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Deep Learning Algorithm for Geological Mapping and Mineral Exploration: A Review on Recent Advancement and Applications

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A B S T R A C T

Deep learning has become a transformative technology in geological mapping and mineral exploration, addressing the complexities of data integration and analysis in these fields. This review critically examines the recent advancements in deep learning applications, focusing on image classification, anomaly detection, predictive modeling, and target identification. A systematic methodology was employed, involving the analysis of relevant and recent studies, highlighting key contributions and persistent challenges. Significant achievements include improved accuracy in mineral prospectivity prediction and automated geological feature detection, supported by the integration of remote sensing, geophysical, and geochemical datasets. However, limitations such as data scarcity, model interpretability, and computational demands persist. Future directions emphasize integrating deep learning with complementary technologies like geographic information systems, internet of things, and high-performance computing, alongside advancements in transfer learning and explainable AI. This review provides a comprehensive analysis of current progress and highlights pathways for advancing deep learning in geological applications.

Keywords: *Deep Learning, Geological Mapping, Mineral Exploration, Predictive Modelling and Anomaly Detection*

1. Introduction

Geological mapping and mineral exploration are critical activities for understanding earth's resources, enabling sustainable management of natural materials, and supporting industries such as mining, energy, and environmental conservation (Zeinab Salehisadati, 2024). Mineral resources are of great significance in the development of the national economy. Prospecting and forecasting are the key to ensure the security of mineral resources supply, promote economic development, and maintain social stability (K. Sun et al., 2024). Traditionally, these fields have relied on manual interpretation, expert knowledge, and conventional statistical methods, which, while effective in many cases, are often labor intensive, time consuming, and limited in their ability to process large, complex data (Aldoseri et al., 2023).

The advent of advanced data acquisition technologies, such as satellite imagery, hyperspectral imaging, and seismic surveys, has further amplified the need for robust, automated methods to extract actionable insights from increasingly voluminous and high dimensional geological (Hasan et al., 2022; Z. Ma & Mei, 2021). In this context, artificial intelligence, and more specifically deep learning, has emerged as a transformative tool (Soori et al., 2023).

Deep learning, a subset of machine learning, involves artificial neural networks with multiple layers capable of learning complex patterns from data (Kufel et al., 2023). Unlike traditional machine learning models that require extensive feature engineering, deep learning algorithms can autonomously learn hierarchical representations, making them particularly suitable for tasks involving image, spectral, and spatiotemporal data (Manakitsa et al., 2024). Models such as convolutional neural networks and recurrent neural networks RNN have shown immense potential in geological applications, ranging from lithological classification and mineral prediction to fault detection and seismic interpretation (Dodda et al., 2023; Xiong et al., 2018). Transformers and attention-based models are also emerging as powerful tools for capturing spatial and temporal dependencies in geological data.

The success of deep learning in geological sciences can be attributed to its ability to integrate multimodal data from diverse sources, including satellite imagery, hyperspectral surveys, and ground-based measurements (Peyghambari & Zhang, 2021), to document the distribution and properties of geological features. Similarly, mineral exploration relies on remote sensing, geochemical analyses, and geophysical surveys to identify potential deposits of valuable minerals (Bedell, 2004). However, integrating these disparate data types and extracting meaningful information present significant challenges. Data heterogeneity, noise, and the scarcity of labeled datasets are persistent obstacles that complicate conventional workflows (Ghazaleh, 2023).

Despite the growing interest in applying deep learning to geological mapping and mineral exploration, research in this domain remains fragmented, with studies often focusing on niche applications or specific datasets. A comprehensive synthesis is essential to consolidate knowledge, and provide a roadmap for future research. This review aims to address this need by systematically analyzing recent advancements in deep learning algorithms for geological mapping and mineral exploration.

2. Research Methodology

To ensure a systematic and comprehensive review of the application of deep learning algorithms in geological mapping and mineral exploration, a structured methodology was adopted. This process involved an exhaustive search for relevant literature, detailed screening, and categorization of research works to identify recent advancements and emerging trends.

2.1 Literature Search

A systematic search strategy was employed to identify existing application of deep learning on geological mapping and mineral exploration. Search was conducted on prominent academic databases, including Science Direct, PubMed, Institute of Electrical and Electronic Engineering (IEEE), Springer, SCOPUS, and Google Scholar. The databases were selected for data identification because they host a collection of high impact publications especially in deep learning. SCOPUS is the largest citation database of research literature and quality web sources. The search strategy utilized Boolean operators AND and OR to identify relevant studies, the query combined keywords such as “Deep learning algorithm” OR “Geological Mapping” OR “Mineral Exploration” to capture studies addressing any of these topics. By linking these terms with OR, the search broadened to include various research works that might use different focal points. To refine the results, AND was applied to ensure that retrieved studies combined these key concepts, such as “Deep learning algorithm” AND “Geological Mapping” AND “Mineral Exploration.” This approach ensured the inclusion of studies that addressed multiple aspects of the review topic while excluding irrelevant material.

2.2 Selection Criteria

The selection criteria for this review focused on ensuring relevance, quality, and recent advancements in the field of deep learning applications for geological mapping and mineral exploration. Studies were included if they specifically addressed the use of deep learning algorithms, such as convolutional neural networks CNN, recurrent neural network RNN, and for tasks related to geological or mineral analysis. Preference was given to research published between 2019 and 2024 to capture the latest developments in the field. Articles written in English and published in peer-reviewed journals or reputable conference proceedings were prioritized. Studies that utilized relevant datasets, including satellite imagery, hyperspectral imaging, or seismic data, were considered. Research outside the scope of geology, such as applications in unrelated fields, was excluded. Duplicate studies identified across databases were removed during the screening process.

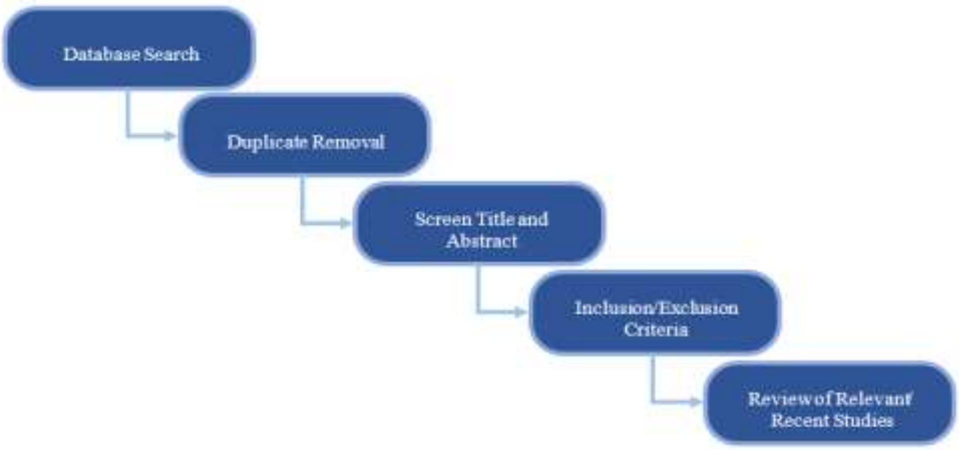

Figure 1: Selection criteria

3. Application of Deep Learning in Geological Mapping

Deep learning has revolutionized geological mapping by enabling the automated analysis and interpretation of complex geospatial data(Laukamp, 2022). This section elaborates on three key areas where deep learning has been applied: Image Classification, Object Detection, and Segmentation. Each subsection provides an overview of the methods, key studies, and their contributions to geological mapping.

