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Research on Prospecting Prediction Method Based on Multi-Source Remote Sensing Images

—A Case Study of Northern Namibia

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Abstract

The mining area in northern Namibia is rich in mineral resources, but the geological structure is complex, and the traditional mineral exploration technology is faced with certain challenges. In this paper, a method of convolutional neural network (CNN) combined with remote sensing data is proposed to delineate the prospecting potential area in this area. By means of calcite mineral distribution map, chlorite mineral distribution map, lithologic structure interpretation map, iron dye hydroxyl alteration map, according to the known ore points, and finally using CNN to classify, the prospecting prospect map is generated, revealing the spatial distribution characteristics of potential mineralization zones. The research results show that CNN technology can effectively improve the accuracy of mineral resources assessment, and help to identify hidden ore bodies, showing a wide application potential in the future mineral exploration.

Keywords

Convolutional Neural Network (CNN), Remote Sensing Data, Mineral Mapping, Copper Mines in Namibia, Prospecting

1. Introduction

Located in southwest Africa, the northern mining area of Namibia is an important mineral resource gathering area with rich mineral resource potential. However, the complex geological structure and diverse geological background in this region, including multi-stage volcanic activity, magma intrusion and orogenic belt evolution, make the mineral exploration work face great challenges [1]. Traditional geological exploration methods, such as geological mapping, geophysical exploration and geochemical exploration, usually have certain limitations in the identification of hidden ore bodies, and their exploration efficiency and accuracy are restricted in complex geological backgrounds [2].

In recent years, remote sensing technology has been widely used in mineral resource exploration due to its wide area, high resolution and high efficiency. Remote sensing image data can obtain the detailed information of surface rocks, minerals and structures, especially in the identification and distribution of altered minerals. Altered minerals, such as calcite and chlorite, are important indicators of mineralization processes and have unique spectral characteristics in remote sensing data, so they can be used to identify potential mineralization zones [3]. For complex geological environments, the potential of remote sensing data combined with automated analysis techniques provides new avenues for mineral exploration [4].

In the automated analysis of mineral exploration, convolutional neural network (CNN), as a deep learning method, has shown outstanding performance. The application of CNN in the field of remote sensing image processing can automatically identify mineraline-related features through multi-level feature extraction and classification of images, greatly improving the efficiency and accuracy of prospecting [5]. Combining the geological feature recognition of remote sensing images with the strong learning ability of CNN can effectively delineate the mineralization zone, especially in the complex geological background, which can reduce the uncertainty of manual interpretation and improve the reliability of prospecting.

In this paper, a method combining convolutional neural network (CNN) and remote sensing data is proposed for delineating prospecting prospects in a mining area in northern Namibia. Based on the analysis of calcite mineral distribution map, chlorite mineral distribution map, lithologic structure interpretation map and iron dye hydroxyl alteration map, combined with known mineral site information, CNN was used to classify and identify different geological features, and finally generate prospecting prospect map to reveal the spatial distribution characteristics of potential mineralization zones. The research results show that the application of CNN combined with remote sensing technology can not only significantly improve the accuracy of mineral resource assessment, but also effectively identify hidden ore bodies, showing a wide application potential in the future mineral exploration.

The purpose of this study is to explore the application of CNN technology in mineral exploration by combining it with remote sensing data, and evaluate its effectiveness in prospecting accuracy and mineralization zone identification. Through the application example of the mining area in northern Namibia, it can provide theoretical and practical support for future prospecting work in similar areas.

2. Regional Geological Overview

Namibia is located in southwest Africa, bordered by Angola and Zambia to the north, Botswana to the east and South Africa to the south. Namibia has a very complex geological history, located in the Damara Orogenic belt and its borders with the La Plata, Congo and Kalahari Cratons, Namibia has experienced several stages of rift extensional and closed evolution, and has been affected by multiple periods of magmatic activity and tectonic movement. The rock strata in the region cover multiple geological periods from Archean to Cenozoic, including sedimentary rocks, metamorphic rocks and magmatic rocks of various types, showing rich geological diversity and huge potential for mineral resources development [6]. The mining area in northwest Namibia is dominated by NW-trending and NE-trending faulting structures, which provide channels for volcanic activity and are important geological conditions for mineralization. The study of metallogenic markers in Namibia is of great significance to the exploitation of mineral resources and economic development. The observation of mining areas in northwest Namibia by remote sensing technology provides scientific direction and theoretical support for mineral exploration.

