the crack state of the rock, and the smaller the crushing effect of the rock itself due to blasting. It is also pointed out that the rock crushing effect can be improved by reducing the minimum resistance line length or increasing the amount of charge. Furthermore, the smaller the line of least resistance, the higher the maximum initial velocity of the crushed material, and this tendency varies depending on the density of cracks in the rock. Therefore, by focusing on the line of least resistance and $Xb_{50}$, it is possible to predict the maximum initial velocity and prevent flyrocks. In addition, from the field tests, it was confirmed that when joint planes are aligned parallel to the bench face, 86% of the fragmented rock with joint strikes in this range will be ejected at angles between 0° and 30°. On the other hand, for joint planes that are oriented oblique or perpendicular to the bench face, only 47% of the fragmented rocks with joint strikes in this range will be ejected at angles between 31° and 60°.

These results demonstrate that the trajectory of blasted material can be predicted by analyzing the orientation of prominent joints at the blast face. The study underscores that systematic measurement and analysis of joint orientations prior to blasting enables accurate prediction of fragment trajectories, thereby helping to mitigate flyrock-related hazards. Moreover, with a T-test p value of 0.0013 between the raw and corrected range values, it is concluded that applying the azimuth for angle correction is essential for accurate flyrock trajectory analysis.

**Chapter 3**: In this chapter, it is mentioned that the importance of machine learning in flyrock prediction during mine blasting. The models such as regression models and classification models were used in order to predict the relationship between flyrocks, blasting design and rock mass conditions. In particular, it is pointed out that for flyrocks during mine blasting, which is the focus of this study, predicting the initial velocity, flight angle, and flight range is essential for predicting the flying behavior of flyrocks. This chapter also introduces XGBoost and neural networks as useful machine learning models for predicting the initial velocity, flight angle, and flight distance of flyrocks, and that it is possible to improve the prediction performance of flyrocks by optimizing hyperparameters using Genetic Algorithms (GA) and Bayesian Optimization (BO). It is also explained that the importance of data preprocessing, feature selection, and data augmentation techniques to improve the model's prediction accuracy. Techniques such as Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), SelectKBest and Combined Average (CA) were used during feature engineering. BoxCox data transformation had the least skew and kurtosis and was adopted for evaluation of the initial velocity, flight angle and range. Interpolation which is a data augmentation method commonly applied to small and/or imbalanced data such as flyrock data was applied. Moreover, the modeling in blasting safety assessment using MATLAB's statistics and machine learning toolbox were explained, providing a framework for risk evaluation.

**Chapter 4**: In this chapter, the machine learning models developed in this study to predict the initial velocity was adopted for evaluations of flight angle, and flight distance of the blast-induced rock fragments. A comprehensive analysis of the model performance by comparing the results of various models was carried out by using the indices of Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination ($R^2$), cross validation mean MAE, cross validation MAE-standard deviation (std) and Pearson correlation coefficient. Additionally, it is introduced that a classification model to predict whether a blast will result in dangerous flyrocks, and evaluate the classification model through a confusion matrix and Receiver Operating Characteristic (ROC) curve.

**Chapter 5**: This chapter concludes that, in the context of flyrocks during blasting in open-cut mines, the relationship between in-situ rock conditions, blasting design, and the flying behavior of flyrocks was clarified. Additionally, a flyrock prediction model was developed using machine learning to accurately predict the initial velocity, flight angle of flyrocks and the flyrock distance under complex on-site conditions, thereby contributing to the establishment of safer mine blasting techniques.