3.0.1 Image Classification

Image classification involves assigning a category label to an entire image or large sections of an image (Prasantha H S, 2023). In geological mapping, this task often focuses on identifying lithological units, vegetation types, or mineralized zones from satellite and hyperspectral imagery (Peyghambari & Zhang, 2021).

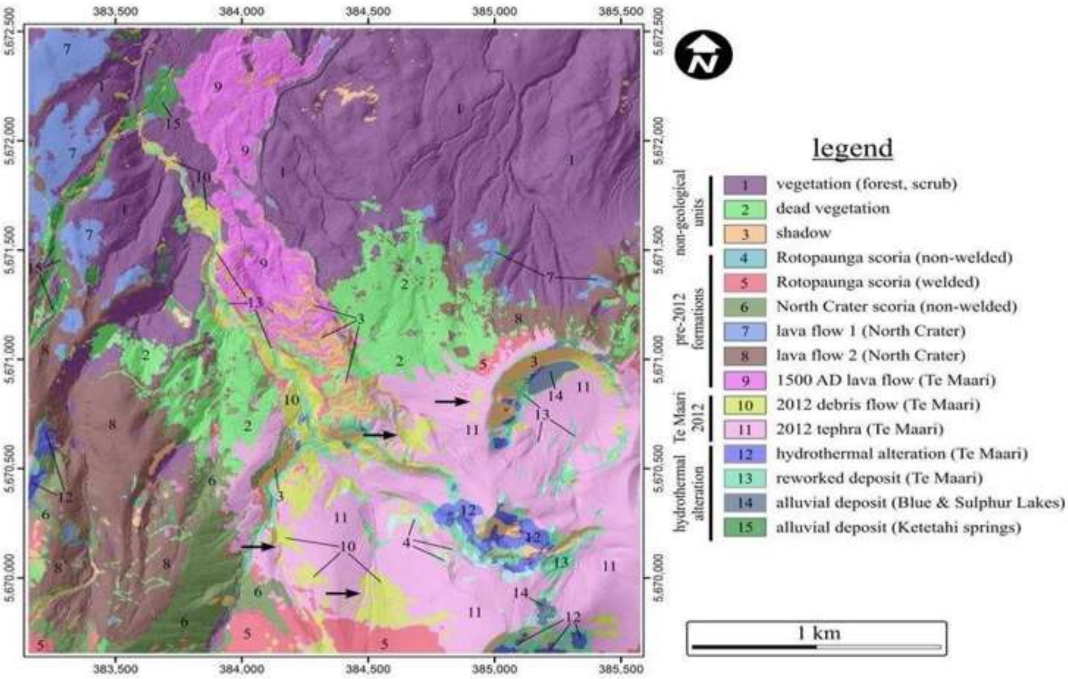

Figure 2: Gelogical map obtained from image classificatin (Kereszturi et al., 2018)

(Y. Zhang et al., 2018) explores geological structure classification using 2206 images with 12 labels. The Inception-v3 model was employed, utilizing both grayscale and color images, alongside a convolutional neural network. Additionally, K-nearest neighbors, artificial neural networks, and extreme gradient boosting were implemented using OpenCV feature extraction. Comparisons revealed poor performance for KNN, ANN, and XGBoost, accuracy 40.0%, while CNN exhibited overfitting. Transfer learning significantly improved performance on the small dataset, achieving 83.3% top-1 and 90.0% top-3 accuracy.

GGMNet a deep neural network was developed by (C. Li et al., 2024) for geological mapping in overburden areas, utilizing satellite Bouguer gravity anomaly data and geological maps. The model achieved a mean pixel accuracy MPA of 63.1% and a frequency weighted intersection over union FWIoU of 42.88%, outperforming state-of-the-art semantic segmentation networks. GGMNet accurately predicted concealed geological structures in the Junggar Basin, including Carboniferous and Devonian formations, granite intrusions, and Proterozoic strata. It demonstrated superior segmentation performance through innovative modules like multiresolution feature extraction and attention refinement, contributing to efficient geological mapping.

(Han et al., 2023) highlights the importance of monitoring the geological environment to address resource scarcity and environmental pollution, essential for sustainable development. Remote sensing technologies, combined with machine learning and deep learning, provide highresolution, cost-effective, and efficient tools for identifying geological elements, leading to significant advancements in geological environment remote sensing. The study outlines challenges in GERS interpretation, such as geological complexity, contextual disturbances, and limitations of RS image quality and types. It reviews RS imaging platforms and advanced ML and DL methods, focusing on applications in lithology, soil, water, glaciers, and geologcal disaster monitoring.

Trends and progress in these fields are thoroughly analyzed.

(Guo et al., 2021) introduces a deep learning-based framework for dynamic legend generation in geological maps, addressing the detection and identification of geological symbols to provide real-time symbol meanings. The study tackles challenges arising from the diversity and random distribution of symbols. It combines a convolutional neural network and a graph convolutional network, with a single symbol detection network for individual symbols and a novel GCN with L2 distance attention for compound symbols. This framework effectively solves geological symbol detection, sets a new benchmark, and supports dynamic legend generation. Data and code are publicly available.

The use of remotely sensed spectral imagery was highlighted by (Harvey & Fotopoulos, 2016), and geodetic data combined with machine learning algorithms for geological mapping and interpretation. The study compares four supervised MLAs naïve Bayes, k-nearest neighbor, random forest, and support vector machines using geological maps of the Sudbury region for calibration and validation. Random forest performed best, with MLA accuracy improving as calibration data distribution became more uniform. Challenges include low performance due to poor spectral images caused by vegetation or water coverage and increased computational demand with larger calibration datasets. Despite these limitations, the technique effectively identifies regions of interest and general rocktype trends, making it valuable for initial geological site investigations and guiding advanced surveys.

Geological geophysical mapping network GGMNet was developed by (Y. Liu et al., 2024) for bedrock prediction in overburden areas, utilizing satellite bouguer gravity anomaly data and a high-resolution geological map. GGMNet incorporates neural architecture search and human designed features, achieving a mean pixel accuracy MPA of 63.1% and a frequency weighted intersection over union FWIoU of 42.88. It outperformed state of the art methods and accurately predicted the concealed geological structures of the Junggar Basin, including strata and granite intrusions, aligning with traditional geophysical observations.

(Gupta et al., 2024) tackles geological image segmentation using advanced deep learning models. A dataset of 950 images covering 19 rock types was prepared with rigorous preprocessing. Finetuned models, including DenseNet201, InceptionV3, and MobileNet V3 large, achieved exceptional accuracy, exceeding 99% in K-Fold cross-validation. Preprocessing enhanced convergence and minimized misclassifications, affirming the approach's effectiveness in rock type classification. (Sang et al., 2020) proposed a high-resolution geological mapping is crucial for mineral and energy exploration but faces challenges due to reliance on traditional field methods constrained by weather, terrain, and personnel. This study proposes a new approach using unmanned aerial vehicles and deep learning algorithms. UAVs capture high-resolution images, complemented by field data for lithology anchoring. The simple linear iterative clustering-convolutional neural network SLIC-CNN algorithm automates mapping by identifying lithologic distributions and outlining rock mass boundaries. Applied to Taili waterfront in Xingcheng City, China, the method achieved an AUC of 0.937 and a Kappa score of 0.8523, producing an accurate high resolution geological map.