The mining areas in northwest Namibia are mainly volcanic sedimentary deposits, and their mineralization is closely related to volcanic activities. During volcanic activity, the ore-forming elements carried by magmatic hydrothermal solution rise to the surface along cracks and faults, and are enriched and deposited under suitable temperature and pressure conditions, resulting in the formation of ore deposits [7]. During the ore-forming process, volcanic rocks and sedimentary rocks combined with each other. Due to the dehydrating metamorphism of subduction zone sediments and oceanic crust under high pressure [8], the mining area was characterized by diverse rock types and a large number of medium-acid intrusive rocks and basic dikes. It is important to distinguish different rock lithology for ore prospecting. Remote sensing images can effectively distinguish different types of rocks by identifying the spectral characteristics, tone and texture characteristics of rocks, thus significantly improving the efficiency of ore prospecting.

The Pan-African orogeny triggered multi-stage tectonic activity in Namibia, creating favorable conditions for the formation of mineral deposits. The area experienced pre-orogenic, orogenic, and post-orogenic periods, especially during the late Proterozoic period with large-scale rifting activity followed by folding deformation. These tectonic processes provided channels for the ascent of magmatic hydrothermal fluids, and tectonic activities were closely related to mineralization. The geological phenomena of tectonic movement often show unique linear features in remote sensing images. Faults and fissures show obvious differences of light and color on both sides in remote sensing images. Remote sensing technology can effectively identify these structural features and provide specific directions for determining metallogenic regions [9].

During the mineralization process, the interaction between magmatic hydrothermal fluid and surrounding rock is accompanied by various alteration processes, and the existence of these alteration minerals is one of the important symbols of mineralization. In the mining area of Namibia, the types and distribution of altered minerals are of great significance to the exploration of mineral resources. These altered minerals can be accurately identified by remote sensing images because of their obvious spectral differences, and the spectral characteristics of different altered mineral combinations are also significantly different. Using remote sensing technology to distinguish these altered minerals can greatly improve the prospecting efficiency [10].

During the mineralization process, due to surface oxidation, some metal elements produced significant oxidation phenomena in the oxidation zone, which showed obvious differences in hue and reflectance compared with the surrounding rocks. These anomalies can be clearly identified in remote sensing images, and exploration of the oxidation zone by remote sensing technology plays an important role in demarcating the mining area during ore prospecting.

Remote sensing technology can be used to effectively observe the geological structure, geological phenomena, rock lithology and altered mineral belt of the mining area in northwest Namibia [11], so as to better understand the metallogenic mechanism and ore-forming signs, and provide scientific basis for remote sensing prospecting. The combination of ore-forming principle and remote sensing technology has a broad application prospect in mineral exploration. Remote sensing technology can provide high-resolution and large-scale geological analysis data, thus significantly improving the accuracy of ore-forming prediction in Namibia's mining areas. The geological map of the study area is shown in Figure 1.

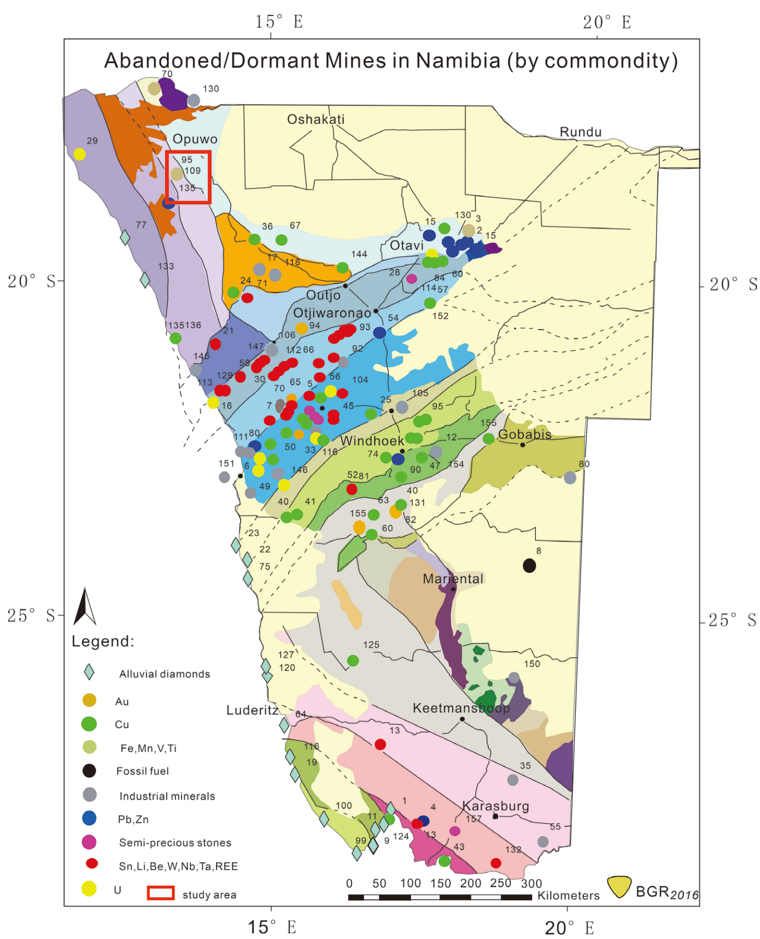

Figure 1. The geological map of the study area.

