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GeoXAttn-Net: Explainable Cross-Attention Network for Ore–Waste Block Classification using Geological and Operational Mining Data

Sami F. Karali [1], Mohammed I. Thanoon [1], Asma A. Ahmed [2], Abed Saif Ahmed Alghawli [3], Monir Abdullah [4], Ahlem Fatnassi [2], Abdulbasit A. Darem [5], Yahia Said [5,*]

[1]*Computing Department, College of Engineering and Computing at Al-Lith, Umm Al-Qura University, Saudi Arabia*
[2]*Department of Computer Science, College of Science, Northern Border University, Arar 73213, Saudi Arabia*
[3]*Computer Science Department, College of Sciences and Humanities, Prince Sattam Bin Abdulaziz University, Aflaj 11912, Saudi Arabia*
[4]*Department of Computer Science and Artificial Intelligence, College of Computing and Information Technology, University of Bisha, Bisha 61922, Saudi Arabia*
[5]*Center for Scientific Research and Entrepreneurship, Northern Border University, 73213, Arar, Saudi Arabia*

Abstract Recently, artificial intelligence and deep learning methods have received significant attention in mining applications because of their ability to support mineral resource evaluation, production planning, and ore-waste decision making. However, ore-waste block classification in open-pit mining environments still remains a challenging task due to complex geological variations, spatial heterogeneity, economic uncertainty, and the dependency between geological and operational mining parameters. Although several machine learning and deep learning models have demonstrated promising performance, many existing methods still suffer from limitations such as insufficient feature interaction learning, weak interpretability, and reduced classification performance when handling multimodal mining data. To address these limitations, this study develops GeoXAttn-Net, an Explainable Cross-Attention Network for ore-waste block classification using geological and operational mining data. The mining block dataset initially undergoes preprocessing stages to enhance data quality and feature consistency. Following that, feature engineering is performed by computing profit margin, ore-to-waste economic ratio, and spatial depth-related information for improving discriminative feature representation. Additionally, SHAP-guided dynamic feature weighting is introduced to estimate feature importance and adaptively refine feature contributions based on SHAP importance scores. Besides, the presented GeoXAttn-Net approach uses separate geological and operational feature encoders to learn physical and economic characteristics of mining blocks. A bidirectional cross-attention fusion mechanism is employed to capture the dependency between geological and operational feature representations. Moreover, transformer-based fusion and SHAP-guided attention refinement are integrated to improve feature interaction learning and model interpretability. Finally, a dense classification head with softmax activation is used for ore-waste classification. Experimental evaluation is conducted using the Open-Pit Mining Block Model Dataset, and the results demonstrate the efficiency of the proposed method in improving ore-waste classification performance and interpretability. Thus, the proposed GeoXAttn-Net approach can support intelligent mining decision-making, mineral resource evaluation, and economically sustainable mine planning applications.

Keywords Ore-Waste Classification, Cross-Attention Network, SHAP Explainability, Open-Pit Mining, Feature Weighting, Deep Learning

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1. Introduction

In the mining process, reducing classification errors of ore and waste in the grade control process is essential for effective resource management. The traditional methods of grade control, as well as ore and waste delineation in

*Correspondence to: Yahia Said, Center for Scientific Research and Entrepreneurship, Northern Border University, Arar 73213, Saudi Arabia.

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the open pit mining process, are mainly based on estimated mineral grades along with an economic cutoff [1]. An alternative method for ore selection was introduced in the 1990s by incorporating financial indicators using an economic classification function together with grade uncertainty analysis. Grade uncertainty is evaluated through various grade realizations from stochastic or geostatistical simulations [2]. The process of ore and waste selection is supported by the analysis of economic impacts of sending a block of mined minerals for processing and waste disposal, along with the associated uneven financial implications [3]. In geological applications, including open-pit mining, autonomous systems must distinguish between minerals of different composition and the waste materials that look alike to standard RGB cameras. Slight variations in reflectance spectra often enable these differences to be identified; such variations can be assessed using a highresolution hyperspectral camera [4]. For instance, in ore-bearing regions, goethite and martite can be differentiated from non-ore-bearing shale regions through finely resolved spectraldomain features from hyperspectral cameras [5].

Since the profitability of mining operations is largely based on precise grade evaluation, the estimate of mineral reserves is a significant component in the mining sector. Mineral reserves estimation faces many challenges related to the geological complexity of ore deposits during field exploration, and the estimation process frequently considers only limited spatial characteristics of the ore body [6]. However, continued research has gradually shown that several important factors, including ore type, geological structure, depositional environment, and degree of mineralization, are essential for reserve evaluation [7]. The convolutional geological modeling related to geometry-based and geostatistical approaches, such as semi-variography, was the first method introduced for reserve estimation. These methods provide several advantages, such as simple computations, better understanding, and effective application in two-dimensional space [8]. Despite their advantages, these methods have some disadvantages, including local discontinuities and failure to account for all important parameters. These approaches are primarily dependent on linear and mathematical formulations, which are relatively simple but challenging to apply in complex geological environments with varying mineralization [9]. Later, different modeling approaches have been developed to address these issues. Standard approaches face difficulties in handling complex time-series information and are inadequate to offer precise predictive results in decision-making [10]. The application of Deep Learning methods provides an effective solution for these issues, which supports a smarter and more effective mining process along with improved quality control. Compared with shallow neural networks, the Deep Neural Networks (DNNs) are capable of capturing high-level, complex, and abstract features because they have a greater number of hidden layers [11]. To achieve high prediction accuracy, two interrelated factors need to be considered when working with a neural network, namely, network architecture and training strategy. In recent decades, several DNN models have emerged, each with various network architectures based on the number of layers, layer shapes, layer types, and inter-layer connections [12]. However, accurate ore-waste block classification is still challenging because of geological complexity and variations in mining-related parameters. In addition, many existing techniques lack proper interpretability for practical mining decision-making.

To overcome these limitations, this study develops GeoXAttn-Net, an Explainable Cross-Attention Network for ore-waste block classification using geological and operational mining data. GeoXAttn-Net is designed to address the challenges of heterogeneous geological and operational information in ore-waste block classification while providing interpretable feature representations. The proposed model utilizes employs SHAP-guided dynamic feature weighting to refine the contribution of individual features, while bidirectional cross-attention allows the method to learn complementary dependencies between geological and operational representations. Transformer-based feature refinement further improves the learned representation for classification. These components are generated to provide a more informative and interpretable learning process for ore-waste block classification and support data-driven mining decision-making. The proposed framework integrates SHAP-guided feature weighting and bidirectional cross-attention fusion to enhance feature interaction learning and interpretability. Additionally, transformer-based fusion is used to improve the representation ability of the proposed method for robust ore-waste classification. The key contributions of this work are outlined as follows:

- To develop GeoXAttn-Net, an explainable cross-attention network for ore-waste block classification utilizing heterogeneous geological and operational mining features.
- To introduce SHAP-guided dynamic feature weighting for estimating feature importance and refining feature contributions.

- To design a bidirectional cross-attention fusion mechanism for learning the dependency between geological and operational feature representations.
- To improve ore-waste classification performance and interpretability using transformer-based feature fusion and attention refinement.
- To evaluate the proposed GeoXAttn-Net model using the Open-Pit Mining Block Model Dataset for intelligent mining decision-making applications.

2. Related Works

This section presents the relevant literature on ore-waste classification, deep learning, and mining-based prediction approaches. Badakhshan et al. [13] developed an innovative technique that incorporates mathematical model along with Q-learning, a RL approach, to improve the results by increasing ore recovery and profitability while reducing waste rock extraction. The major factors of the system clearly include coverage prevention, compensation for effects, environmental expenses, and mitigation as essential elements of economic value. Huang et al. [14] examined an enhanced Inception and ResNet-v2 methodologies for graphite ore grade identification. Initially, to improve the extraction of global features from mining data, a GAP method is integrated into the Inception and ResNet framework. Moreover, a convolutional layer was integrated at the end of the method to manage channel dimensions, and the LeakyReLU activation method was adopted to overcome these limitations. Kenzhaliyev et al. [15] addressed these difficulties to leverage innovative ML methodology to improve the efficacy of pyrometallurgical processes, including composition prediction, waste minimization, and slag optimization. With the integration of real-time and synthetic information, the authors developed a system capable of performing both forward forecasts, evaluating matte and slag configurations from ore features, and backward prediction, implying ore compositions from outcome attributes.