(Bachri et al., 2020) This study evaluates the application of the Random Forest algorithm for geological mapping in the Msaidira-Souk Al Had region of southern Morocco using Sentinel2A multispectral imagery and ALOS/PALSAR digital elevation models DEM. By integrating spectral, textural, and geomorphic features, the method achieves high classification accuracy 91% and a Kappa coefficient of 0.88. Techniques like principal component analysis PCA and texture analysis GLCM enhance lithological differentiation. The results demonstrate the potential of Random Forests and remote sensing data for efficient and precise geological mapping, supporting mineral exploration and economic development.

A machine learning based geological mapping workflow was proposed by (W. Wang et al., 2024) that integrates remote sensing, field data, and geochemical samples, utilizing the light gradient boosting machine LightGBM algorithm. Applied in the Duolong mineral district, Tibet, the model achieved 91.6% prediction accuracy by mapping only 21% of the area with 540 geochemical samples. The approach employed PCA for dimensionality reduction, iterative training, and probability-based route optimization, significantly enhancing mapping efficiency.

Key lithological units were predicted with high accuracy, although diorite showed lower performance due to sparse data. The method emphasizes structured data acquisition and offers a scalable strategy for predictive geological mapping

3.0.2 Object Detection

Object detection tasks focus on identifying and localizing geological features, such as faults, fractures, and ore bodies, within remote sensing and geophysical datasets (Elhag & Alshamsi, 2019). This approach allows for precise mapping of geological structures crucial for resource exploration (W. Wang et al., 2024).

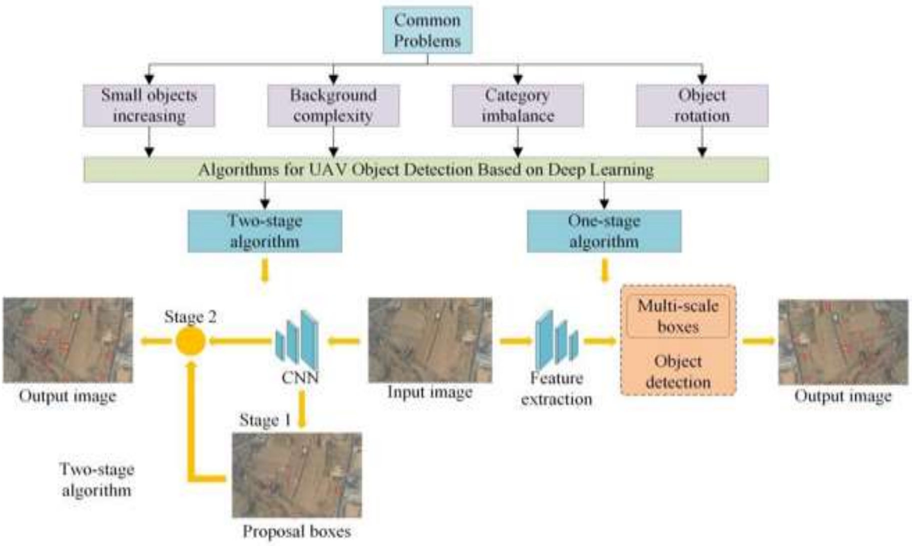

Figure 3: Object detection for UAV based on deep learning (Tang et al., 2023)

(Lin et al., 2022) presents the 2.5D Channel Attention U-net (2.5D CAU-net) to enhance fault identification in seismic data while addressing limitations of traditional 2D and 3D neural networks. The model processes four adjacent seismic slices, leveraging their correlations to improve fault detection while reducing labeling effort and computational complexity. Tested on synthetic and real seismic datasets, the 2.5D CAU-net demonstrated improved efficiency and accuracy. Larger seismic data cropping strategies enhance fault feature recognition but risk overfitting with limited training data. Overall, the approach provides a balanced and effective solution for fault identification in geologic studies.

(Dilhan & Siyambalapitiya, 2022) highlights the inefficiencies of traditional methods in digitizing 2D geological maps and introduces a state-of-the-art feature detection methodology using deep learning. Due to hardware limitations in processing high-resolution geological maps, a sliding window approach is proposed. Models trained with transfer learning including YOLOv3, SSD, Faster-RCNN, and SSD_RetinaNet—achieved high precision, with SSD_RetinaNet achieving the highest AP 0.97, followed by YOLOv3 0.96, which outperformed others in F1 recall and score. This automated process enhances the accuracy and efficiency of geological feature detection and digitization, offering a robust solution for geo-oriented projects and high-resolution map analysis.

(Oakley et al., 2024) explores automated workflows for detecting geological folds from map data using both unsupervised and supervised machine learning. The unsupervised approach employs regular expression matching to identify fold-like patterns, followed by HDBSCAN clustering to group these patterns into distinct folds without prior knowledge of their number. The supervised method uses synthetic fold models to train a convolutional neural network for fold identification based on map and topographic data. Both methods are tested on synthetic and real datasets, demonstrating the potential for automated, faster, and less subjective geological interpretations compared to traditional human analysis.

DeepLandforms a toolset design for landform mapping was introduced by (Nodjoumi et al., 2023) using deep learning techniques. It aims to streamline the creation of thematic maps, such as geolithological and geomorphological maps, by addressing time-consuming tasks like object discretization and reducing interpretative biases caused by mapper experience. DeepLandforms provides a comprehensive, customizable workflow for dataset preparation, model training, monitoring, and inference, utilizing open-source libraries and validated methodologies. Its applicability is demonstrated through mapping sinkhole-like landforms on Mars, showcasing its potential for diverse planetary and terrestrial applications in future research.

(Ghorbanzadeh et al., 2022) explores integrating a deep learning model with rule-based object-based image analysis OBIA for landslide detection from satellite imagery. A ResU-Net model was trained on Sentinel-2 imagery, and OBIA with four rulesets was applied to the original dataset and the ResU-Net heatmap. The heatmap provided pixel-level probabilities for landslide classification. Three scenarios ResU-Net, OBIA, and ResU-Net-OBIA were evaluated against a manual landslide inventory using precision, recall, and F1-score metrics. Results show the integrated ResU-Net-OBIA approach significantly outperforms the standalone methods, achieving F1-scores 8% and 22% higher than ResU-Net and OBIA, respectively.

(Wu et al., 2020) addresses the challenges of traditional spring water resource acquisition in Xinjiang, China, by leveraging remote sensing and artificial intelligence. Using YOLOv3, a deep learning framework, the researchers developed a model for detecting springs from 0.8mresolution remote sensing images. A dataset of 512x512 annotated images was used to train the model. The resulting detection model achieved a mean average precision (mAP) of 0.973, demonstrating high accuracy. This method provides a scalable and efficient tool for monitoring and protecting natural water resources, supporting environmental initiatives under the Belt and Road framework.