The lithostratigraphy of this region spans multiple geological periods from the

Archean to the Cenozoic, encompassing various types of sedimentary rocks, metamorphic rocks, and magmatic rocks. This exhibits rich geological diversity and holds great potential for mineral resource development.

In the mining areas of northwestern Namibia, fault structures trending NW and NE are predominantly developed. These structures provide pathways for volcanic activities and represent crucial geological conditions for mineralization. Mineralization in this region is closely associated with volcanic activities. During volcanic eruptions, ore-forming elements carried by magmatic hydrothermal fluids ascend along fractures and faults, and accumulate and deposit under suitable temperature and pressure conditions, thus forming ore deposits.

During the mineralization process, volcanic rocks interact with sedimentary rocks. Due to the dehydration and metamorphism of sediments in the subduction zone and the oceanic crust under high pressure, a diverse range of rock types have formed in this area, with a large number of intermediate-acidic intrusive rocks and basic dikes developing. These geological features are of great significance for mineral resource exploration. Remote sensing technology can effectively identify these geological features, thereby enhancing the efficiency and accuracy of mineralization research.

3. Research Methods

In this study, the convolutional neural network (CNN) combined with remote sensing data was used to identify and delineate the prospecting potential area of the mining area in northern Namibia. The specific research method includes the following steps:

First, remote sensing technology was used to collect large-scale multi-spectral data from mining areas in northern Namibia, and basic geological data such as chalcopyrite distribution map and iron stain hydroxyl alteration map were obtained [12]. The spectral characteristics of different minerals and lithologies are extracted from these geological data by remote sensing image processing technology to form multi-layer data maps to ensure the accuracy and consistency of the spatial distribution of geological features and their reflection spectral characteristics.

Secondly, based on the existing geological exploration data and known mineral information, the metallogenic markers in the mining area are comprehensively interpreted and verified by means of geostatistical analysis. Combined with mineral distribution information extracted from remote sensing data, the geological structure characteristics of mining areas in northern Namibia were analyzed in detail, and the interrelationship between fault structure and mineralization zone was clarified. In particular, through the information of iron staining and hydroxyl alteration on the surface, the possible ore-forming hydrothermal activity areas are identified [13].

Then, on the basis of the above geological data and interpretation results, the convolutional neural network (CNN) is used to construct the classification model of prospecting prospect area. Specifically, data pre-processing of remote sensing images, including image de-noising, spectral correction and standardization processing, was carried out to ensure the clarity and consistency of data [14]. Next, the processed remote sensing data was paired with known ore spots, and CNN was used for model training through supervised learning to identify ore-forming related features. In the training process, the performance of the model was evaluated by cross-validation method to ensure the robustness and accuracy of the model on the new data [15].

After model training was completed, the CNN model was applied to the remote sensing data of the entire mining area in the study area to generate prospecting prospect maps and reveal the spatial distribution characteristics of potential mineralization zones in the mining area. Finally, the reliability of the model results is verified based on the comparison between the predicted results of the model and the existing ore spots. The research shows that the convolutional neural network combined with remote sensing data can effectively improve the accuracy of mineral resources assessment, and show significant advantages in the identification of hidden ore bodies.

This Convolutional Neural Network (CNN) architecture takes multi-source remote sensing image data as input. After pre-processing, the data enters the network. The network structure consists of multiple convolutional layers. The first convolutional layer uses 32 filters of size 3×3, with a stride of 1, a padding method of "same", and the ReLU activation function. The second convolutional layer uses 64 filters of size 3×3, with a stride of 1, a padding method of "same", and also adopts the ReLU activation function.

After that is the pooling layer. It uses 2×2 max-pooling with a stride of 2 to reduce the size of the feature map. Then comes the fully-connected layer. The first fully-connected layer has 128 neurons with the ReLU activation function. The second fully-connected layer has 64 neurons, and its activation function is also ReLU. The number of neurons in the output layer is determined according to the number of classes in the classification task. The Softmax activation function is used to convert the output into a probability distribution.

During the training process, the input data is first pre-processed, including image denoising, spectral correction, and standardization to ensure the clarity and consistency of the data. Then, the processed remote sensing data is paired with the known ore-point information, and the model is trained in a supervised learning manner. The cross-entropy loss is used as the loss function, and the Adam optimizer is used as the optimizer. The performance of the model is evaluated by the cross-validation method to ensure its robustness and accuracy on new data.

