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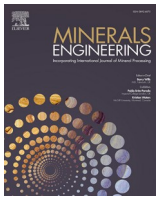

Prediction of grade and recovery in flotation from physicochemical and operational aspects using machine learning models

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ABSTRACT

Machine learning (ML) models for predicting flotation behavior focus on operational variables. Fundamental aspects, e.g., physicochemical variables that describe mineral surfaces for bubble–particle interactions, are largely neglected in these models; however, these physicochemical variables of mineral particles, including bubbles and pulp, influence the flotation behavior. Thus, this study aimed to advance the prediction of flotation behavior by including physicochemical variables. Among four ML models used for the prediction, the random forest model had the best performance and was therefore subsequently used to investigate variable importance. Contact angle, particle diameter, bubble diameter, particle charge, collector concentration, flotation time, and number of mineral species were the most important variables. Limitations (e.g., assumptions and empiricism) and implications of our study were presented. Finally, our expectation was to encourage more attention to physicochemistry in flotation using ML for a more generalized empirical flotation model.

1. Introduction

Gaudin and Kitchener indicated that physicochemical phenomena displayed by mineral surfaces plays a significant part in flotation (Gaudin, 1932; Ralston, 2020). Based on the observation that extremely small amounts of collector added to a flotation system cause substantial differences in the flotation behavior of different minerals, researchers examined the relationship between the surface properties of minerals and bubbles and their flotation (Guven et al., 2015; Yoon and Mao, 1996). Collectors and other reagents in a flotation system generate adsorption and chemical reactions on surfaces, e.g., a clean pyrite floated strongly but when its surface was oxidized, it floated poorly (Gaudin, 1932). Similarly, with clean chalcopyrite, pulp potential manipulated the chalcopyrite flotation (Heyes and Trahar, 1977). Surface alterations, depending on the presence of reagents, influence the flotation behavior, thus, there is a physicochemical aspect (i.e., surface chemistry) that affects flotation. The Derjaguin–Landau–Verwey–Overbeek (DLVO) theory offers a method to examine the physicochemical variables of surfaces (minerals and bubbles) and their relationship with flotation behavior (surface forces that describe bubble–particle interactions). Bubble–mineral interactions based on DLVO theory can be included in mechanistic models that describe flotation kinetics (Gomez-Flores et al., 2020a; Gomez-Flores et al., 2020b). Thus, DLVO theory is an appropriate tool to describe the fundamentals of flotation behavior.

Variables such as collector and frother concentration, adsorption, size, liberation degree, air and water flow rate, mass flow, and circuit design influence the flotation behavior (Wills and Finch, 2016). Researchers have taken the task of modeling and predicting flotation behavior using mechanistic or empirical models. In “kind learning environments” (e.g., repeated patterns and high–quality measurements), machine learning (ML) is suitable for empirical modeling of a multivariable unit operation. Table 1 lists a literature review on modeling of flotation using ML models. Operational variables and neural networks (NN) have been commonly used to model flotation. Note that supervised ML is the dominant ML approach, except for semisupervised ML (genetic algorithms) in Hu et al. (2013) and Pirouzan et al. (2014). Moreover, physicochemical variables were neglected for the modeling and there was a lack of information on database quality based on descriptive statistics. Thus, physicochemical variables and detailed database description were included in our work. The physicochemical variables were selected based on DLVO theory. Multivariable linear regression (MLR), k–nearest neighbors (KNN), decision tree (DT), and random forest (RF) were the ML models to model and predict flotation

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