(Kaur & Singh, 2022) reviews advancements in object detection, a critical computer vision task involving locating objects in images and videos. It systematically analyzes traditional, twostage, and one-stage object detection techniques, alongside dataset preparation, annotation tools, and performance evaluation metrics. The research highlights differences in architecture, optimization functions, and training strategies among detection methods, emphasizing the improvements achieved with deep neural networks. A comparative analysis is provided, and key research challenges and future directions are discussed, offering a comprehensive understanding of current trends and advancements in object detection.

(Melo & Li, 2021) addresses the challenge of geology differentiation in greenfield exploration areas where prior geological information is limited. It focuses on integrating multiple inverted physical property models to identify geological units quantitatively. Using unsupervised machine learning methods, including five clustering techniques, the study evaluates their performance in analyzing inverted susceptibility, density, and conductivity models derived from a synthetic geological model. Results indicate that correlation-based clustering performs best, effectively identifying relationships between physical properties diagnostic of geological units. This integration produces a quasi-geology model, representing inferred geological units and their spatial distribution. The findings demonstrate that minimally constrained, individually inverted models can provide sufficient information for joint geological unit identification.

3.0.3 Segmentation

Semantic and instance segmentation techniques are widely used to delineate geological boundaries and classify features at a pixel level (Wołk & Tatara, 2024). These methods enable the creation of high-resolution geological maps that are essential for detailed exploration activities(Thomas Ramos & Sappa, 2024). (Saxton et al., 2024) introduces an AI-driven method for extracting polygon and point features from historical geologic maps, crucial for assessing mineral resources essential to the energy transition. The approach uses map legends as prompts for one-shot segmentation and detection, integrating a human-in-the-loop system to enhance accuracy through expert input. Tested on datasets from the AI4CMA DARPA Challenge, the method achieved a median F1 score of 0.91 for polygon segmentation and 0.73 for point detection with abundant annotations, surpassing existing benchmarks. This innovative digitization process supports informed policymaking and resource management for the global energy transition.

introduced a methodology for lithological mapping in densely vegetated areas using sentinel-2 optical imagery and SRTM DEM terrain data combined with machine learning algorithms. The study area in Fujian Province, China, posed challenges due to high vegetation cover. Five machine learning algorisms MD, CART, SVM, RF, and GBDT were evaluated, with GBDT achieving the highest classification accuracy 63.18%, Kappa: 0.565 when integrating sentinel-2 and DEM data. The study highlights the efficacy of combining spectral and terrain features for improving rock classification accuracy and suggests that RF and GBDT are robust for such tasks, especially in complex terrains.

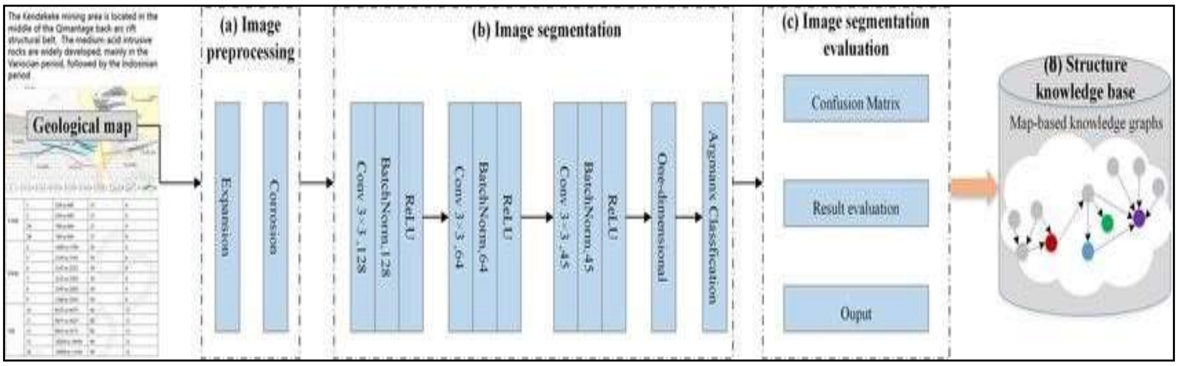

Figure 4: Basic image to segment of a geological map (Y. Chen et al., 2024)

(EL ATILLAH et al., 2021) explores the use of segmentation and classification algorithms for creating geological maps, hydrothermal alterations, and lineaments using multispectral images from Landsat 7, Landsat 8, Aster, and Sentinel-2A. Sentinel-2A's 10m resolution images were processed using algorithms like K-means, Isodata, Watershed, efficient graph-based segmentation, and thresholding. Results show that the Watershed algorithm is useful for topographic and hydraulic studies, while thresholding and graph-based segmentation struggle with geological discrimination. In contrast, the Isodata and K-means algorithms demonstrated strong capabilities in geological differentiation, highlighting their effectiveness in geological mapping.

(S. Wang et al., 2023) addresses challenges in geological remote sensing interpretation GRSI, such as complex spatial distribution and high inter-class similarity of geological elements, which make annotation costly and accuracy limited. To overcome these issues, the study proposes AdvSemi-OCGNet, an adversarial semi-supervised segmentation network integrating objectcontext and global-attention mechanisms. Combining a baseline generator OCGNet and a full convolution discriminator FCD, the model generates pseudo-labels from high-confidence unlabeled samples for iterative semi-supervised segmentation. A conditional random field refines results by eliminating misclassified areas. Tested on diverse geological elements across two regions, the model demonstrates superior segmentation performance with limited labeled samples, enhancing GRSI efficiency.

(Maxwell et al., 2020) explores using historic topographic maps and deep learning semantic segmentation, specifically a modified UNet based on convolutional neural networks, to map surface mine disturbances in the Appalachian region. Utilizing data from Kentucky, the model achieved high accuracy (Dice coefficient = 0.902, Precision = 0.891, Recall = 0.917). While performance decreased when applied to new geographic extents in Ohio (Dice = 0.837) and Virginia (Dice = 0.763), it remained strong. Reducing the training sample size from 84 to 15 maps slightly impacted performance, suggesting the method's efficiency with limited data. The study highlights the potential of deep learning segmentation to automate mapping tasks, reducing manual labor and expanding workflows for analyzing historic cartographic data.

(Z. Chen et al., 2020) applied the U-Net deep learning architecture, originally developed for biomedical imaging, to analyze geological features in scanning electron microscope SEM images of shale samples. By incorporating a revised weight function and spatial statistics-based local variability, the U-Net model effectively distinguishes clay aggregates from matrix mineral particles and organic matter. Using TensorFlow, 8000 image slices 256 × 256 pixels were processed for semantic segmentation and feature extraction, achieving an intersection over union IOU of 91.7% during validation. Applied to 300 SEM image tiles from devonian duvernay shale samples, the model successfully segmented clay aggregates despite similar grey levels with other particles. This approach proves to be a cost-effective and efficient method for texture-based feature extraction, offering geoscientists valuable quantitative insights into geological characteristics.

(Schüßler et al., 2024) explores UAV-based geological mapping combined with deep learning for texture classification and segmentation in dynamic coastal areas. UAV surveys captured high-resolution imagery across five coastal sites, documenting textures like vegetation, chalk, glacial till, sand, water, and cobble under various conditions. Two approaches were tested: classification, which assigns a single label to texture patches, and semantic segmentation, which labels each pixel.Custom CNNs and ResNet50 were used for classification, achieving 95% accuracy.