Wang et al. [16] proposed a TBM rock muck particle size examination approach on the basis of DL and digital image processing. The major purpose is to capture real-world morphological parameters of rock muck imaging, providing information for assessing rock mass quality and supporting dynamic excavation. An LED light source and an industrial camera are employed to create an image detection model for mineral features. Zhou et al. [17] investigated an enhanced YOLOv8n system for detecting dual distinctive thin-vein metal ores such as wolframite and gold ore. By considering the computation restraints in underground settings, a three-optimizer methodology is presented. The ECA module is placed before the SPPF pooling layer to improve feature representation for rocks and ores. Zairov et al. [18] introduced a reproducible and practical architecture to create an ore classification algorithm that could be developed at the edge. Li et al. [19] discussed a blasting ore size recognition approach based on an efficient dehazing network and multi-dimensional feature fusion, which is based on YOLOv8. Firstly, the authors developed an efficient defogging backbone system that integrates a scalable backbone and feature attention; thus, the method can effectively capture the attributes of ore images and improve the model's robustness to dust interference in the crushing ore process.

Herrera et al. [20] addressed the modern usage of soft computing (SC) methodologies in the mining sector, with a unified focus on flotation, pyrometallurgical, comminution, and hydrometallurgical processes, and the collection of SC systems and models to identify key variables. In this, an SC strategy is introduced to improve the control and prediction precision for mineral waste disposal, particularly concentrating on tailings, and the process of leaching destroys the database system. In [21] several effective DL techniques are employed for the identification of ore classes. In this study, four distinct experiments (feature extraction, transfer learning, and classification with SVM, feature selection with optimizer methodology, and ensemble models) are evaluated, and the algorithms are distinguished in classification measures. This paper exhibits that an effective DL strategy can identify ore classes with greater accuracy and have important potential applications in the mining sector. Abdolmaleki et al. [22] developed the usage of Portable X-ray Fluorescence (pXRF) system as an effective and economical way for supporting grade control in a gold mine. Rock instances gathered from blasted muck piles were examined through pXRF, and after data preprocessing, 15 elements were detected as consistent predictors. Since geochemical datasets are compositional, the centered log-ratio (CLR) conversion was employed, prior to principal component analysis

Table 1. Overview of ore-waste block classification systems

Authors/Years	Objectives	Mining domain	ML/ AI models	Key Outcomes
Badakhshan et al. [13] (2026)	To reduce waste rock in open-pit mine design using intelligent optimizer algorithms.	Open-pit mining design	Q-learning and reinforcement learning methods.	Improved pit design with reduced waste rock
Huang et al. [14] (2025)	To improve graphite ore grade detection employing DL methods.	Graphite mining	improved Inception and ResNet-v2 techniques.	Accuracy of 94.81%.
Kenzhaliyevet al. [15] (2025)	To develop an intelligent model for enhancing efficiency and minimizing waste in copper production.	Copper production	Gradient boosting and SVM approaches.	R2 of 0.9951.
Wang et al. [16] (2025)	To estimate particle size distribution from TBM rock muck images.	TBMtunneling	Faster R-CNN model	Accurate particle size estimation achieved
Zhou et al. [17] (2026)	To detect thin-vein precious metal ores using enhancedYOLO-valgorithms.	Precious metal ores	YOLOv8n model	mAP50 of 98.3%.
Zairovet al. [18] (2026)	To design areal-worldore sorting system using edge-deployed YOLO models	Open-pit mining	YOLOv5n approach	AUC of 0.895.
Li et al. [19] (2026)	To detect blasting ore size under poor visibility using enhanced image processing and DL approaches.	Blasting ore operations	DL and YOLOv8n algorithms.	mAP50 of 88.1%.
Herrera et al. [20] (2023)	To review soft computing applications in mining and propose approaches for waste disposal.	Mining & metallurgy	ANN and fuzzy algorithms.	Domain-wide framework was developed.
Yurdakul et al. [21] (2025)	By integrating optimized CNN ensembles and feature-fusion approaches to improve ore classification	Ore classification	CNN, and ensemble models.	Better ore classification accuracy.
Abdolmaleki et al. [22] (2026)	By using portable XRF (pXRF) geochemical measurements to enhance mine-site ore grade control.	Ore grade control and geochemical analysis	Random forest	Robust ore-grade prediction employing-pXRFinformation.
Zhou et al. [23] (2025)	For developing a rapid rock-mass classification architecture for underground mining.	Underground mining and rock-mass classification	ML and semantic segmentation	Accurate automated rock-mass classification.
Ramos et al. [24] (2025)	To predict silica content in iron-ore flotation while providing interpretable model outcomes.	Iron-ore flotation and mineral processing	ML techniques	Effective and interpretable silica prediction.

(PCA) to generate unrelated scores of the component. Three feature sets namely CLR-transformed data, PCA, and raw geochemical data, were utilized to evaluate the RF classification algorithm for distinguishing ore from waste.

Ramos et al. [23] proposed the growth of an interpretable ML technique to predict silica content in the concentration of iron ore flotation method. The explainable boosting machine (EBM) model is selected for its capability to offer explainable insights into the factor underlying every prediction, enabling operators to achieve a deeper understanding of process states and make informed process changes. Zhou et al. [24] introduced an

improved AI-based rock mass classification model. Initially, three diverse kinds of ML approaches, such as tree-based methods, a stacking ensemble model, and Graph Neural Networks (GNNs), are used to predict uniaxial compressive strength (UCS) depends on field information. Following this, three semantic segmentation structures are relatively used to identify joint fractures from field-captured rock surface imaging. After, a multi-stage clustering-fitting model is designed to obtain key joint parameters from the segmented images. Lastly, the model is used to a real mining case for ore rock mass identification. Table 1 presents the existing ore–waste recognition models, including their objectives, mining domains, ML/AI techniques, and key outcomes. Table 1 presents the existing ore–waste recognition models, including their objectives, mining domains, ML/AI techniques, and key outcomes.

2.1. Research Gap

Although existing ML and DL methodologies have shown promising performance in ore waste classification, ore grade identification, and mining-related prediction, numerous limitations remain. Most existing literatures mainly concentrate on enhancing classification or prediction performance, whereas the economic and spatial characteristics of mining blocks are not sufficiently integrated into the learning process. Particularly, factors like profit margin, economic stripping ratio, and spatial depth can provide valuable information for differentiating economically viable ore from waste, but these factors are not consistently incorporated as predictive features. Additionally, existing methodologies generally rely on fixed feature representations and do not dynamically modify feature contributions based on their influence on model predictions.

In addition, although explainable methods such as SHAP have been applied to interpret mining-related models, their use for dynamically refining feature contributions during model training remains limited. Existing DL approaches also provide limited consideration of the interactions between geological and operational features, which may restrict the model's ability to capture complementary information from these feature domains. Therefore, there is a need for an integrated framework that combines economic and spatial feature engineering with SHAP-guided dynamic feature weighting and bidirectional cross-attention fusion. These gaps motivate the development of a unified framework that integrates economic and spatial information, dynamically refines feature contributions, and captures the interactions between geological and operational features for effective and interpretable ore-waste classification.

3. Proposed Methodology

Fig. 1 demonstrates the overall architecture of the proposed GeoXAttn-Net model for ore-waste block classification using geological and operational mining data. The presented method proceeds through a sequence of processes as described below:

- Step 1: The mining block dataset is initially given for preprocessing and feature engineering.
- Step 2: SHAP-guided dynamic feature weighting is applied to estimate feature importance.
- Step 3: Geological and operational feature encoders learn the physical and economic characteristics of mining blocks.
- Step 4: Bidirectional cross-attention fusion is used to capture feature dependency between geological and operational data.
- Step 5: Transformer-based fusion improves feature interaction learning.
- Step 6: Finally, the dense classification layer with softmax activation predicts ore and waste classes.