After the training is completed, the CNN model is applied to the remote sensing data of the entire study area to generate a prospecting potential map, revealing the spatial distribution characteristics of potential mineralized areas. The model can effectively learn and identify the geological features related to mineralization, generate a high-precision prospecting potential map, and provide a scientific basis for mineral resource exploration.

In this study, the proposed method based on Convolutional Neural Networks (CNN) demonstrates significant performance advantages when processing remote sensing data from the mining areas in northern Namibia. CNNs generally outperform traditional algorithms, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), in image classification tasks. For example, CNN accuracy can exceed 90% on the CIFAR-10 dataset, while SVM and KNN accuracy usually hovers around 70%. In this study, the CNN method also exhibited higher accuracy in identifying and delineating potential mineral exploration areas, primarily due to CNN's powerful feature extraction capabilities, which can automatically learn and recognize complex image features, thus more accurately identifying geological features related to mineralization. In object detection tasks, CNN-based models such as YOLO and Faster R-CNN can detect multiple objects in images in real time, whereas traditional algorithms like HOG + SVM struggle to achieve similar results. In this research, the CNN model effectively identifies and locates geological structural features, such as fault structures and mineralized zones, in remote sensing images, which are crucial for studying mineralization. Moreover, CNNs offer significant advantages in processing large-scale data. Despite the relatively complex training process, which requires considerable computational resources and time, CNNs outperform traditional algorithms in handling high-dimensional data. In this study, the CNN method is capable of processing vast amounts of multispectral remote sensing data and, through multiple layers of convolution and pooling operations, effectively extracts and integrates features at various levels, thereby generating high-precision mineral exploration potential maps. In conclusion, CNN-based methods demonstrate significant performance advantages in image classification and object detection tasks, particularly in processing complex remote sensing image data. The high accuracy and robust feature extraction capabilities of CNNs make them of great value in mineralization research.

4. Results

The Convolutional neural network (CNN) combined with remote sensing data was used to delineate the prospecting prospect area in the northern mining area of Namibia, and the research results have achieved remarkable results. Firstly, through the analysis of chalcopyrite distribution map, the areas with more concentrated surface alteration characteristics were identified. These mineral distribution maps can effectively reflect the geological background related to metallogenic activities, especially the areas closely related to magmatic hydrothermal alteration process, and provide basic data support for the delineation of mineralization zones.

Secondly, through the comprehensive analysis of lithologic structure interpretation map and iron dye hydroxyl alteration map, the spatial distribution relationship between the main fault structure and the mineralization zone is clarified, and the controlling role of the fault zone in the mineralization process is revealed. The results show that the NW and NE trending fault structures provide channels for the rise of ore-forming hydrothermal fluids, and these tectonic zones often show significant mineralization characteristics. Combined with the information of iron staining and hydroxyl alteration, the possibility of mineralization is further verified.

Through the classification training of convolutional neural network, a prospecting prospect map of the northern mining area of Namibia is generated, which reveals the spatial distribution characteristics of multiple potential mineralization zones. The results show that the CNN model can effectively identify the mineralized regions around the known ore spots, and successfully identify several new potential mineralized zones. These newly identified mineralized zones are mainly distributed in areas previously thought to have complex geological conditions, which is not conducive to mineralization, indicating the advantages of CNN in dealing with complex geological conditions.

In addition, the generated prospecting prospect map was evaluated using validation data of known mineral sites, and the results showed that the mineralized areas predicted by the model had a high spatial agreement with the actual mineral sites. This indicates that the prospecting method using CNN combined with remote sensing data not only improves the accuracy of mineralized area identification, but also reduces the uncertainty and subjective bias in the manual interpretation process, providing a reliable method for the identification of concealed ore bodies.

Overall, the results of this study demonstrate the great potential of convolutional neural networks combined with remote sensing data in mineral exploration. Through the combination of multi-source remote sensing data and deep learning, the accuracy and efficiency of prospecting prospect prediction is effectively improved. Especially in the area with complex geological structures, the CNN model has shown superior performance. This provides a strong theoretical and practical support for future mineral resource exploration, especially for the identification of hidden ore bodies. The map of hydroxyl distribution is shown in **Figure 2**.

The map of iron staining distribution is shown in **Figure 3**.

In order to extract information related to chalcopyrite, usually only the bands in the ASTER image that reflect the reflection characteristics of rocks and minerals are selected. Bands 1 - 7 of the ASTER image in the study area are selected for principal component analysis. After observing the loadings and spatial distributions of each principal component, it is found that the third principal component (PC3) can better highlight the abnormal information related to chalcopyrite. Therefore, PC3 is chosen as the result of chalcopyrite information extraction. The map of Chalcopyrite distribution is shown in **Figure 4**.

Based on the information layers extracted above, a CNN model was established, trained, and used for prediction, and the prospecting target area in the study area is obtained. The map of target area is shown in **Figure 5**.

