Identification and Prospecting Prediction of Marine Geological Anomalies Based on Deep Learning

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Abstract: The need for deep-sea mineral exploration has become more urgent as marine resources become increasingly scarce. In order to effectively identify marine geological anomalies and improve the accuracy of prospecting prediction, this study proposes a multi-modal data fusion method based on deep learning to achieve anomaly identification and prospecting prediction. Based on the fusion of multi-source data such as ocean seismic waves, magnetism, gravity, etc., the method adopts adaptive feature extraction technology, and uses a double-branch prediction network to perform anomaly identification and mineral enrichment prediction. Finally, the results of this paper show that the system performs well in multi-regional seabed geological data, among which the enrichment of copper ore is 3.5%, and the enrichment of nickel ore is 1.2%. The comprehensive analysis shows that the model and its integrated platform have strong robustness in the complex marine environment, which can effectively improve the efficiency of mineral exploration.

1 INTRODUCTION

The exploitation of marine mineral resources has become a key component of the global economy, but due to the complexity of the deep-sea environment, traditional geological exploration methods have many challenges in terms of cost and efficiency. In order to solve the above problems, some researchers have proposed that deep-sea geological anomalies can be identified based on the joint analysis of magnetic and gravity data (Chao, Wang, et al. 2023), but this method cannot effectively deal with the complexity of multimodal data. Some researchers have also proposed that a simple machine learning system based on seismic wave data can be used to accomplish related tasks. However, due to the ignorance of the importance of spatial features and multimodal fusion, the results are not accurate enough. In addition, some researchers have also tried to estimate mineral enrichment based on geochemical data analysis (De, Cocchi et al. 2024), but due to the scarcity of sampling sites, it is not possible to predict the full range of mineral distribution (Kim, Golynsky, et al. 2022). In order to solve these limitations, this paper uses deep learning algorithms and integrates multi-modal data, and at the same time, based on adaptive feature extraction and dual-branch network prediction, in order to significantly improve the accuracy of marine geological anomaly identification and mineral prediction. This method can cope with the complexity of marine data and provide new ideas for future deep-sea mineral exploration. This chapter analyzes the complexity of the deep-sea environment based on the current situation of marine geological resources development, studies the shortcomings of various marine geological anomaly identification and prospecting prediction algorithms, and puts forward the development and application advantages of deep learning in the current environment, and helps people realize that it is of practical significance to apply deep learning algorithms to marine geological anomaly identification and prospecting prediction.

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2 RELATED WORKS

2.1 Deep Learning and Multimodal Data Fusion will Better Reflect the Characteristics of Marine Geological Anomalies

When dealing with complex geological data, a single data source generally cannot fully reflect the characteristics of marine geological anomalies, so multimodal data fusion technology is necessary (Kochetov, Shepelev, et al. 2023). The theory of multimodal data fusion is based on the use of heterogeneous data from different sources, such as seismic waves, magnetism, gravity, etc., based on a unified framework (Kusnida, Albab, et al. 2023), to perform processing, so that the model can extract information from multiple dimensions and capture the internal correlation between different modalities. The attention mechanism and convolutional neural network provided by deep learning will provide a strong theoretical basis for this kind of fusion (Liu, Wu, et al. 2023), which can automatically identify the importance of each modal data and dynamically adjust the weight of each data in the overall features. This method can not only improve the efficiency of data utilization, but also effectively enhance the system's ability to identify anomalies (Ma, Chao, et al. 2024), especially to adapt to the complexity of marine geological data.

2.2 The Research Role of Adaptive Feature Extraction and Two-Branch Prediction in the Field of Marine Geology

The theory of adaptive feature extraction refers to the dynamic adjustment of the convolution kernel and feature extraction process to adapt to the changes of geological features in different regions (Ma, Liu, et al. 2023), so as to facilitate the efficient extraction of useful information in complex and changeable environments. This is of great significance for the spatial heterogeneity of marine geology, as the geological structure of different seabed areas varies significantly. At the same time, the two-branch prediction theory combined with the idea of multi-task learning (Sang, Long, et al. 2023) will complete the task of identifying marine geological anomalies and predicting mineral enrichment based on the shared underlying characteristics. This approach can effectively improve the efficiency of the model and achieve the prediction of different goals under the same framework, and it will also be optimized based on the joint loss function, which will help the system to have high accuracy and robustness when handling complex tasks (Zhang, Liu, et al. 2023).