3.1. Dataset Description

This section describes the Open-Pit Mining Block Model Dataset [25] utilized for ore-waste block classification. This dataset is a produced representation of an open-pit mining block model, designed to signify spatial, geological, operational, and economic characteristics associated with open-pit mining. It comprises 75,000 individual blocks,

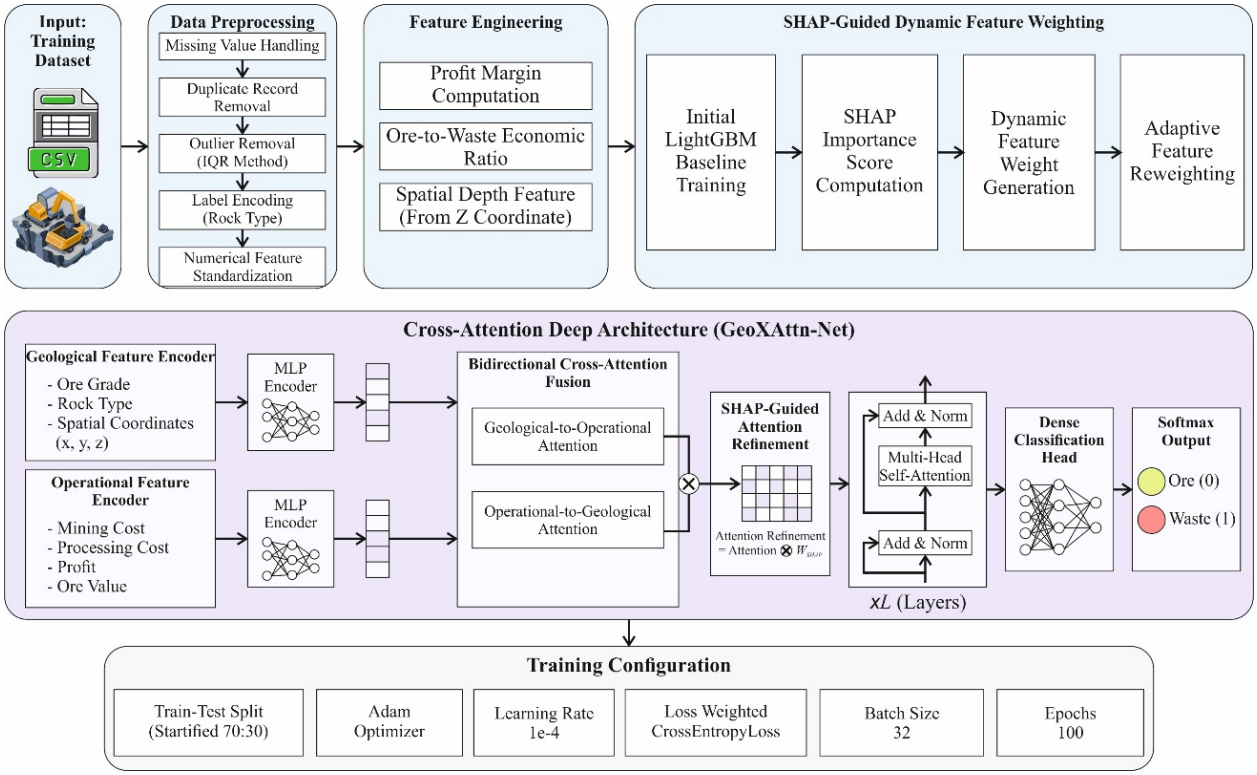


Figure 1. Overall architecture of the proposed GeoXAttn-Net approach

Table 2. Details of datasets

Classes	No. of Instances
Ore (0)	59978
Waste (1)	15022
Total Instances	75000

every individual signifying a unit of earth material with related features that impacts decision-making in mine planning and resource assessment. The dataset includes crucial parameters like operational costs, tonnage, ore grade, and economic value. The calculated profit value and respective binary target label specify if the block is considered economically possible for extraction. This setup helps numerous categories of evaluation, including resource categorization, production scheduling, and profitability valuations. The dataset is a generated representation of an open-pit mining block model rather than a documented site-specific my dataset. The publicly available dataset description does not signify a particular mine, drill-hole database, variogram model, or geostatistical simulation procedure utilized for its generation. Consequently, the spatial coordinates are considered as block-level spatial attributes in this study, and the proposed model is conducted as a data-driven classification approach rather than as a validated geological continuity model. Table 2 represents the dataset, which contains two classes, like ore (0) and waste (1), with a total of 75,000 instances.

3.2. Data Preprocessing

This section explains the preprocessing steps used to improve the quality and consistency of the mining dataset. In this article, the data preprocessing phases comprise data cleaning, missing value handling, duplicate record removal, outlier removal using the IQR method, label encoding, and numerical feature standardization [26].

Data Cleaning: The data cleaning process is performed to prepare high-quality inputs for robust model training rather than solely focusing on eliminating redundant information. It involves removing incorrect data that may affect the outcomes of the ML method, including duplicate records, missing values, and outliers using the IQR method.

Label Encoding: Label encoding is a method of transforming categorical or text data (non-numeric data) into numerical data to make them suitable for ML methods and is an important phase of data preprocessing. In this work, the Rock_Type feature encompasses categorical data. Through the label encoding, the categorical values are transformed into numerical representations.

Numerical Feature Standardization: Numerical feature standardization is used to rescale the data without changing their types. It is a vital stage of data preprocessing in AI and ML techniques. The main objective of standardization is to transform the original values to a common scale without substantial variations in the data range. The standardized data values depend on the standard deviation (SD) and mean value. The values are standardized based on the attribute values, as shown in Eq. (1),

$$Z = \frac{x - \mu}{\sigma} \tag{1}$$

Z implies the standardized data feature, x denotes the original data value, μ and σ represent the mean and standard deviation of the features.

3.3. Feature Engineering

Feature engineering in mining and geological applications converts the original data into predictive, actionable variables. These engineered features quantify the spatial and economic feasibility of an ore block, thereby representing the physical geometry of extraction and financial viability [27].

Profit Margin Computation: This computes the net economic returns per extracted module or block. This can be dynamically integrated with changing metal prices, operational costs, and recovery rates.

Data value: It converts the original geological grades into financial targets and directly aligns the ML optimization objectives with corporate financial KPIs.

Ore-to-Waste Economic Ratio: It is also called the net economic stripping ratio (NESR), which assesses whether the removal of overlying waste rock is justified by the underlying ore value.

Data value: The standard stripping ratios are only calculated for the physical volume. This engineered ratio utilizes an economic weight, thus preventing the system from categorizing lower-grade but extremely expensive-to-expose blocks as cost-effective.

Spatial Depth Feature from Z Co-ordinate: The feature transforms the absolute image coordinates (elevation) into comparative geological information. During the underground or open-pit mining process, absolute elevation has limited predictive value without contextual information.

Data Value: It can encode the vital domain information, like vertical seam continuity and distance-to-surface. This information can be obtained from spatial dependencies; for instance, deeper zones may indicate greater compaction, grade depletion, or fluctuating geomechanical conditions and can be used to determine the pit floor limits precisely.

3.4. SHAP-Guided Dynamic Feature Weighting

This section explains the SHAP-guided feature weighting strategy leveraged for estimating feature importance and refining feature contributions. The main contribution of this study is the SHAP-Guided Dynamic Feature Weighting, which operates as follows [28]:

- Initialization of LightGBM Baseline Training
- SHAP importance score computation
- Dynamic feature weight generation
- Adaptive feature reweighting

By employing SHAP, the importance of each feature dimension is determined based on the output classes. The original SHAP values are processed as given below:

- The values are aggregated to obtain the positive and negative contributions.
- The values are averaged across all 1000 instances to obtain the representative importance vector.
- Normalization to the range [0, 1] using min–max scaling.

To prevent erratic weight changes caused by epoch-to-epoch variability in SHAP estimation, temporal smoothing is applied using an exponential moving average (EMA) with a β value.

In the 1st epoch (t = 1),

$$SHAP(1)_{EMA} = SHAP(1) \tag{2}$$

If the condition is (t $>$ 1), the following expression is given by,

$$SHAP(t)_{EMA} = \beta \times SHAP(t-1)_{EMA} + (1 - \beta) \times SHAP(t) \tag{3}$$

The EMA-smoothed SHAP values are used to modify feature contributions through element-wise multiplication.

$$W_{SHAP} = W_{Original} \odot SHAP_{EMA} \tag{4}$$

The final weights are obtained through blending, where α represents the blending parameter.

$$W_{final} = \alpha \times W_{SHAP} + (1 - \alpha) \times W_{Original} \tag{5}$$

The final feature weights are then applied, completing one SHAP adjustment cycle. This process is repeated after each training epoch.