5. Discussion

In this study, the convolutional neural network (CNN) combined with remote sensing data is used to predict the prospecting potential of the mining area in northern Namibia, and encouraging results have been obtained. The results show that the CNN prospecting method combined with multi-source remote sensing data has significant advantages in identifying potential mineralization zones and improving prospecting accuracy. These results have important implications for addressing the challenges of complex geological background and concealed ore body identification in mineral exploration.

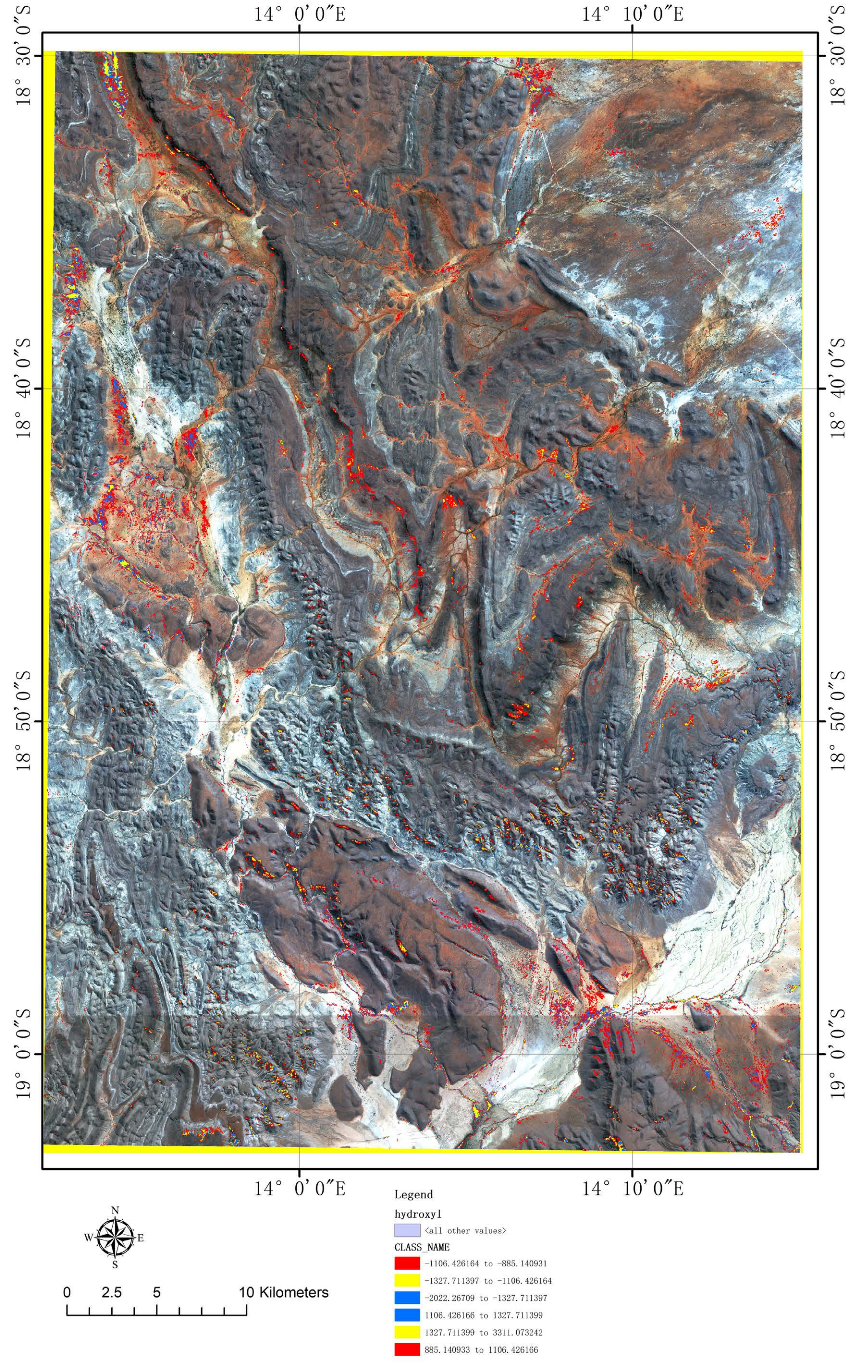

Figure 2. The map of hydroxyl distribution.