3 ABNORMAL MARINE GEOLOGICAL STRUCTURES, YOUR PRESET COMPARISON FOR MINERAL EXPLORATION

3.1 Construction of a Comprehensive Platform for Anomaly Identification and Prospecting Prediction Based on Deep Learning

A complete and integrated platform requires a multifaceted composition. In this study, the comprehensive platform has several functionally important components, each of which is very important and has its own function. In this process, the data acquisition and preprocessing component is a complex process that collects raw data from a variety of ocean data sources and cleanses, normalizes, and normalizes it. This component needs to process a large amount of multi-modal data, such as seismic waves, magnetics, gravity, geochemical data, etc., and after processing, the data format can be unified and high-quality to adapt to the input of deep learning models. The multimodal data fusion component needs to perform weighted fusion of geological data from different sources based on the attention mechanism, and further generate a unified representation of marine geological features. Based on the dynamic evaluation and fusion of the importance of each modal data feature, the component will effectively ensure that the model can effectively apply the information of each data type, so as to improve the accuracy of anomaly recognition. The adaptive feature extraction component is responsible for the use of adaptive convolution networks to extract spatial features from marine geological data. The component can dynamically adjust the convolution kernel according to the complexity of the marine geological environment to capture geological changes at different scales. The focus of this component is to accurately identify the spatial location and morphology of anomalies, and to provide key features for subsequent predictions. What the Dual Branch Prediction Component does is to perform geological anomaly identification and mineral enrichment prediction at the same time. The component is based on a two-branch architecture, one of which ensures that the location and scope of the anomaly can be controlled, and the other part ensures that the mineral content and distribution of the anomaly can be effectively assessed. These two branches share the results of the underlying feature extraction to ensure the collaborative execution of the identification and prediction tasks. The system training and evaluation component is designed to manage the training process of the system and continuously evaluate and adjust the performance of the model. This component is based on techniques such as backpropagation to effectively optimize the parameters of the model, and uses the joint loss function to perform multi-task training. In addition, it needs to be responsible for ensuring the accuracy and generalization ability of the validation set evaluation system during the training process, and if necessary, the component also needs to adjust the hyperparameters to improve the prediction effect of the system. The purpose of the adaptive optimization component is to dynamically adjust the training hyperparameters of the model, such as the improvement rate, to ensure that the system can converge stably in the complex marine environment. According to the gradient change and the fluctuation of the loss function, the component adaptively adjusts the improvement rate to prevent the model from falling into the local optimal solution and overfitting phenomenon, so as to improve the overall robustness and adaptability of the system.

3.2 Fusion of Multi-Source Data Such as Marine Seismic Waves, Magnetism, Gravity, etc., Adaptive Feature Extraction, and Algorithm Calculation

The process of identifying marine geological anomalies involves a variety of geological and physical data, such as seismic waves and magnetic data, which reveal different aspects of the seabed environment. Therefore, the model must be based on multi-modal data fusion to jointly use the information from these different data sources to obtain more specific and comprehensive geological structure characteristics. In this paper, we design an attention-driven feature fusion method, which is mainly based on the importance of weighted data of different modalities to generate a comprehensive feature representation, so as to facilitate more accurate identification of the complex structure of anomalies. See Eq. (1) for this.