3.5. Cross-Attention Deep Architecture (GeoXAttn-Net)

This section explains the architecture of the proposed GeoXAttn-Net model for ore-waste block classification. The internal architecture of the proposed approach, including the geological encoder, operational encoder, and bidirectional cross-attention fusion, is illustrated in Fig. 2.

Geological Feature Encoder

The geological feature encoder denotes the spatial and physical properties of every mining block.

- Ore_Grade (%)
- Rock_Type
- X Co-ordinate
- Y Co-ordinate
- Z Co-ordinate

These features define the spatial location and geological structures of all the blocks in the deposit.

Operational Feature Encoder

The operational feature encoder characterizes the economic and cost-specific aspects of every mining block.

- Mining_Cost (¥)
- Processing_Cost (¥)
- Ore_Value (¥/tonne)
- Profit (¥)

These features define the economic possibility for the extraction of all blocks.

Bidirectional Cross-Attention Fusion Module

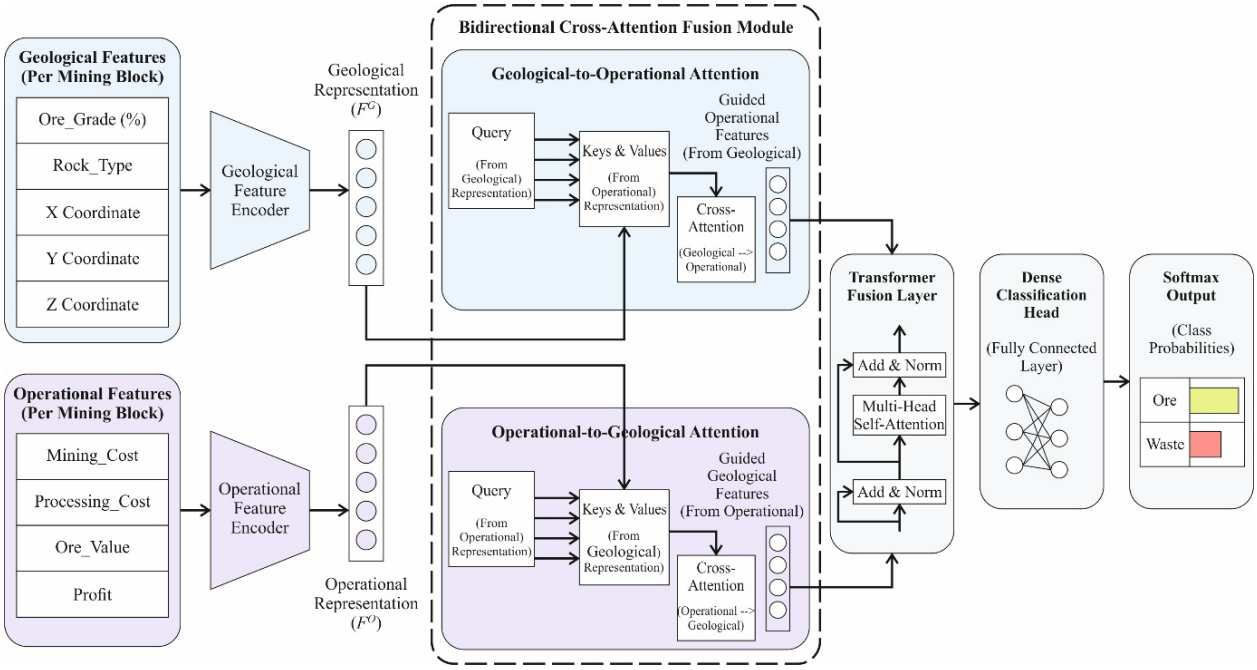


Figure 2. Internal architecture of the proposed approach demonstrating geological encoder, operational encoder, and bidirectional cross-attention fusion.

In this section, the bidirectional cross-attention fusion method is developed to enable mutual guidance and feature optimization [29]. This model comprises dual complementary sub-modules, namely operational-to-geological attention and geological-to-operational attention. These two sub-modules operate on the outputs of the previous feature representations, thereby enabling fine-grained feature selection (FS) and interaction. Geological-to-Operational Attention: The cross-attention mechanism is calculated by,

$$A^{(G\to O)} = \text{softmax}\left(\frac{Q^{(G\to O)}(K^O)^T}{\sqrt{d_{attn}}}\right) \tag{6}$$

$$F_{cross}^{(G\to O)} = A^{(G\to O)}V^O \tag{7}$$

Generally, the cross-attention output encodes the guided feature data.

Operational-to-Geological Attention: The cross-attention mechanism is evaluated as

$$A^{(O\to G)} = \text{softmax}\left(\frac{Q^{(O\to G)}(K^G)^T}{\sqrt{d_{attn}}}\right) \tag{8}$$

$$F_{cross}^{(O\to G)} = A^{(O\to G)}V^G \tag{9}$$

Here, the cross-attention output encodes the guided feature data.

SHAP-Guided Attention Refinement

The SHAP explainability technique is used to develop SHAP-guided attention refinement, which leverages the explanatory ability of SHAP values to iteratively reduce the feature sets [30]. Mean absolute SHAP values are used to rank the features based on their average contribution to the model's predictions. The feature importance can be calculated by applying the mean absolute SHAP values,

$$I_f = \frac{1}{N}\sum_{i=1}^{N} \mid SHAP_{i,f} \mid \tag{10}$$

Here, the term $SHAP_{i,f}$ indicates the SHAP value of feature f, for instance, i, the parameter I_f refers to the significance of feature f, and the term N represents the count of instances. The fusion module acquires the feature representations and handles them with the transformer-based fusion layer. It allows representation learning and deep feature interaction. The fused representation has been entered into the fully connected (FC) dense layer using the softmax activation function and prediction of the probability function over the categorizes [31]. The output of softmax is determined by,

$$\text{Softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}} \tag{11}$$

Now, the mathematical representation is $z = (z_1, ..., z_C) \in \mathbb{R}^C$denotes the input vector. Finally, the output provides the annotation for every class, such as ore and waste.

3.6. Training Strategy

This section presents the training settings and optimization strategy employed for training the proposed model. The Adam optimization method integrates the advantages of the RMSProp and AdaGrad methods [32]. For each parameter, this method retains the squared gradients and moving averages of the gradients:

The mathematical form of 1st and 2nd moment estimation is calculated by

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\, g_t \tag{12}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)\, g_t^2 \tag{13}$$

Here, the parameter g_t refers to the gradient corresponding to iteration t, the decay rate for 1st moment ($\beta_1 = 0.9$), and 2nd moment ($\beta_2 = 0.999$)

The bias-corrected estimation is represented by

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{14}$$

$$\widehat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{15}$$

The parameter update rule calculation is given below

$$\theta_t = \theta_{t-1} - \eta \frac{\widehat{m}_t}{\sqrt{\widehat{v}_t} + \epsilon} \tag{16}$$

Here, the symbol θ_t indicates model parameters with respect to step t, the value $\epsilon = 10^{-8}$ represents the small constant for numerical stability, and the mathematical value of $\eta = 1 \times 10^{-4}$ is the learning rate.

Table 3 shows the parameter settings of the proposed framework that uses the Adam optimizer with a learning rate of 1×10^{-4}, weight decay of 1×10^{-5}, and gradient clipping at 1.0. The model is trained for 100 epochs with a batch size of 32 using weighted cross-entropy loss and a stratified data split. For interpretability, SHAP utilizes LightGBM as the baseline with 1,000 instances and Min–Max normalization, combined with EMA weight smoothing and adaptive feature reweighting. Additionally, the framework comprises MLP-based geological and operational encoders, bidirectional cross-attention, and transformer-based feature fusion. Lastly, a fully connected classification head with softmax activation produces predictions for two output classes.