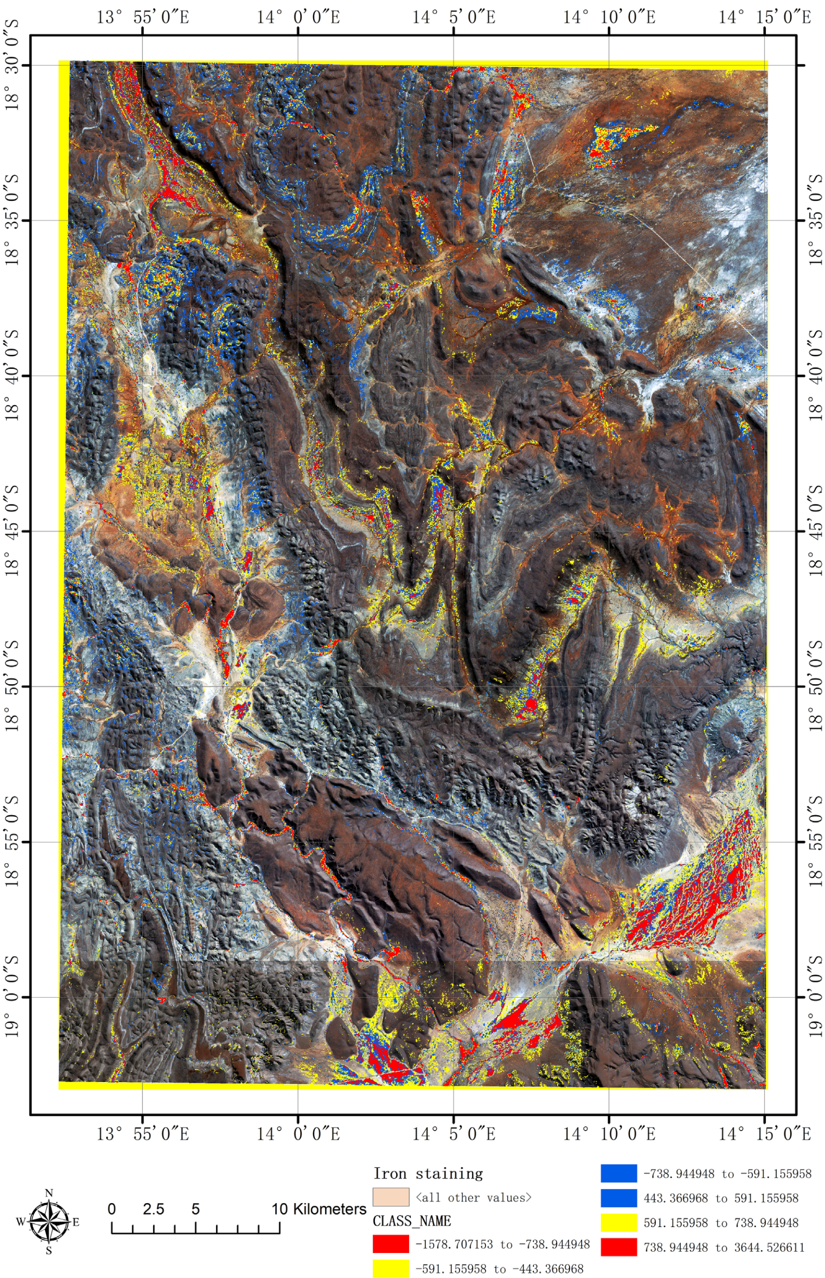

Figure 3. The map of iron staining distribution.

First of all, through the comprehensive analysis of chalcopyrite distribution map and other geological feature layers, the study successfully delineated the possible ore-forming area. The close relationship between these mineral distribution maps and ore-forming hydrothermal activities has been verified. In traditional methods, the accuracy of mineral prediction is often limited by the complexity of geological structures, but the combination of remote sensing data and deep learning model can consider a variety of metallogenic factors more comprehensively, and improve the accuracy of mineralization zone prediction. This result shows that remote sensing technology can effectively extract geological information related to mineralization on a large scale, and CNN model can well learn and identify the spatial distribution of these geological features.

