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ARTIFICIAL INTELLIGENCE IN HYPERSPECTRAL REMOTE SENSING FOR MINERAL PROSPECTING

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Abstract : Mineral prospecting is a key part of the mining industry, focusing on exploring geological features to locate potential mineral deposits. Hyperspectral remote sensing data from satellites and airborne platforms has proven highly effective in addressing common challenges in mineral exploration. This technology is particularly useful for mapping lithology and mineral alterations across various ore mineralization environments. By providing detailed spectral and spatial information, hyperspectral imagery supports early stages of exploration by analyzing Earth's surface features comprehensively. In recent years, combining artificial intelligence (AI) with hyperspectral remote sensing has significantly improved the efficiency and accuracy of mineral prospecting. Studies show that AI algorithms, when integrated with traditional image processing techniques and geological surveys, play a growing role in advancing lithological mapping and mineral exploration using hyperspectral data. This study highlights the growing importance of AI-based approaches in mineral prospecting, offering solutions to overcome traditional challenges and accelerating the exploration process. As both AI and hyperspectral technology continues to advance, their combined potential is poised to revolutionize the future of mineral exploration.

***IndexTerms* - Hyperspectral, AI, remote sensing, mineral.**

I. Introduction

Hyperspectral data acquisition involves the collection of continuous and contiguous spectral bands using advanced remote sensing sensors, precisely engineered to capture the diagnostic absorption and reflection properties of Earth's surface materials. Hyperspectral imagery has emerged as a powerful tool in a wide array of Earth and planetary applications, including geological mapping, agriculture, water quality, environment, forestry and military operations (Guha, 2020; Sivakumar et al., 2017; Sivakumar et al., 2016; Sivakumar and Neelakantan, 2015; Bedini, 2012). By providing detailed spectral information across broad wavelength ranges—spanning the visible and near-infrared to the short-wave infrared, enable accurate identification and characterization of mineralogical and lithological compositions.

Lithological mapping and mineral prospecting using Hyperspectral remote sensing have seen a significant rise in research, with over 145 papers on lithology and more than 1000 on mineralogy published in the past six years (Hajaj et al., 2024). This growth highlights the increasing importance of hyperspectral data in geological studies. Additionally, the deployment of advanced hyperspectral satellite sensors has greatly improved global access to high-resolution spectral data, benefiting worldwide.

Despite its potential, the processing and analysis of hyperspectral data remain challenging due to its inherent complexity and high dimensionality. In recent years, artificial intelligence (AI) techniques, particularly machine learning (ML) and deep learning (DL) algorithms, have shown remarkable promise in addressing these challenges and extracting critical insights from hyperspectral datasets (Shirmard et al., 2022). These innovative AI-driven approaches, combined with advanced image processing methods, have enabled the extraction of mineralogical and lithological information from complex metallogenic regions and remote areas.

The computational capabilities of ML and DL algorithms empower exploration geologists to overcome challenges at various stages of mineral exploration campaigns, facilitating more efficient and accurate assessments. Consequently, the integration of Hyperspectral imagery with cutting-edge AI techniques represents a transformative approach, offering immense potential for advancing lithological mapping and mineral exploration in the future.

II. Hyperspectral Technology

Minerals possess specific chemical compositions and lattice structures that influence their reflection, transmission, absorption, and emission properties of electromagnetic waves, which are captured in hyperspectral remote sensing images. The diagnostic spectral features of minerals and rocks in the electromagnetic spectrum provide valuable insights for identifying mineral compositions. Wall rock alteration, a critical indicator of mineralization, involves alteration minerals rich in ions like Fe^{2+}, Fe^{3+},

OH^-, and CO_3^{2-}. The electronic transitions, vibrations, and rotations of these ions or ion groups create distinctive spectral features observable in remote sensing imagery. Minerals can be identified effectively by analyzing the unique absorption features in their diagnostic bands. Key absorption characteristics include depth, width, area, position, and symmetry (Hecker et al., 2019). Combining multiple absorption features provides a more detailed representation of these bands, improving the accuracy of mineral identification. However, relying solely on a single absorption band may not capture enough detail about a mineral's spectral properties. Alternatively, spectral similarity methods compare the identified spectrum to a reference spectrum to measure how closely they match. For instance, the Spectral Angle Mapper (SAM) method evaluates similarity by calculating the angle between the identified and reference spectral vectors in multidimensional space (Dennison et al., 2004). Despite their usefulness, mineral spectra can vary under different imaging conditions, leading to changes in reflectance and diversity in spectra for the same mineral. Therefore, it is crucial to explore the intrinsic features of mineral spectra that distinguish minerals while remaining robust against varying imaging conditions.