Table 3. Parameter setting

Category	Parameter	Setting
Optimizer	Optimizer	Adam
Optimizer	Learning Rate	1×10^{-4}
Optimizer	β_1	0.9
Optimizer	β_2	0.999
Optimizer	Epsilon	1×10^{-8}
Optimizer	Weight Decay	1×10^{-5}
Optimizer	Gradient Clipping	1.0
Training	Batch Size	32
Training	Epochs	100
Training	Loss Function	Weighted Cross-Entropy
Training	Train–Test Split	70:30 and 80:20
Training	Data Split	Stratified
SHAP Module	Baseline Model	LightGBM
SHAP Module	SHAP Samples	1000
SHAP Module	SHAP Normalization	Min–Max [0,1]
SHAP Module	Weight Smoothing	EMA
SHAP Module	Feature Reweighting	Adaptive
Architecture	Geological Encoder	MLP
Architecture	Operational Encoder	MLP
Architecture	Cross-Attention	Bidirectional
Architecture	Attention Directions	Geo→Operational+Operational→Geo
Architecture	Fusion	Transformer
Architecture	Classification Head	Fully Connected
Architecture	Output Activation	Softmax
Architecture	Output Classes	2

4. Experimental Results and Discussion

This section discusses the experimental results and performance analysis of the presented GeoXAttn-Net model.

4.1. Experimental Setup

The empirical assessment of the proposed GeoXAttn-Net method has been conducted by the Open-Pit Mining Block Model Dataset obtained from Kaggle. In the dataset, there are 75,000 mining blocks with operational mining, spatial, and geological features. From these overall samples, there are 59,978 samples related to the ore class, although 15,022 instances are associated with the waste class. The dataset has been separated by employing the stratified train–test split to maintain class balance in the training and testing phase. The proposed technique can be trained by the Adam optimizer with a batch size of 32, 100 epochs, and a learning rate of 1e-4The model's performance is assessed by employing confusion matrix analysis, precision, accuracy, MCC, F1-Score, and recall.

4.2. Performance Analysis

Fig. 3 present the confusion matrices of the GeoXAttn-Net approach with 80:20 of train-test split. The results show a higher correspondence among the actual and predicted ore/waste classes to evaluate classification performance.

Table 4 shows the ore/waste classifier outcome of the GeoXAttn-Net approach with an 80:20 train-test split. From this analysis, the GeoXAttn-Net model achieves an $accur_y$ of 93.87% in TRAIP and $accur_y$ of 93.96% in TESIP. In contrast, the MCC of 80.42% for the TRAIP and MCC of 80.97% for the TESIP confirm the effectiveness and robustness of the proposed system in accurately classifying ore and waste samples.

with 80:20 split

Fig. 4 displays the ROC curve assessment of the GeoXAttn-Net approach by utilizing an 80:20 split. The experimentation outcomes exhibit that the model reliably accomplishes greater ROC scores for 2 classes, representing efficient separation between classes. This stable progression of the ore and waste classes emphasizes the stability of the model and is effective in gaining precise classification.

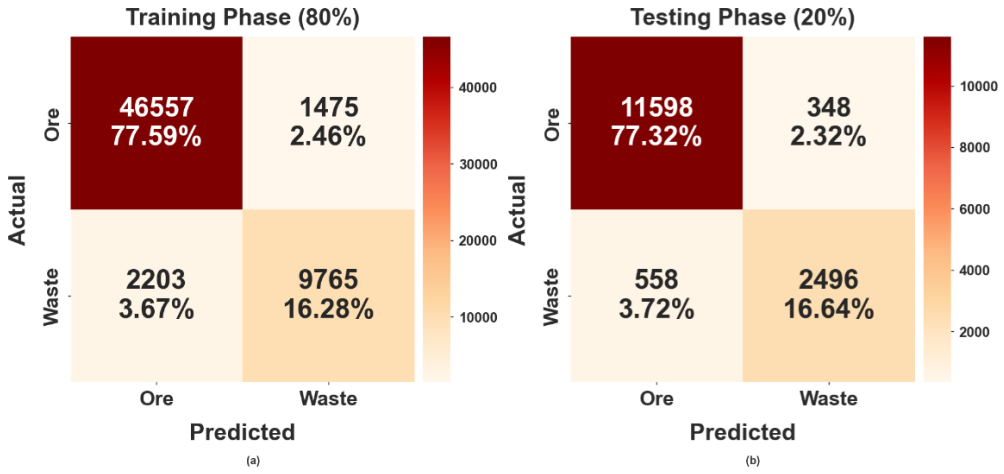


Figure 3. Confusion matrices of the GeoXAttn-Net method with 80:20 split

Table 4. Ore/waste classifier result of the GeoXAttn-Net method

Metrics	**TRAIP (80%)**	**TESTP (20%)**
Accuracy	93.87	93.96
Precision	91.18	91.59
Recall	89.26	89.41
F1-Score	90.18	90.44
MCC	80.42	80.97

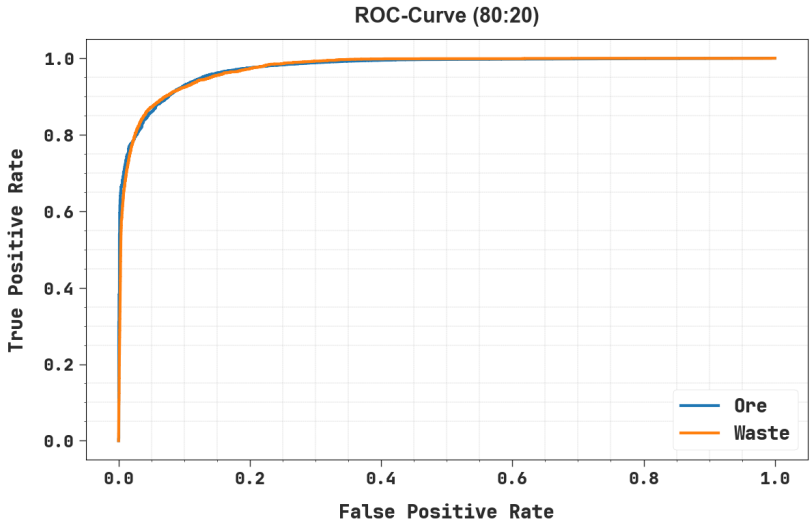


Figure 4. ROC- curve of the GeoXAttn-Net system with 80:20

Fig. 5 present the confusion matrices of the GeoXAttn-Net approach with 70:30 of train-test split. The outcome indicates robust agreement among the predicted and actual ore/waste classes to assess classification performance.

Table 5 illustrates the ore/waste classifier result of the GeoXAttn-Net system with a 70:30 train-test split. In this evaluation, the GeoXAttn-Net technique realizes an $accur_y$ of 95.05% in TRAIP and $accur_y$ of 94.73% in TESIP, while the MCC of 84.34% for the TRAIP and MCC of 82.93% for the TESIP confirm that the efficiency of the proposed model in correctly categorizing ore and waste samples.

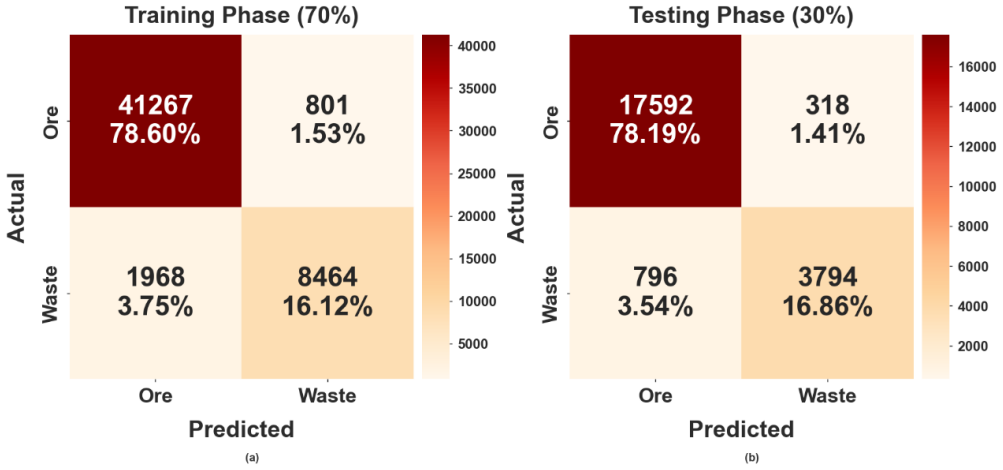


Figure 5. Confusion matrices of the GeoXAttn-Net method with 70:30 split

Table 5. Ore/waste classifier result of the GeoXAttn-Net method

Metrics	**TRAIP (70%)**	**TESTP (30%)**
Accuracy	95.05	94.73
Precision	93.97	93.40
Recall	90.44	89.62
F1-Score	92.06	91.35
MCC	84.34	82.93

with 70:30 split

Fig. 6 demonstrates the ROC curve evaluation of the GeoXAttn-Net method by employing a 70:30 split. The simulation outcome values indicate that the model constantly realizes higher ROC scores for two classes, specifying effective separation between classes. This steady pattern with the ore and waste classes highlights the robustness and the model's consistency for performing an accurate classification process.