3.1 Application of Deep Learning in Mineral Exploration

The application of deep learning in mineral exploration has revolutionized traditional methods by enabling efficient analysis of vast and complex geological datasets. Deep learning models excel in integrating multi-source data, such as remote sensing imagery, geochemical analyses, and geophysical surveys, to uncover patterns indicative of mineral deposits (Zuo et al., 2019). These advancements have facilitated predictive modeling, anomaly detection, and target identification, addressing challenges that were previously insurmountable with conventional approaches (Fadli et al., 2024).

By employing advanced architectures like convolutional neural networks, recurrent neural networks, and ensemble learning methods, researchers can achieve high accuracy in mapping mineralized zones and predicting resource locations (Shirmard et al., 2022). Deep learning also enables the extraction of subtle patterns from noisy or incomplete data, making it a powerful tool for exploring remote or geologically complex regions (Q. Zhang & Wang, 2024). Despite its transformative potential, challenges such as limited labeled datasets, high computational costs, and interpretability issues persist, necessitating ongoing research and innovation (Jim et al., 2024).

3.1.1 Predictive Modeling

Predictive modeling is a cornerstone of mineral exploration, leveraging deep learning to forecast mineral prospectivity in specific regions. These models integrate multi-source data, such as geological, geophysical, and geochemical datasets, to identify patterns indicative of mineral deposits (T. Sun et al., 2020a).

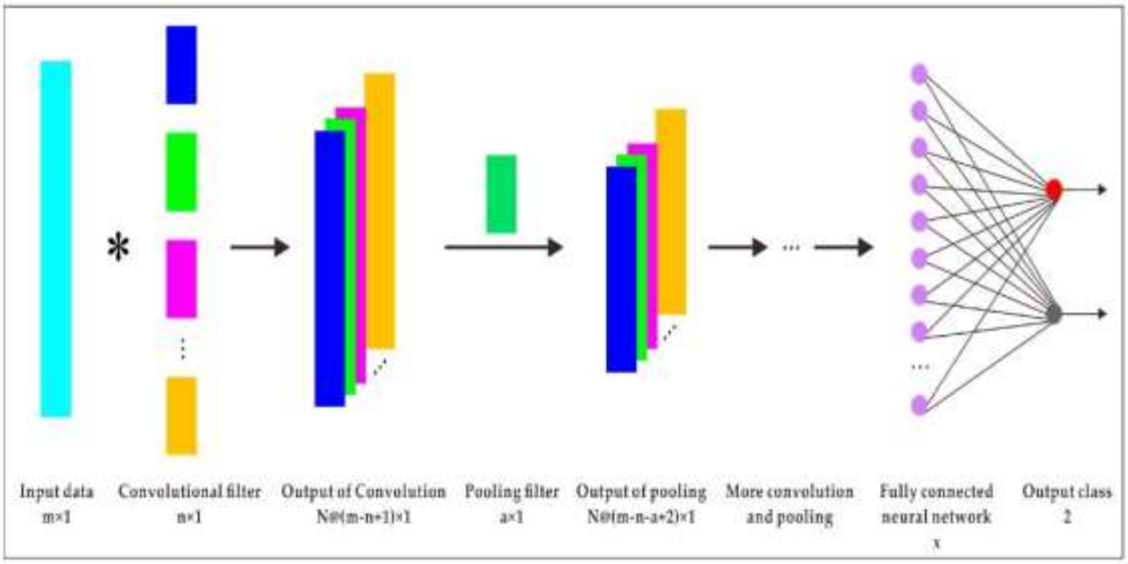

Figure 5: Predictive modeling of mineral exploration (T. Sun et al., 2020b)

A deep regression neural network DRNN was applied by (Xu et al., 2021) for mineral prospectivity mapping MPM in the Yawan-Daqiao area, Gansu, China. Using multi-source data such as geological, geophysical, and geochemical inputs, the DRNN was trained to identify patterns associated with mineralization, particularly gold deposits. The area, part of the West Qinling structural belt, features complex geological structures and formations favorable for gold mineralization. Key data included strata, fault structures, gravity anomalies, and the geochemical distribution of elements like Au, Sb, and Hg. The DRNN model utilized a fully connected neural network architecture with optimized hyperparameters to enhance prediction accuracy. Results demonstrated the DRNN's ability to integrate diverse data sources, reduce noise, and produce an accurate prospectivity map, highlighting areas with high potential for gold deposits. This approach outperformed traditional methods, offering a more reliable tool for mineral exploration.

Similarly, (Dong & Zhang, 2024) employ an interpretable deep learning method for mineral prospectivity mapping. The study focused on predicting porphyry copper deposits PCDs in the North American Cordillera. The deep forest model dynamically adjusts complexity, avoids the black box problem of deep learning, and emphasizes the importance of geological and geochemical features like euclidean distances to faults, fault density, gravity anomalies, and geochemical anomalies in stream sediments. compared to random forest, DNNs, CNNs, Transformer models, and GCNs, deep forest demonstrated superior performance in robustness, computational efficiency, and interpretability. The model achieved a testing accuracy of 90.4%, outperforming other methods.

(Mohammadzadeh et al., 2023) combines support vector machine and bat algorithm to optimize mineral prospectivity mapping for copper-gold deposits in NW Iran. By analyzing geological, geochemical, and remote sensing data, the hybrid SVM-BA model outperformed the single SVM model, achieving higher accuracy ROC 0.8 in identifying mineralization zones. The results confirm the hybrid model's effectiveness in mineral exploration.

(Mezned, 2023) used machine learning methods, including partial least squares regression and support vector machine, to predict the abundance of phosphate minerals fluorapatite and dolomite. Predictions were based on VNIR-SWIR hyperspectral reflectance and X-Ray Diffraction XRD data. Results indicated that the SWIR region was critical for predicting both minerals. The PLSR model performed better for fluorapatite prediction, while the SVM model showed superior results for dolomite prediction. (H. He et al., 2024) proposed an ensemble learning approach combining convolutional neural networks and self-attention mechanisms for mineral prospectivity prediction in the

Bawanggou gold mine area, South Qinling, China. Six CNN models (MobileNet V2, ResNet 50, VGG 16, AlexNet, LeNet, and VIT) were utilized for feature extraction from 14 gold mineralization factors, achieving individual model accuracies over 94%, with ResNet 50 reaching the highest accuracy of 96.92%. Ensemble learning improved prediction stability and accuracy, correctly identifying all known ore-bearing and non-ore-bearing areas, while also delineating four high potential gold prospecting regions. (Mahboob et al., 2024) proposed a machine learning driven framework for predictive mineral prospectivity mapping MPM in the North Waziristan region of Pakistan. The study evaluated convolutional neural networks, random forest, and support vector machine models using nine predictor maps derived from satellite remote sensing and limited field data. Random forest exhibited the highest predictive efficiency, correctly identifying 81.81% of known deposits within 14.79% of the area, outperforming convolutional neural network and support vector machine in terms of interpretability and consistency. Hydrothermal alterations and topographic variables were identified as key criteria.