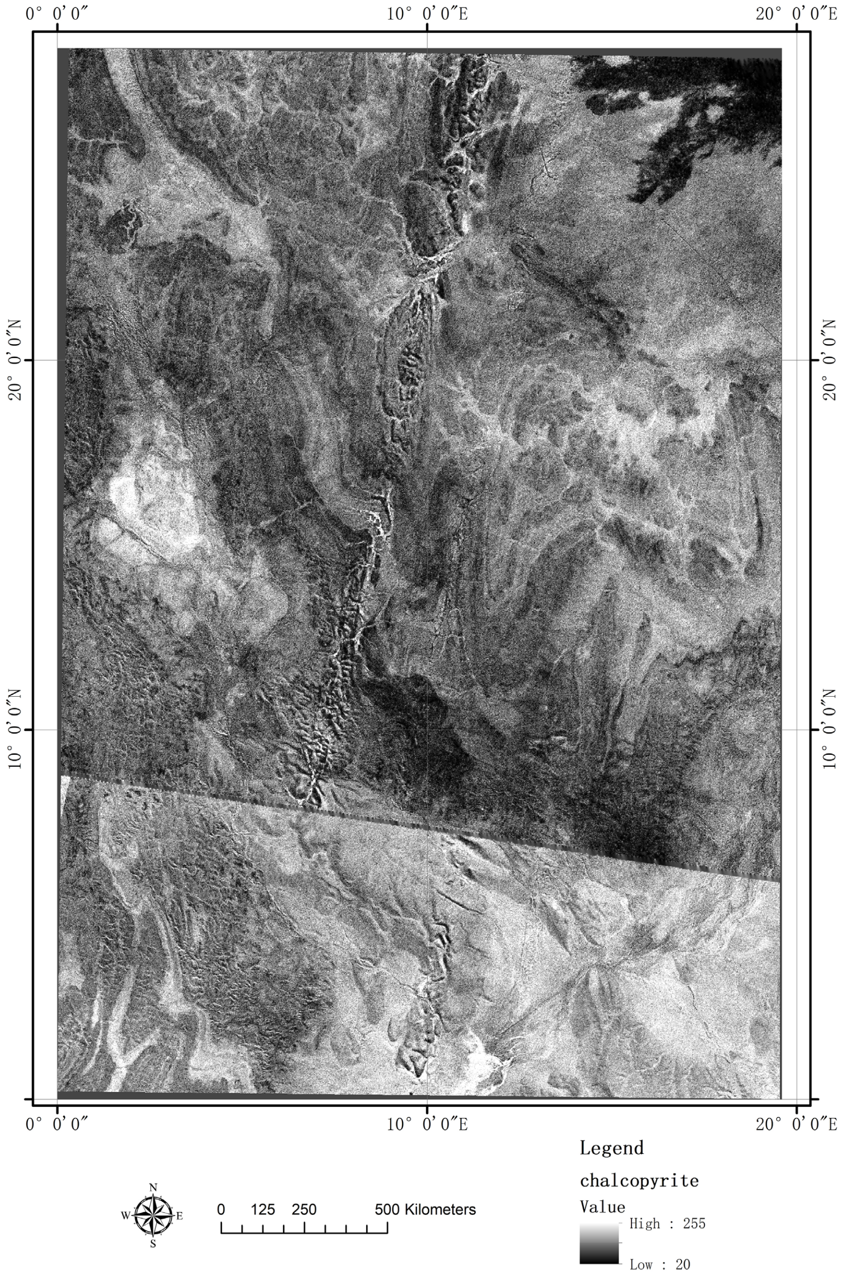

Figure 4. The map of Chalcopyrite distribution.

Secondly, CNN was used to carry out supervised learning on remote sensing data in the research process, and through continuous training of the model, the prospecting prospect map was finally generated. The verification of known ore points by the model shows high accuracy and reliability. This result shows that the CNN model can extract mineralized zone features with high accuracy in the face of complex and diverse geological conditions, and predict new potential mineralized regions on this basis. This means that CNN can overcome the uncertainty and subjective bias of manual interpretation in traditional exploration techniques, and play a more objective and efficient role in mineral resource assessment. This provides scientific basis and guidance for further exploration of mining areas.