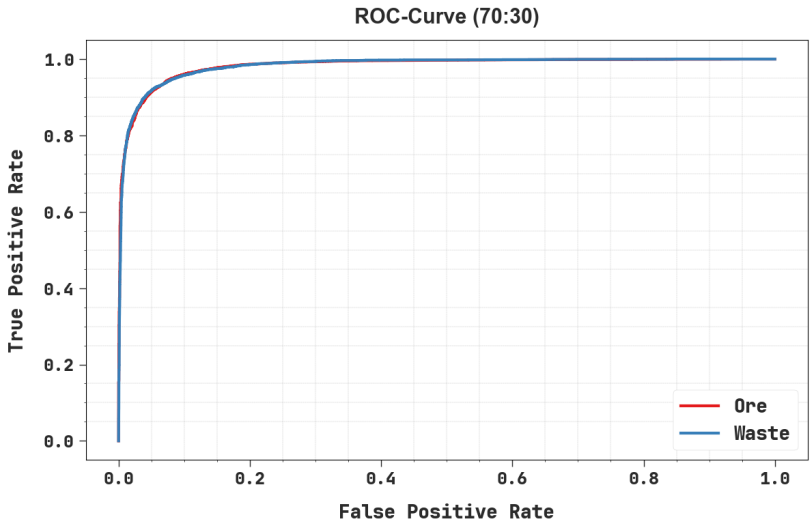


Figure 6. ROC-curve of the GeoXAttn-Net approach with 70:30

Table 6. Table 6

Techniques	Accuracy	Error Rate	Precision	Recall	F1-score
ConvNext	80.21	19.79	80.28	80.21	80.15
EffiicientNet-v2	80.98	19.02	81.11	80.98	80.88
MaxViT-T	82.19	17.81	82.03	82.19	82.07
2S_DenseViT	83.11	16.89	83.33	83.11	83.05
GarbageNet	92.60	7.40	92.73	89.66	91.17
ElectroSortNet	87.50	12.50	87.80	87.20	86.80
CBAM	85.30	14.70	85.60	85.30	85.40
DenseNet121	89.19	10.81	90.06	86.69	89.62
InceptionResNetV2	87.32	12.68	89.69	85.03	88.49
MobileNetV2	88.15	11.85	89.98	85.86	87.87
XGBoost[36]	63.91	36.09	64.38	62.74	63.55
CatBoost[36]	69.24	30.76	69.83	68.41	69.11
LightGBM[36]	70.63	29.37	71.24	69.52	70.37
TabNet[36]	68.11	31.89	68.94	67.38	68.15
GeoXAttn-Net	95.05	4.95	93.97	90.44	92.06

4.3. Comparative Evaluation

To ensure a fair comparison, each evaluated models were trained and tested utilizing the same dataset, pre-processing procedure, data partitioning strategy, and evaluation metrics. The same experimental protocol was maintained across the proposed model and baseline models to reduce the influence of experimental settings on comparative performance. Table 6 and Fig. 7 show the comparison result of the GeoXAttn-Net system with existing methods using evaluation metrics and error rate [33-36]. The finding shows that the HDRL-MGHRR method achieves better performance. The outcome indicated that the XGBoost, CatBoost, LightGBM, and TabNet obtains $accur_y$ performance between 63.91% and 70.63%, while ConvNext, EffiicientNet-v2, MaxViT-T, and 2S_DenseViTmethods ElectroSortNet CBAM, InceptionResNet V2, and MobileNetV2 approaches have slightly higher outcomes. Besides, the DenseNet121 and GarbageNet methods have reached moderate performance. At the same time, the proposed GeoXAttn-Net system has achieved greater performance with $aaccur_y$ of 95.05%, $preci_n$ of 93.97%, $recal_l$ of 90.44%, and $F1_{score}$ of 92.06%. It also shows a low error rate of 4.95%, demonstrating both effectiveness and computational efficiency.

Table 6 Comparison result of the GeoXAttn-Net approach with existing methods

4.4. Ablation Study

Table 7 present the ablation study of the GeoXAttn-Net approach with various measures. The result implied that the baseline simple concatenation requires better performance, while unidirectional cross-attention obtain effective relationship between operational and geological characteristics. Bidirectional cross-attention further enhances the outcomes by enabling data exchange between both feature streams. Even though eliminating feature weighting whereas retaining bidirectional cross-attention preserves enhanced performance. The proposed (Bidirectional Cross-Attention + SHAP-Guided Dynamic Weighting) method has achieved better performance with $accur_y$ of 95.05%, $preci_n$ of 93.97%, $recal_l$ of 90.44%, and $F1_{score}$ of 92.06%, demonstrating the effectiveness of the combined architecture.

Table 7 Ablation study of the GeoXAttn-Net method

4.5. Interpretability Results

Fig. 8 portrays an SHAP analysis exhibiting both global and local feature importance of the model. The global importance indicates that Rock_Type is the leading feature impacting the model prediction, with the highest mean SHAP value. The figure represents that Rock_Type has the highest mean absolute SHAP value (10.729), makes it the dominant feature influencing the predictions of GeoXAttn-Net on the evaluated dataset. This represents a strong model-level dependence on Rock_Type for distinguishing ore and waste blocks. Moreover, SHAP importance reflects the contribution learned by the model from the available data and should not be interpreted