3.1.2 Anomaly Detection

Anomaly detection in mineral exploration involves identifying irregularities or deviations in geological data that may indicate the presence of mineral deposits (Tao et al., 2019). This process often utilizes advanced technologies such as geophysical surveys, geochemical analyses, and remote sensing imagery (Haritha & Haritha, 2023). Deep learning methods have also excelled in detecting geological anomalies, which often serve as precursors to mineralization. Anomaly detection involves identifying outliers or unexpected patterns in geochemical or geophysical datasets (Zuo et al., 2019).

(C. Zhang & Zuo, 2024) Introduces an adversarial autoencoder network that incorporates geological knowledge to enhance geochemical anomaly detection for tungsten mineralization in southern Jiangxi, China. Using Yanshanian granites and faults as ore controlling factors, the approach employs multifractal singularity analysis to establish ore forming regularities, which guide the model's latent vector. Comparisons of models with and without geological constraints showed that those integrating prior geological information performed better in anomaly detection. This method effectively combines deep learning with geological insights, addressing limitations of purely data driven models and improving geochemical exploration.

(Bigdeli et al., 2023) addresses the challenge of identifying local geochemical anomalies in stream sediment samples for regional-scale exploration in the Torud-Chahshirin belt , northeast Iran. A methodology combining singularity mapping, random forests, success rate curves, and the t-Student method was applied. Efficient geochemical signatures for Au, Cu, Pb, and Zn were identified through success rate curves and transformed via centered log ratio transformation. Structural factors like NE trending faults and fault density were also determined as critical criteria. The random forest model, using singular mapping based geochemical layers and structural factors, produced an anomaly map with high accuracy 98.85%, effectively highlighting weak geochemical prospectivity areas and demonstrating its reliability for mineral exploration.

(Nwaila et al., 2022) introduces an AI based unsupervised anomaly detection method for identifying iron deposits using Landsat-8 OLI satellite imagery. The approach is novel in its knowledge guided detection, lack of assumptions about anomaly signatures, and use of machine learning algorithms to balance explainability and performance. The method operates in three stages: satellite imagery acquisition and band selection, predictive modeling and anomaly detection, and anomaly map construction and analysis. Tested on the Assen iron deposit in South Africa, it successfully detected known and previously unknown deposit features while reducing background noise and enhancing visual contrast. Principal component analysis was used to summarize anomalies, demonstrating the method's robustness and suitability for mineral exploration, particularly in data-sparse greenfield areas.

(Bourdeau et al., 2023) Integrates predictive analytics into the entire geochemical survey pipeline, focusing on predicting elemental concentrations during the data generation stage. Using lake sediment geochemical data from northern Manitoba, Canada, it emphasizes elements from the Canadian Critical Minerals list. The approach modernizes legacy data through predictive modeling and geochemical anomaly detection to identify new exploration targets. The integration, termed "predictive geochemical exploration," shifts from traditional grid-based sampling to agile, data driven, multi scale methods. It introduces a natural uncertainty categorization scheme, guiding future surveys and de-risking exploration practices. This framework enhances the efficiency of geochemical surveys and supports time-sensitive mineral exploration.\

(Farhadi et al., 2022) presents a hybrid machine learning model for predicting geochemical concentrations of Pb and Zn in mineral exploration. Four regression algorithms KNN, SVR, GBR, and RFR were combined in the hybrid machine learning model, which outperformed individual models in prediction accuracy, evaluated using correlation coefficient, MAE, and MSE metrics. The data, collected from in situ soil, were analyzed using concentration-area fractal modeling to classify geochemical anomalies. The fractal model identified five geochemical populations, with anomalous regions correlating to mining activities and core drilling data. The results demonstrate the effectiveness of the hybrid machine learning approach in ore grade estimation and geochemical anomaly detection.

(Y. Chen & Shayilan, 2022) applied dictionary learning algorithms for multivariate geochemical anomaly detection in gold mineral exploration. By training overcomplete dictionaries with geochemical data, the sparse representations of data points effectively describe the geochemical background. The Euclidean distance between data points and their sparse representations quantifies anomaly levels. Five dictionary learning models were tested in Chengde district, Hebei Province, China, and compared with KNN, combined KNN, and GMM models. Results showed that dictionary learning models outperformed others in ROC and AUC metrics and efficiently identified gold prospective areas. These areas, though limited in size, encompassed most known gold deposits and aligned with favorable ore-forming factors such as magmatic intrusion zones and NE-trending faults. The findings validate dictionary learning as a promising technique for geochemical anomaly detection and mineral exploration targeting, warranting further testing in complex geochemical regions.

(S. Zhang et al., 2019) applied the auto-encoder networks and DBSCAN clustering to detect geochemical anomalies, leveraging dimensionality reduction and clustering techniques. Compositional data transformation ILR was also tested, revealing its influence on anomaly detection. Receiver operating characteristic ROC analysis confirmed the anomalies' association with gold mineralization, and optimal thresholds were set using the Youden index. The findings suggest further exploration near faults and magmatic rocks, demonstrating the effectiveness of auto-encoder networks for geochemical anomaly detection.

(Gonçalves et al., 2024) analyzed a 2007 geochemical survey in the western Yilgarn Craton, Western Australia, using singularity mapping and k-means clustering to identify potential Cu-Zn-Pb and Ni-Cu deposits. A composite singularity map was created by linearly combining element-specific maps, weighted by element-to-element correlation coefficients. K-means clustering with 4–5 clusters effectively distinguished mineralized sites, accurately classifying 60– 80% of known Cu and Ni deposits. Criteria based on singularity thresholds and cluster membership were used to identify new potential mineralization targets outside known sites. The results highlight the effectiveness of singularity mapping and clustering for regional geochemical anomaly detection and mineral exploration. (M. Cao et al., 2023) focused on detecting geochemical anomalies linked to Femineralization in the Hunjiang area, Jilin Province, China, using an optimized Random Forest model. The optimization incorporated "Beetle Antennae Search" and "Competitive Mechanism" to enhance parameter selection and identify global optimal solutions. Compared to the original model, the optimized Random Forest significantly improved anomaly detection accuracy and efficiency, showing strong spatial correlations with known iron polymetallic deposits. This approach provides a robust tool for geochemical exploration and mineral resource identification in the region.

3.1.3 Target Identification

Target Identification in mineral exploration refers to the process of delineating specific zones within a geological area that are highly prospective for containing mineral deposits (Partington et al., 2024). This involves analyzing multiple types of data such as geophysical surveys and remote sensing imagery to identify patterns, features that indicate the presence of valuable mineral resources (Y. Chen et al., 2023). Deep learning has significantly advanced target identification, enabling precise delineation of mineralized zones (L. He et al., 2024). By combining remote sensing imagery, geochemical data, and geophysical surveys, deep learning models can identify specific targets for exploration (Nugroho et al., 2023).