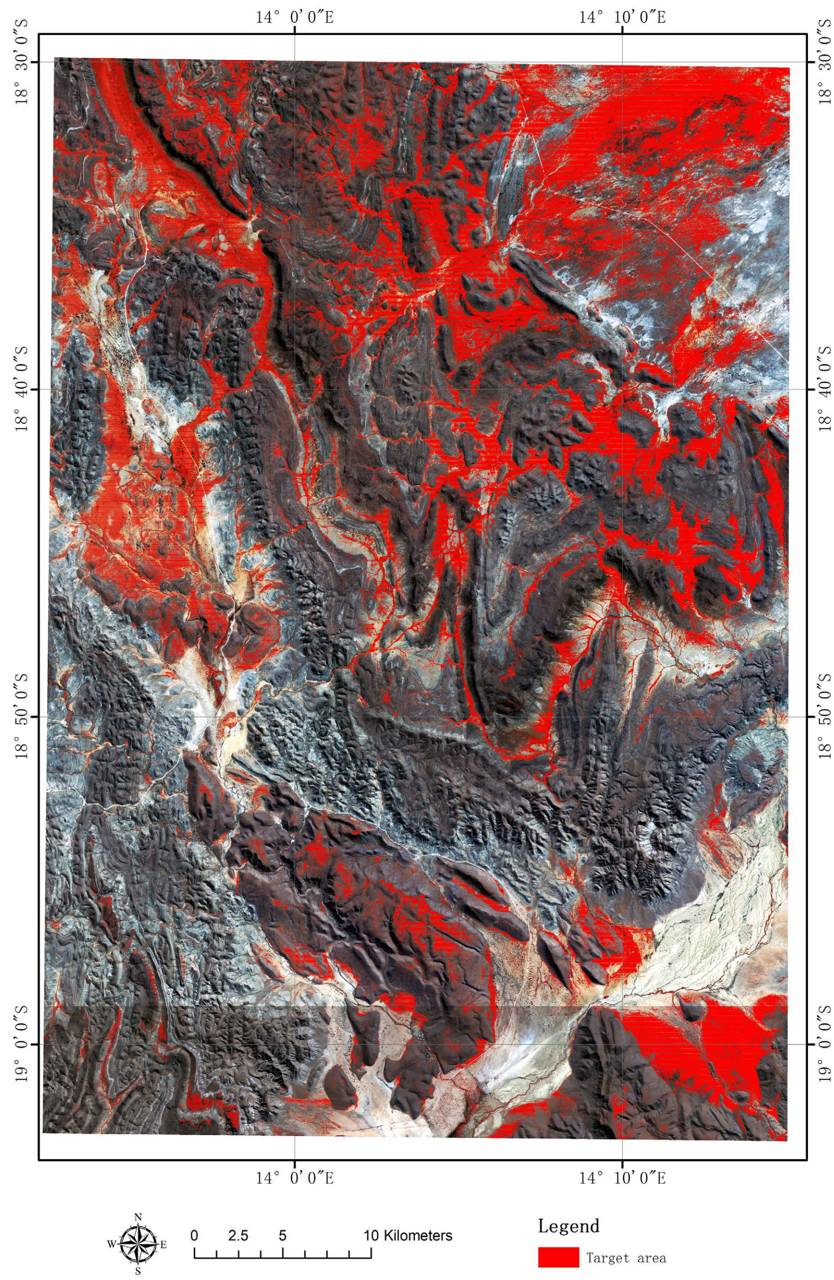

Figure 5. The map of target area.

In addition, the application of convolutional neural network greatly improves the exploration efficiency and completes the analysis and processing of a large amount of remote sensing data in a short period of time. Compared with traditional manual methods, its advantages in time cost and economic cost are obvious. However, the CNN method also has some limitations, such as strong dependence on training data, especially in the case of insufficient sample quantity and quality, which may lead to insufficient generalization ability of the model. In order to solve this problem, future studies may consider the application of multi-source data fusion and transfer learning techniques to improve the generalization ability and robustness of the model.

Another finding of this study is that the CNN-based prospecting model successfully identified multiple potential mineralization zones in areas previously considered to have complex geological conditions that are not conducive to mineralization, a result that challenges the constraints of metallogenic conditions in the traditional concept of prospecting. This finding shows that the machine learning model can identify patterns and trends that are difficult to detect in human interpretation from multi-dimensional data, thus providing new perspectives for prospecting. Future studies could further optimize the model parameters and introduce more geological and geophysical data to more fully describe the complexity of the metallogenic system.

To sum up, this study validates the great potential of convolutional neural networks combined with remote sensing data in mineral exploration. CNN technology can significantly improve the accuracy of mineral resource assessment, especially in the area of complex geological structure and hidden ore bodies, showing a strong application prospect.

6. Conclusions

In this study, a new prospecting method combining convolutional neural network (CNN) and remote sensing data is proposed, which is applied to the delineation of prospective mining areas in northern Namibia, and remarkable results have been achieved. The results show that the combination of CNN and remote sensing data can effectively improve the accuracy of mineral resource assessment, especially in areas with complex geological structures, and can better reveal the spatial distribution characteristics of potential mineralization zones. This method successfully overcomes the limitation of traditional mineral exploration methods in complex geological environment, and provides a reliable solution for delineating mineralized zones.

Through comprehensive analysis of remote sensing data of calcite mineral distribution, chlorite mineral distribution, lithologic structure and iron stain hydroxyl alteration, CNN model can effectively learn and identify geological features related to mineralization, and generate high-precision prospecting prospect map. The verification results show that the mineralized area predicted by the model is in good agreement with the known ore spots, which proves that the method has strong applicability and high efficiency in mineral exploration.

In addition, this study also reveals the significant advantages of convolutional neural networks in identifying hidden ore bodies. The model can not only identify mineralization features around known ore sites, but also successfully predict potential mineralization zones in areas previously thought to be unfavorable for mineralization. This finding provides new ideas for mineral exploration and shows that deep learning technology has unique advantages and potential in dealing with complex geological backgrounds.

Overall, this study demonstrates the broad application prospect of convolutional neural networks combined with remote sensing data in mineral resource exploration in the future. Through the combination of deep learning and remote sensing technology, the problems of accuracy and efficiency in traditional prospecting technology are effectively solved, and a new direction for mineral exploration under complex geological conditions is provided.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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