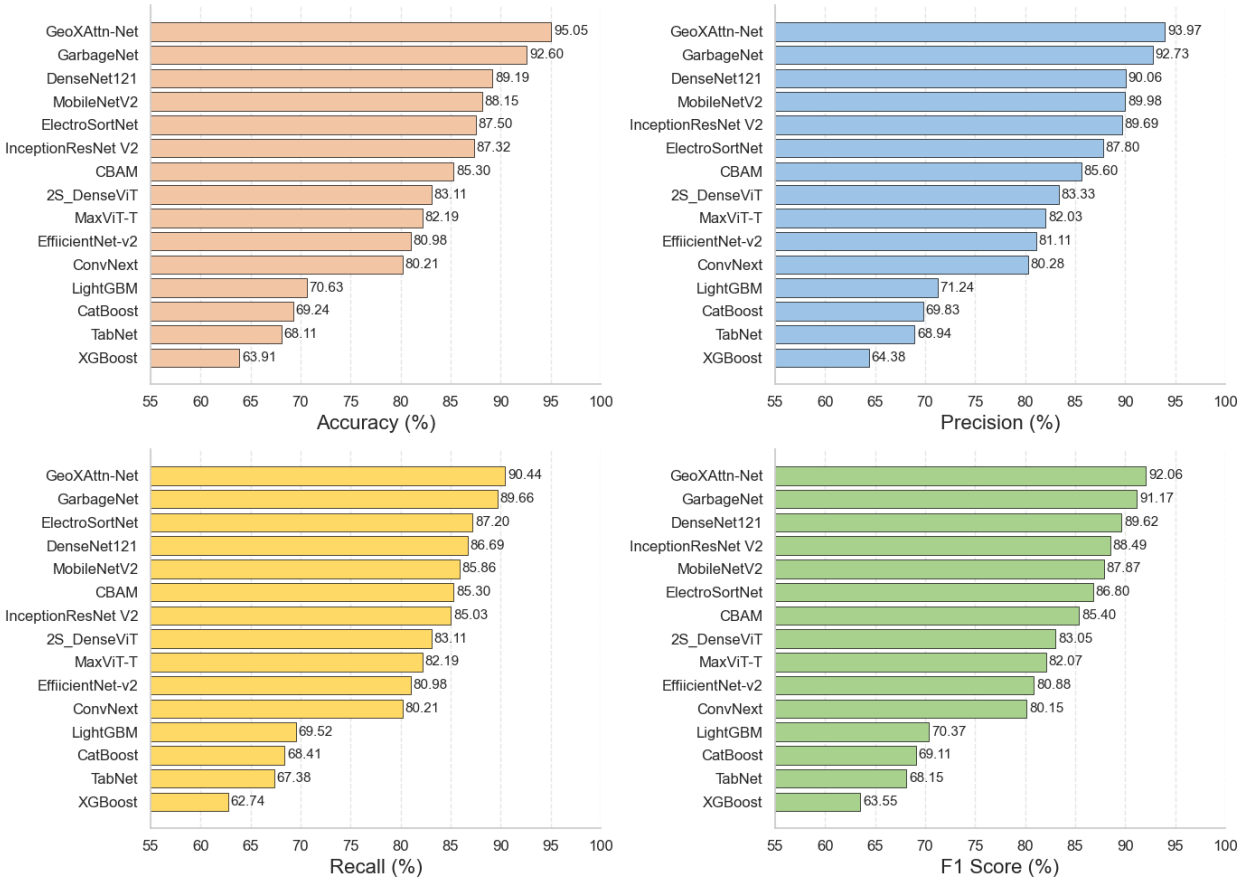


Figure 7. Comparison of the outcome of the GeoXAttn-Net method with metrics

Table 7. Table 7

Techniques	**Accuracy**	**Precision**	**Recall**	**F1-score**
Simple Concatenation	92.64	91.58	87.96	89.72
Unidirectional Cross-Attention	93.58	92.46	88.84	90.41
Bidirectional Cross-Attention	94.26	93.21	89.62	91.36
Bidirectional Cross-Attention + No Feature Weighting	94.71	93.62	90.18	91.87
Proposed: Bidirectional Cross-Attention + SHAP-Guided Dynamic Weighting	95.05	93.97	90.44	92.06

as a direct measure of the geological or economic significance of a feature. The relatively low SHAP contributions of Ore_Grade, Profit, Mining_Cost, Processing_Cost, and other variable shows that their additional predictive contribution is limited after the information captured by Rock_Type is considered. Consequently, the observed dominance of Rock_Type is treated as a dataset-specific finding rather than a general conclusion regarding mining decision factors.

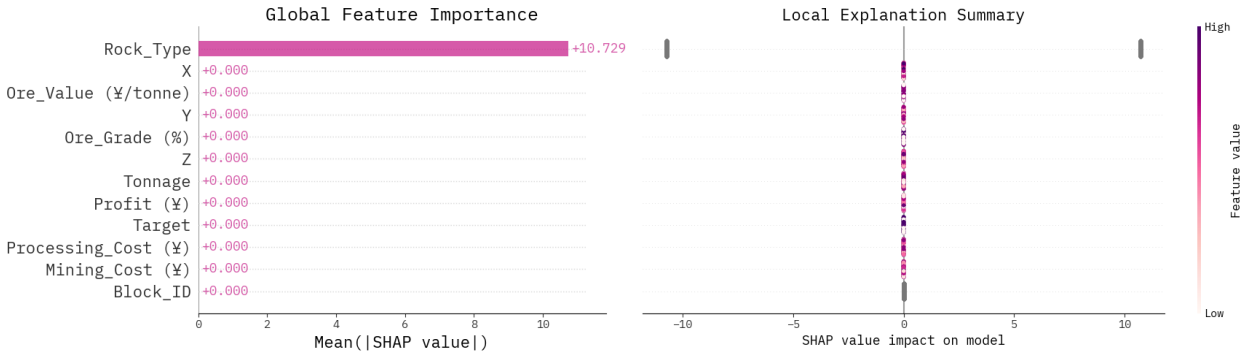


Figure 8. SHAP value for the global and local explanation

The simulation results exhibit that the proposed GeoXAttn-Net technique accomplished higher classification performance when compared with the existing DL approach. The framework gained an $accur_y$ of 95.05%, $preci_n$ of 93.97%, $recal_l$ of 90.44%, and $F1_{score}$ of 92.06%, which specifies efficient ore–waste block classification ability. The ablation analysis also exhibits that combining feature engineering, operational and geological encoders, and bidirectional cross-attention fusion increased the overall classification. Also, the SHAP-guided feature weighting offers greater learning of feature importance and better interpretability of the proposed model. Although GeoXAttn-Net has a relatively improved framework, its components are designed to model interactions between geological and operational features that may not be captured through direct feature learning. Thus, the additional complexity is associated with enhanced feature interaction modeling and explainability rather than classification alone.

5. Conclusion and Future Work

This study developed GeoXAttn-Net, an Explainable Cross-Attention Network for ore–waste block classification using geological and operational mining data. The mining block dataset initially underwent preprocessing stages to improve data quality and feature consistency. Subsequently, feature engineering was performed by computing profit margin, ore-to-waste economic ratio, and spatial depth-related information for enhancing discriminative feature representation. In addition, SHAP-guided dynamic feature weighting was introduced to estimate feature importance and adaptively refine feature contributions based on SHAP importance scores. Furthermore, the presented GeoXAttn-Net approach utilized separate geological and operational feature encoders for learning the physical and economic characteristics of mining blocks. A bidirectional cross-attention fusion was employed to capture the relation between geological and operational feature representations. Moreover, transformer-based fusion and SHAP-guided attention refinement were incorporated to enhance feature interaction learning and model interpretability. Finally, a dense classification head with softmax activation was utilized for ore-waste classification. Experimental evaluation was carried out using the Open-Pit Mining Block Model Dataset, and the results showed the improved performance of the presented GeoXAttn-Net approach in enhancing ore-waste classification performance and interpretability.

GeoXAttn-Net offers an interpretable data-driven methodology for ore-waste block classification, allowing feature-level insights that can support resource assessment and mine-planning analysis. The model is intended as a decision-support approach to complement, rather than replace, established geological and economic evaluation practices. The major limitation of this study is the utilization of a generated block-model dataset without detailed information on the underlying mine or geostatistical modelling procedure. Additionally, the improved contribution of Rock_Type observed in the SHAP analysis may be specific to the evaluated dataset. The utilization of conventional train-test partitioning also limits assessment of spatial generalization. Thus, validation utilizing real mine datasets with geographically separated test regions is required to further establish the robustness and

generalizability of the proposed approach. Future work will concentrate on validating the proposed framework utilizing real mine datasets and spatially separated evaluation settings to further assess its generalizability across various geological environments. In future, the proposed GeoXAttn-Net model could be prolonged utilizing real-time mining sensor data and larger-scale geological datasets to improve ore-waste classification performance further. The class imbalance may influence model learning and performance; although weighted loss is utilized, further validation with balanced sampling and additional real-mine datasets are required. Furthermore, advanced XAI approaches and hybrid attention mechanisms can be incorporated to improve interpretability and feature interaction learning. The model can also be performed for other mineral exploration and intelligent mine planning applications.

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Data Availability Statement: The data that support the findings of this study are openly available in Kaggle repository at https://www.kaggle.com/datasets/ziya07/open-pit-mining-block-model-dataset/data, reference number [21].