III. AI AND HYPERSPECTRAL IMAGE FOR MINERAL IDENTIFICATION

In the last ten years, machine learning (ML) and deep learning (DL) techniques have increasingly become the main approaches for remote sensing interpretation. The number of publications in this field has surged from 75 to 2510. These advanced methods have played a key role in improving the accuracy, efficiency, and automation of remote sensing image interpretation (Han et al., 2023). Hyperspectral remote sensing data alongside AI algorithms has been shown to make mineral exploration easier and more effective. Machine learning is gaining attention in remote sensing data analysis as a way to address challenges in geological and mineral exploration. With the rapid growth of machine learning and deep learning methods, it is essential to outline a clear roadmap for future work in this field (Bachri et al., 2019). Machine learning algorithms, a branch of artificial intelligence (AI), are designed to automatically extract insights from data using statistical or non-statistical methods. These classification techniques are categorized into two main types i) Unsupervised classification - groups rock types based solely on their spectral characteristics, without relying on predefined training zones. The process typically results in spectral clustering through iterative techniques (De, 2012; Sahoo, 2017); ii) Supervised classification - assigns groups of similar pixels to specific classes representing different rock types. It achieves this by comparing the pixels with each other and with those whose lithology is already known. Advancements in supervised image classification techniques using machine learning algorithms have significantly enhanced geological studies with remote sensing data (Bachri et al., 2019). Many researchers have applied AI techniques to identify minerals in various regions using data from different hyperspectral sensors. For example, Barkley et al., (2019) used the Support Vector Machine algorithm to map lithology and demonstrated that the classification approach effectively produced an image containing lithological units. These units included formations such as silt, alluvium, limestone, dolomite, conglomerate, sandstone, rhyolite, andesite, granodiorite, quartzite, lutite, and ignimbrite; Kumar et al, 2020 attempted to automated the lithological mapping using spectral enhancement techniques and Machine Learning Algorithms using Airborne Visible Infrared Imaging Spectroradiometer-Next Generation (AVIRIS-NG) hyperspectral data in the greenstone belt of the Hutti area to map the potential zone of gold mineralization; Cracknell et al., (2104), conducted a detailed comparison of five machine learning algorithms: Naive Bayes, k-Nearest Neighbors, Random Forests, Support Vector Machines, and Artificial Neural Networks, for a supervised lithology classification task. The findings highlight that algorithm like Random Forests are effective tools for producing reliable initial predictions, aiding practical geological mapping with commonly available geophysical data; Sun et al., (2024) reviewed various deep learning algorithms and found that they offer significant advantages over traditional prospecting prediction methods. Algorithms like DAE, CNN, RNN, and GAN have improved prospecting prediction techniques in different ways, playing a crucial role in advancing mineral exploration and development.

IV. DISCUSSION

The integration of artificial intelligence with hyperspectral remote sensing has ushered in a new era for mineral prospecting, offering substantial improvements in both efficiency and accuracy. Over the past decade, the development of AI techniques, particularly machine learning (ML) and deep learning (DL), has transformed the way hyperspectral data is analyzed and interpreted. These advanced technologies have greatly enhanced the capacity of remote sensing to identify mineral deposits and map lithological units, overcoming many of the challenges traditionally associated with mineral exploration. Hyperspectral remote sensing is a powerful tool due to its ability to capture detailed spectral information across a wide range of wavelengths. This allows for precise identification of mineralogical and lithological compositions on Earth's surface. As mineral exploration increasingly relies on this technology, the challenge remains to process and analyze the vast and complex data generated by hyperspectral imagery. The inherent complexity and high dimensionality of hyperspectral data make it difficult to extract meaningful insights manually, which is where AI techniques come into play. The ability of AI algorithms to handle large datasets and identify patterns without human intervention has been a major factor in improving the overall efficiency of mineral prospecting.

Machine learning algorithms have gained widespread use in the analysis of hyperspectral data. Two primary types of classification techniques—supervised and unsupervised—have been applied to this task. Supervised classification, where known lithological types are used to train the model, has proven highly effective in accurately categorizing rock types based on their spectral signatures. Conversely, unsupervised classification, which groups rock types based solely on their spectral properties, has also been valuable for initial exploratory phases where training data may be scarce. Both methods have demonstrated their utility in mineral exploration, offering flexibility and adaptability depending on the available data. However, challenges still exist in the application of AI for hyperspectral data analysis. One of the primary challenges is the variability of mineral spectra due to changing environmental and imaging conditions. Factors such as atmospheric conditions, sensor calibration, and even the time of data acquisition can influence spectral reflectance, making it difficult to achieve consistent results. To address this issue, it is essential to explore the intrinsic features of mineral spectra that are robust against these variations. This could involve developing more advanced AI models capable of recognizing spectral patterns even under less-than-ideal conditions. Moreover, the increasing volume of hyperspectral data poses another challenge. While AI techniques excel at handling large datasets, the need for computational power and memory resources grows as the amount of data increases. As remote sensing technology continues to improve, generating higher resolution and larger datasets, it will be essential to continue refining AI algorithms to ensure they remain efficient and effective at scale.

Looking ahead, the integration of AI with hyperspectral remote sensing holds immense potential for the future of mineral prospecting. The combination of AI's analytical power with the detailed spectral data from hyperspectral imagery could revolutionize mineral exploration by reducing costs, speeding up the exploration process, and improving the accuracy of mineral deposit identification. The growing body of research, as evidenced by the increase in publications in this field, indicates that AI and hyperspectral remote sensing will continue to be crucial tools for the mining industry. Further advancements in both AI algorithms and hyperspectral sensor technology will likely drive even more sophisticated applications in the coming years, making mineral exploration more efficient, cost-effective, and accessible.

V. CONCLUSION

Integration of artificial intelligence with hyperspectral remote sensing has significantly advanced mineral prospecting, improving both efficiency and accuracy. Machine learning and deep learning techniques have proven effective in processing and analyzing complex hyperspectral data, enabling precise lithological mapping and mineral identification. Despite challenges like variability in mineral spectra and large data volumes, AI continues to offer promising solutions for overcoming these issues. As hyperspectral sensor technology evolves, the potential for AI to enhance mineral exploration grows. The combination of these technologies represents a transformative approach in the mining industry. Future research will likely further refine these methods, enhancing their application. Overall, AI-driven hyperspectral remote sensing holds great promise for the future of mineral exploration.

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