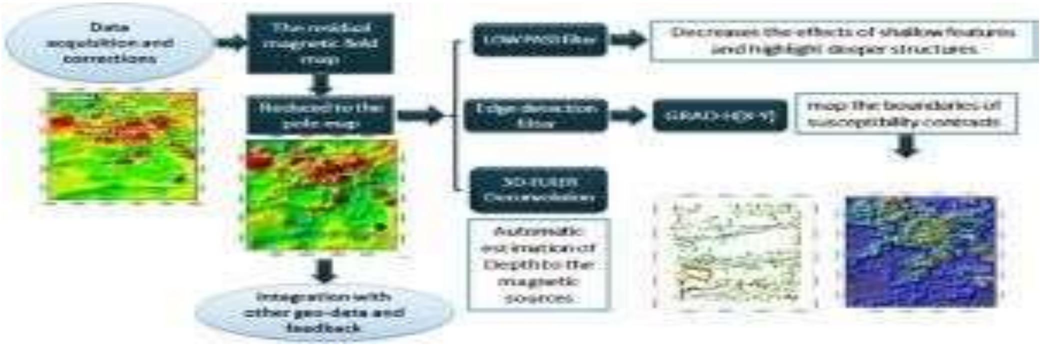

Figure 6: Identification of potential mineral exploration targets (Tazi et al., 2022)

(Qin, 2024) reviews advancements in target detection within computer vision, focusing on deep learning models and their performance using the COCO dataset. A comparative analysis highlights model effectiveness based on mean average precision and input dimensions. YOLOv3 stands out for its balance of high-speed detection and significant accuracy, making it suitable for real-time applications. Despite its smaller input size, YOLOv3 performs comparably to more complex systems, emphasizing design efficiency and processing speed. The research highlights opportunities for future optimizations to improve detection tasks, with implications for academic and industrial real-time applications.

(Juliani & Juliani, 2021) investigates the application of deep learning for analyzing terrain morphology and identifying patterns relevant to deep-sea mineral exploration. It introduces a network-based representational similarity analysis RSA to compare geospatial data features and discover mineral-associated patterns. Using convolutional neural networks CNN, the model processes bathymetric and geological data, automating the classification of seabed features like ridges and slopes. By extracting latent features and correlating them with mineral occurrence data, the approach identifies unexplored areas with potential mineral deposits. Validation on real-world datasets highlights the method's effectiveness in supporting deep-sea mineral exploration efforts.

A comparative study was conducted by (Shirmard et al., 2022) using of convolutional neural networks and conventional machine learning methods, including support vector machines and multilayer perceptrons, for lithological mapping using remote sensing data. CNNs combined with ASTER data achieved the highest classification accuracy, correctly identifying almost all lithological units in the study area in southeast Iran. The study demonstrated that CNNs outperformed SVMs and MLPs in accuracy and adaptability, providing a reliable framework for low-cost lithological mapping and mineral exploration in remote regions. (Qiu et al., 2024) proposes a system for semantic information extraction and search from mineral exploration reports using text mining and deep learning methods. The system extracts geologically relevant keywords using latent dirichlet allocation LDA, builds topic graphs, and constructs knowledge graphs by recognizing geological entities and their relationships with the BERT-BiLSTM-CRF model. It processes over 77,000 reports, separating text, figures, and tables, and transforms unstructured data into structured formats for semantic queries. The proposed method significantly enhances the speed and accuracy of processing geological data, enabling efficient identification of mineral systems and geological relationships.

The multiscale feature attention framework MFAF was proposed by (L. Gao et al., 2023) for intelligent mineral deposit identification and prediction in the Jinshan research area of China's Qin-hang metallogenic belt. The framework utilizes the multiscale feature channel attention net MFCA-Net and convolution spatial attention net CSA-Net to enhance geological image features and resolve challenges like scarce labeled data and fine irregular geological features. MFAF achieved significant improvements, with optimized ResNet18 reaching an accuracy of 72.66%, AUC of 73.46%, and F1-Score of 63.71%. The model predicted areas covering 100% of known deposits and identified high potential zones for further exploration.

4. Challenges and Limitations

Despite the rapid advancements and successful applications of deep learning in geological mapping and mineral exploration, several challenges and limitations persist. These issues can impede the widespread adoption of these techniques in real world scenarios. Among the most pressing challenges are concerns related to data quality and availability, the interpretability of complex models, and the computational resources required to implement and deploy these methods.

4.1 Data Quality and Availability

One of the most significant limitations in applying deep learning to geological mapping and mineral exploration is the availability and quality of data (W. Wang et al., 2024). Geological datasets are often sparse, unevenly distributed, and collected under varying conditions, leading to significant challenges in developing robust and generalizable models (H. Li et al., 2024). In many studies, the lack of standardized, high-quality datasets has been a critical barrier, limiting the capacity of deep learning models to learn the full variability of geological features. For instance, (X. Cao et al., 2024) highlighted the challenges of integrating multi-source data such as geological, geophysical, and geochemical inputs due to inconsistencies in data quality and collection protocols. Additionally, many deep learning models rely heavily on labeled datasets for training. However, the scarcity of annotated geological datasets makes it challenging to train accurate models, particularly in underexplored or remote regions. This limitation often forces researchers to depend on synthetic or simulated datasets, which may not fully capture the complexity of realworld scenarios. (C. Zhang et al., 2022) utilized autoencoder networks for anomaly detection but faced difficulties due to the limited availability of high-quality geochemical data, which impacted the model's performance and generalizability. Another significant issue is the heterogeneity of data sources, such as hyperspectral imagery, geophysical surveys, and geochemical analyses. These datasets often vary in resolution, format, and noise levels, making their integration a complex task. Studies like(Y. Gao & Sun, 2023) have shown that addressing data heterogeneity requires sophisticated preprocessing and normalization techniques, which add to the computational overhead and risk of introducing biases.

4.2 Interpretability and Explainability

The black-box nature of deep learning models is another major limitation that hinders their widespread adoption in geological applications (Zhao et al., 2024). Geologists and domain experts often require interpretable and explainable results to trust and validate the predictions made by these models(Dahal & Lombardo, 2023). However, many state-of-the-art deep learning models, such as convolutional neural networks and transformers, operate as complex systems with millions of parameters, making it difficult to understand their internal decision-making processes. Several studies have attempted to address this issue. (Dong & Zhang, 2024) introduced the deep forest model, which dynamically adjusts its complexity and offers improved interpretability compared to traditional deep learning models. This approach allows geologists to understand the importance of specific geological and geochemical features, such as fault density and gravity anomalies, in predicting mineral prospectivity. Despite these efforts, the lack of standardized frameworks for explainability remains a significant challenge. Techniques such as feature importance analysis and saliency maps are often used to provide insights into model behavior, but these methods are not universally applicable across all geological datasets and tasks (Ghaffarian et al., 2023). Moreover, as noted by(Bigdeli et al., 2023), explainability is crucial for gaining stakeholder confidence, particularly in high-stakes applications such as mineral exploration and environmental conservation.

4.3 Computational Resources

The computational demands of deep learning models represent another critical limitation, particularly for resource constrained settings (H.-I. Liu et al., 2024). Training deep learning models for geological mapping and mineral exploration often requires significant computational power, including high-performance GPUs or TPUs, large memory capacities, and extensive storage (Saupi Teri et al., 2022). For instance, (M. Cao et al., 2023) highlighted the computational challenges associated with training an optimized random forest model for geochemical anomaly detection, which required advanced optimization techniques and significant hardware resources.