REFERENCES

1. Balakera, N., Katika, T., Konstantinidis, F.K., Giariskanis, F., Tsimiklis, G., Karaseitanidis, G., and Amditis, A., 2026. The design of ore sorting prototype within the transition from Mine 4.0 to Mine 5.0: human-centric approach. Procedia Computer Science, 277, pp.2606-2611.
2. Eryeşil, Y., Kahramanli Örnek, H. and Taşdemir, Ş., 2026. Optimizing solid waste classification using deep learning and grey wolf optimizer for recycling efficiency. International Journal of Environmental Science and Technology, 23(1), p.44.
3. Tshanga, M., Ncube, L. and Thamaga, K.H., 2026. Monitoring the impacts of mining activities on land cover using remote sensing technologies and machine learning in the Musonoi copper–cobalt deposit in the Democratic Republic of Congo. Geocarto International, 41(1), p.2620330.
4. Mohsin, M., Rovetta, S., Masulli, F. and Cabri, A., 2026. Extraction of critical raw materials from waste printed circuit boards using machine learning and computer vision. IEEE Access, 14, pp.50230-50245.
5. Thiruchittampalam, S., Banerjee, B.P., Glenn, N.F. and Raval, S., 2025. A systematic review of machine learning-based remote sensing data analysis for geological and mined materials characterisation. European Journal of Remote Sensing, 58(1), p.2524622.
6. Balakera, N., Konstantinidis, F.K., Sifnaios, S., Tsimiklis, G. and Amditis, A., 2025, February. Ore sorter as part of Mining 4.0 from mechatronics approach. In 2025 11th International Conference on Mechatronics and Robotics Engineering (ICMRE) (pp. 359-363). IEEE.
7. Sunkari, E.D., Muhammed, A.B. and Basit, A.W., 2025. Application of Machine Learning Algorithms to Predict Rock Types Using Geochemical Data: A Case Study from the Obuasi Gold District, Ghana. In Geology and Gold Mineralization in Ghana: Geological Provinces and Gold Mineralization (pp. 235-260). Cham: Springer Nature Switzerland.
8. Pandey, A.C., Swain, S.K. and Dwivedi, C.S., 2025. Mapping iron oxides with Landsat-8/OLI imagery from iron ore deposit in Singhbhum craton, eastern India: Its implication to mineral exploration. Ore and Energy Resource Geology, 18, p.100089.
9. Deressa, G.W., Choudhary, B.S. and Jilo, N.Z., 2025. Advanced bench design and technical challenges in open pit mining: a comprehensive review of stability and productivity. Arabian Journal of Geosciences, 18(1), p.28.
10. Zhou, B., Elmo, D., Chen, X., Wu, Y. and Li, G., 2025. Optimization of Structural Parameters in Sublevel Caving: Insights from Ore-Waste Rock Movement Patterns. Mining, Metallurgy & Exploration, 42(3), pp.1677-1691.
11. Buelga Díaz, A., Castañón Fernández, C. and Diego Álvarez, I., 2025. Grade Control in One of the Biggest Open Pit Mines in Europe: Corta Atalaya, Riotinto. Minerals, 15(1), p.44.
12. Shan, Y., Ke, L., Jun, X. and Shuai, L., 2025. Multi-objective optimisation based on NSGA-II of mine cut-off grade from the perspective of resource security. International Journal of Mining, Reclamation and Environment, pp.1-20.
13. Badakhshan, N., Bakhtavar, E., Shahriar, K., Khosravi, H., Afraei, S. and Maremi, A., 2026. A Q-learning approach to waste rock reduction in open-pit mine design based on cleaner production principles. Scientific Reports.
14. Huang, X., Pan, R. and Wang, J., 2025. A graphite ore grade recognition method based on improved Inception-ResNet-v2 model. IEEE Access.
15. Kenzhaliyev, B., Imankulov, T., Mukhanbet, A., Kvyatkovskiy, S., Dyussebekova, M. and Tasmurzayev, N., 2025. Intelligent system for reducing waste and enhancing efficiency in copper production using machine learning. Metals, 15(2), p.186.
16. Wang, Z.Q., Liu, Y.Z., Zhang, W.F., Chen, S.Q., Zhou, J.W., Li, H.B., Yang, Y.C., Yang, Y.M. and Liu, Y., 2025. A Deep Learning-Based Method for Particle Size Distribution Analysis From TBM Rock Muck Images. Advances in Civil Engineering, 2025(1), p.5542242.
17. Zhou, H., Li, Y., Wang, Y., Zhou, H. and Li, K., 2026. Research on Image Detection of Thin-Vein Precious Metal Ores and Rocks Based on Improved YOLOv8n. Applied Sciences, 16(2), p.988.

18. Zairov, S., Umirzokov, A., Abdufattokhov, S., Vladimir, D., Akhmatnurov, D., Eshonkulov, U., Zamaliyev, N., Mekhmonov, M., Gulmurodov, J. and Ravil, M., 2026. A pragmatic and reproducible framework for real-time ore sorting in open-pit mining using a lightweight edge-deployed YOLO model. Journal of Engineering and Applied Science, 73(1), p.43.
19. Li, P., Xie, S., Zhang, W., Chen, D., Peng, S., Fang, W. and Zeng, D., 2026. Blasting ore size detection based on efficient dehazing network and multi-dimensional feature fusion. Scientific Reports.
20. Herrera, N., Sinche Gonzalez, M., Okkonen, J. and Mollehuara, R., 2023. Soft computing application in mining, mineral processing and metallurgy with an approach to using it in mineral waste disposal. Minerals, 13(11), p.1450.
21. Yurdakul, M., Uyar, K. and Taşdemir, Ş., 2025. Enhanced ore classification through optimized CNN ensembles and feature fusion. *Iran Journal of Computer Science*, *8*(2), pp.491-509.
22. Abdolmaleki, M., Ghadernejad, S., Ordóñez-Calderón, J.C. and Esmaeili, K., 2026. Enhancing Ore Grade Control at the Mine Site Using pXRF Geochemical Data: A Random Forest–Based Approach. *Mining, Metallurgy & Exploration*, pp.1-20.
23. Zhou, Z., Yu, J., Gao, J., Cai, X. and Wang, Z., 2025. Rapid rock mass classification framework using machine learning and semantic segmentation for underground mining. Engineering Applications of Artificial Intelligence, 159, p.111530.
24. Ramos, K., Frade, A., Santos, I. and Pinto, T., 2025. Interpretable Prediction of Silica Content in Iron Ore Flotation Using Machine Learning. IFAC-PapersOnLine, 59(32), pp.132-137.
25. https://www.kaggle.com/datasets/ziya07/open-pit-mining-block-model-dataset/data
26. Alkhammash, E.H., Hadjouni, M. and Elshewey, A.M., 2022. A hybrid ensemble stacking model for gender voice recognition approach. Electronics, 11(11), p.1750.
27. Cobîrzan, N., Muntean, R., Thalmaier, G. and Felseghi, R.A., 2022. Recycling of mining waste in the production of masonry units. Materials, 15(2), p.594.
28. Guha, S. and Bhandage, V., 2026. Explainable-AI guided Deep Learning for Glaucoma Detection: Feature-Weighting Approach using SHAP Values. IEEE Access.
29. Zhang, L., Yang, Y., He, Z., Li, G., Zhao, F., Hua, W., Xiao, G. and Zhang, J., 2026. Multimodal Remote Sensing Image Classification Based on Dynamic Group Convolution and Bidirectional Guided Cross-Attention Fusion. Remote Sensing, 18(7), p.1066.
30. Nti, I.K. and Nyarko-Boateng, O., 2025. SHAP-Guided Feature Refinement for Robust and Interpretable Malware Detection in Memory Forensics.
31. Ahmed, M.W., Alotaibi, M., Alotaibi, S.R., Alhammadi, D.A., Algarni, A., Jalal, A. and Cho, J., 2025. A novel remote sensing recognition using modified GMM segmentation and denseNet. Ieee Access, 13, pp.9372-9390.
32. Alshaari, H. and Alqahtani, S., 2025. Deep-EFNet: An Optimized EfficientNetB0 Architecture With Dual Regularization for Scalable Multi-Class Brain Tumor Classification in MRI. IEEE Access.
33. Sayem, F.R., Islam, M.S.B., Naznine, M., Nashbat, M., Hasan-Zia, M., Kunju, A.K.A., Khandakar, A., Ashraf, A., Majid, M.E., Kashem, S.B.A., and Chowdhury, M.E., 2025. Enhancing waste sorting and recycling efficiency: robust deep learning-based approach for classification and detection. *Neural Computing and Applications*, *37*(6), pp.4567-4583.
34. Lingamuthu, V., Sellappan, D., Balu, S., Raghabu, S.M.A., Sureshkumar, A., Govindarajan, P.K., and Bhopal, V.I.T., 2025. ARCNet: A Novel Deep Learning Model for Robust Solid Waste Image Classification in Waste Management Systems. *International Arab Journal of Information Technology (IAJIT)*, *22*(6).
35. Single, S., Iranmanesh, S., and Raad, R., 2023. Realwaste: a novel real-life data set for landfill waste classification using deep learning. *Information*, *14*(12), p.633.
36. Danish, A., Feng, Z., Liu, L.L., Zhang, S.H., Khan, K., Rahman, I.U. and Ullah, Z., 2026. Tree-based and deep learning models for landslide susceptibility assessment with imbalanced data. *Journal of Rock Mechanics and Geotechnical Engineering*.