Graph Neural Network for Mineral Prospectivity Mapping – A Possible Solution to Maximise Utilization of Geological Relationships

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Numerous attempts at mineral prospectivity mapping (MPM) have been made with different machine learning models employing various exploration data as inputs, which have met with different degrees of success. In particular, information about geological relationships is still not well utilised as a data input type, largely due to the limitations of the models used. This omission reduces the impact of geological input for the training process, which in turn affects the degree of success of such models. This situation also limits the ability to incorporate insight from geologists as domain experts in order to improve model performance. In this study, we address this issue by presenting a simple case study that demonstrates the use of neighbouring relationships between geological units to generate mineral prospectivity maps. We represent this relationship by converting geological map data into a graph format that consists of nodes (objects) and edges (relations). The training process uses graph neural network (GNN) algorithms, which are a group of deep neural network algorithms that can operate in graphical space. The approach was applied to generate a prospectivity map for three metal commodities (tin, lead, and copper) in the United Kingdom, and we compared this performance with several machine learning approaches (support vector machine, random forest, gradient boost, and deep neural network). Our study shows that utilising GNN in MPM is beneficial since it can highlight certain lithological boundaries that may potentially be related to mineral occurrences. Despite the model not having explicitly received information about lithological boundaries as a data input, the model can infer such geological relationships implicitly from the provided graph. In addition, GNN also shows higher accuracy and precision scores in certain scenarios when compared to other approaches.