Furthermore, the increasing complexity of deep learning architectures, such as transformers and ensemble model, exacerbates these computational demands. These models often require long training times and consume substantial energy, raising concerns about their sustainability and scalability (Rane et al., 2024). As noted by (Mahboob et al., 2024), the iterative training process for integrating geospatial datasets using advanced machine learning workflows can be both time-consuming and resource-intensive. In addition to training, deploying deep learning models in real-world scenarios poses challenges. For example, real-time applications such as UAV-based geological mapping require models that can process high-resolution imagery efficiently. However, the computational overhead of these models often limits their deployment in field settings, particularly in remote or resource-limited regions. Techniques like model compression and quantization have been proposed to address these challenges, but their adoption in geological applications remains limited.

Table 1: Summary of challenges and limitations in deep learning for geological mapping and mineral exploration.

Challenges	**Description**	**Example**	**References**
Data quality and availability	Sparse, unevenly distributed datasets and inconsistencies in multisource data integration.	Limited geochemical data reduced model accuracy; challenges integrating multi-source inputs.	(W. Wang et al., 2024; Y. Gao & Sun, 2023; H. Li et al., 2024)
Interpretability and Explainability	Models operate as black boxes, making it difficult for experts to validate predictions.	Deep forest improved interpretability; saliency maps used for explaining model predictions.	(Bigdeli et al., 2023; Dahal & Lombardo, 2023; Dong & Zhang, 2024; Ghaffarian et al., 2023; Zhao et al., 2024)
Computational Resources	High computational demands limit scalability and deployment in resource-constrained settings.	Training geochemical models required significant hardware; UAV mapping faced real-time limits.	(H.-I. Liu et al., 2024; Mahboob et al., 2024; Rane et al., 2023; Saupi Teri et al., 2022)

5. Future Directions

The integration of deep learning into geological mapping and mineral exploration has yielded significant advancements, yet numerous challenges remain. Addressing these challenges requires forward-thinking approaches that enhance the scalability, efficiency, and interpretability of models. Future research directions encompass integrating deep learning with complementary technologies, utilizing transfer learning and domain adaptation to overcome data scarcity, and promoting explainable AI for greater transparency and trust.

5.1 Integration with Other Technologies

The integration of deep learning with complementary technologies is poised to revolutionize geological mapping and mineral exploration. Emerging technologies such as Geographic Information Systems Internet of Things, and high-performance computing have the potential to overcome current limitations, enabling more precise and scalable solutions.

Geographic information systems GIS platforms provide a powerful medium for visualizing and analyzing geological and spatial data (Lü et al., 2019). When combined with deep learning models, GIS can enhance the understanding of spatial patterns in geological formations and mineral deposits (Mohan & M.V.S.S, 2022). For instance, GIS integration with convolutional neural networks allows for the automated extraction of features from satellite images and geospatial datasets, enabling real-time mapping and anomaly detection (Jaafar et al., 2024). Studies such as (Qiu et al., 2024) have demonstrated how GIS frameworks coupled with semantic segmentation models can refine geological interpretations, especially in mineral-rich regions.

Internet of Things IoT-enabled devices and sensors can facilitate the continuous acquisition of geological and environmental data, creating a dynamic feedback loop for deep learning models (Rane et al., 2023). By integrating IoT systems with neural networks, real-time monitoring of geological changes becomes feasible, allowing for more responsive mineral exploration strategies (X. Cao et al., 2024). For example, in remote areas, IoT can capture seismic, thermal, or geochemical data, which deep learning models can analyze for mineral prospectivity mapping (Mahboob et al., 2024). The IoT-deep learning synergy also enables automated anomaly detection, reducing reliance on manual interventions.

High-performance computing computational intensity of deep learning algorithms often presents scalability challenges, particularly when processing high-resolution satellite imagery or hyperspectral data (S. Zhang et al., 2022). High-performance computing HPC infrastructure addresses this limitation by accelerating model training and inference processes. For example, HPC clusters can process terabyte-scale remote sensing datasets, enabling simultaneous training of multiple models to optimize geological mapping accuracy (L. Gao et al., 2023). Future research should prioritize developing scalable workflows that integrate HPC with deep learning to achieve more efficient and comprehensive geological analyses.

5.2 Transfer Learning and Domain Adaptation

Data scarcity remains a critical limitation in applying deep learning to geological mapping and mineral exploration. Transfer learning and domain adaptation provide innovative solutions to overcome this challenge by adopting pre-trained models and aligning datasets from different regions or domains. Transfer learning involves using models pre-trained on large datasets from one domain and fine-tuning them for specific tasks in another domain (Vrbancic & Podgorelec, 2020). For example, models pre-trained on hyperspectral data for vegetation classification can be adapted for lithological classification, reducing the need for extensive training data (Han et al., 2023). This approach has been particularly effective in mineral exploration, where geological data from one region can inform predictions in geologically similar areas. For instance, (H. He et al., 2024) demonstrated the successful application of transfer learning for gold prospectivity mapping, achieving high accuracy even in data-scarce regions.

Domain adaptation techniques address discrepancies between the source and target datasets, enabling models to generalize across regions with varying geological conditions (Shin, 2024). Approaches such as adversarial training, feature alignment, and style transfer have shown promise in bridging domain gaps. For example, (L. Gao et al., 2023) utilized adversarial domain adaptation to align spectral features from different satellite platforms, improving mineral anomaly detection in heterogeneous datasets. This is particularly valuable for regions with mixed geological features, where conventional models often struggle to maintain accuracy.

5.3 Explainable AI and Interpretability

The lack of interpretability in deep learning models remains a significant barrier to their adoption in geological sciences. Explainable AI aims to make these models more transparent, enabling domain experts to understand the reasoning behind predictions and fostering trust in AI-driven solutions.

Several techniques have been developed to make deep learning models interpretable. Saliency maps, for instance, visualize the regions of input data that contribute most to a model's prediction (Huff et al., 2021). These have been applied to highlight critical features in hyperspectral images, aiding in mineral identification (Dong & Zhang, 2024). Similarly, SHAP (shapley additive explanations) and LIME (local interpretable model-agnostic explanations) provide insights into feature importance, allowing geologists to validate model predictions against domain knowledge (X. Ma et al., 2023).

Explainability is particularly important in tasks such as mineral prospectivity mapping and anomaly detection, where model outputs directly influence exploration decisions (Zuo et al., 2024). For example, (Y. Liu et al., 2024) used saliency maps to identify key geophysical anomalies associated with gold deposits, ensuring that the model's decisions aligned with geological evidence. This not only enhances model reliability but also enables geologists to refine exploration strategies based on interpretable outputs.

6. Conclusion

Deep learning has emerged as a transformative tool for geological mapping and mineral exploration, offering unprecedented capabilities for automating complex workflows and integrating diverse data sources. This review highlights the advancements in areas such as image classification, predictive modeling, and anomaly detection, demonstrating the significant potential of deep learning models to improve accuracy, scalability, and efficiency in geological applications. Despite these advancements, challenges such as data quality, interpretability, and computational demands persist, limiting the widespread adoption of deep learning in real-world scenarios. Future research should focus on addressing these limitations by developing standardized datasets, incorporating explainable AI techniques, and leveraging complementary technologies like GIS, IoT, and HPC to enhance model performance and generalizability. With continued innovation, deep learning has the potential to transform geological exploration and contribute to sustainable resource management.

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