$$h_{fused} = \sum_{i=1}^{m} \alpha_i h_i \tag{1}$$

In this formula, h_{fused} it is the integrated feature representation after fusion, which mainly refers to the overall characteristics of the final geological environment obtained by the system when processing multimodal data. It can ensure that the model will consider the characteristics of different data sources when making decisions, so as to enhance the prediction ability of the system. h_iIt refers to the features extracted from different data modes, such as the waveform features in seismic waves and the intensity characteristics of magnetic anomalies. The purpose of these features is to provide the model with different perspectives of marine geological anomalies and lay the groundwork for subsequent fusion. α_iRepresents weights, which are based on attention mechanism learning and can dynamically allocate the contribution of each data source based on the validity of different modal data. For example, in a certain region, if the magnetic data is more revealing about the anomaly, then the model will automatically increase the weight of the modality to enhance the influence of the feature.

Marine geological data have significant spatial heterogeneity, which means that the geological characteristics of different regions may be significantly different. In order to accurately capture these differences, an adaptive convolutional kernel is designed in the construction of the system, so that the size and weight of the convolution kernel can be flexibly adjusted according to the geological complexity of different regions. This adaptive convolution enables effective modeling of complex geological structures, especially when capturing the spatial distribution of marine anomalies. See Eq. (2) for this.

$$f_{ij} = \sum_{k=1}^{K} W_k (x_{i+k,j+k}) \tag{2}$$

In this formula, it f_{ij}represents the output feature after adaptive convolution, which refers to the system's understanding of the anomaly at a certain spatial location. This output will be used to determine whether the area contains geological anomalies or not. $(x_{i+k,j+k})$ Representing the input features, which specifically refer to the geological data of adjacent areas, based on capturing these neighborhood features, the convolution operation will further assist the model, allowing the model to understand the local geological environment more comprehensively. W_kRepresents the weight of the convolution kernel, which can be dynamically adjusted according to the geological characteristics of different regions. When the geological information of a certain area has a large change, then the convolution kernel will fully capture the details of the anomaly based on weight adjustment.

In addition to identifying the spatial location of marine geological anomalies, it is also necessary to assess the possible mineral enrichment within them. To this end, the system adopts a double-branch network structure to perform anomaly identification and mineral enrichment prediction respectively. This type of architecture allows the system to complete both tasks in parallel based on a shared feature representation to improve the overall efficiency and prediction accuracy of the model. For this, see Eq. (3).

$$y_{anomaly} = f_{anomaly}(h_{shared}), \quad y_{mineral} = f_{mineral}(h_{shared}) \qquad (3)$$

In this formula, y_{anomaly}it represents the output of the anomaly identification branch, which is used to predict whether there are geological anomalies in the seabed area, and their specific location and morphology. The main purpose of this branch is to quickly locate anomalous objects. y_{mineral}Represents the output of the Mineral Enrichment Prediction Branch, which is used to estimate the mineral content of the anomaly. Based on this prediction, it can provide a basis for subsequent prospecting decisions. (h_{shared}) Represents a shared feature that is used to support common feature extraction for both tasks. Its function is to integrate the features extracted by multi-modal data and spatial convolution to ensure the synergy between anomaly identification and mineral prediction.

3.3 Two-branch Prediction Network Application

In this link, it is necessary to optimize the identification of anomalies and the prediction of mineral enrichment at the same time based on the joint loss function. Based on multi-task learning, the model can complete two tasks in continuous reinforcement learning to improve the efficiency and accuracy of the system. Depending on the needs of the task, the system can adjust the weights during the exercise to ensure that more attention is paid to a particular task. For example, the value that can be increased in scenarios where the anomaly identification task is more important λ_{anomaly}.

In the optimization process of marine geological anomaly identification and prospecting detection model based on deep learning, it is necessary to introduce geological prior knowledge to effectively guide gradient update. This approach allows the model to perform faster convergence in targeted regions, especially in regions where anomalies are known or present, and based on this, the accuracy of the system can be realistically improved. Gradient enhancement means that the gradient update amplitude of a specific area should be increased when the parameters are systematically updated based on prior knowledge in the geological field. Based on this, it will effectively ensure that the model receives more attention in key geological anomaly areas and captures potential geological anomalies more quickly.

The system then has to deal with the multi-scale characteristics of marine geology, that is, the seabed topography and geological structure in different regions may span multiple scales. To this end, a multi-scale regularization strategy is designed to prevent the system from overfitting information of a specific scale based on capturing local and global geological features at the same time. For this, see Eq. (4).

$$L_{reg} = \lambda \sum_{i=1}^{n} \left(\theta_i^2 + \sum_j \left(\theta_i - \theta_j \right)^2 \right) \qquad (4)$$

In this formula, L_{reg}this is the regularized loss term to help the model maintain stability and accuracy. In the identification of marine geological anomalies, the geological structure is complex and diverse, so the model has to deal with different types of anomalies, so if the system is too sensitive to some specific data, it is likely to make its performance on new data too poor. In this way, the excessive fluctuations of system parameters can be effectively reduced, and the model can be prevented from "remembering" the characteristics of specific regions, so as to enhance the generalization ability of the model in different ocean regions and better identify unknown geological anomalies. $\lambda$is the regularization coefficient, which can control the intensity of regularization. In the "prospecting forecast", if the λvalue is large, it means that the integrated platform places more emphasis on the stability of the system to prevent the system from performing poorly in areas with large data fluctuations, such as complex seabed geological structures. However, if the value is too large, it means that the model may ignore subtle geological changes, such as the characteristics of small-scale mineral-rich areas, so the integrated platform will adjust the value according to the specific geological characteristics λ to make the model have a balanced performance in different scenarios. θ_i represents the first parameter of the model i. For marine geological data, the operating system parameters i refer to the ability of the model to deal with specific geological features, such as seismic wave characteristics and magnetic anomalies in a certain area. The purpose of the regularization term θ_i^2 is to constrain the parameters of the operating system and ensure that the parameters are not too large, so that the model will not rely too much on a certain data feature when dealing with different geological structures, but can judge the enrichment of minerals in the anomaly according to a variety of characteristics. In this way, the overfitting of the operating system to certain extreme geological features will be avoided and its adaptability will be enhanced. $\sum_j(\theta_i - \theta_j)^2$ It is used to constrain the differences between different model parameters, especially the correlation between geological features in adjacent areas. In the marine geological environment, the geological characteristics of adjacent areas generally have some spatial continuity, such as the thickness of sedimentary layers and the distribution of faults, which will not change drastically suddenly. Therefore, the purpose of this project is to ensure that the operating system can capture the continuity of geological features when dealing with these areas, that is, the model parameters will not fluctuate drastically between adjacent areas. For example, when an operating system predicts the mineral enrichment of an area, if the geological conditions of the area are similar to those of adjacent areas, the differences in parameters should also be consistent, which can help the model to more accurately identify the distribution of potential mineral resources. n Represents the number of parameters, which refers to the total number of parameters that must be optimized on the entire marine geological dataset of the deep learning system.

Because of the complexity and dynamic changes of the marine environment, such as violent fluctuations in seabed topography, ocean currents, geological movements, etc., the deep learning model needs to flexibly adjust the learning rate according to the changes in data characteristics to ensure a stable and efficient exercise process. The adaptive improvement rate mechanism can enable the operating system to balance the learning speed and training stability in the face of these complex situations, and at the same time, ensure that the model will not affect the convergence of the operating system due to unreasonable improvement rate setting on the basis of accurately capturing geological anomalies. See Eq. (5) for this.

$$\alpha_{t+1} = \alpha_t \cdot \frac{1}{1 + \beta|\nabla L_t|} \tag{5}$$

In this formula, represents the α_t t rate of improvement at the first iteration, which controls the pace at which the model updates parameters at each step. Its function is to determine how quickly the operating system responds to current errors. If the improvement rate is too large, the deep learning model may miss the optimal parameters. If it is too small, the workout time of the operating system will increase significantly. ∇L_t Represents the gradient of the current loss function, which is the size of the model's current error on the input data. If the gradient is large, it means that the characteristics learned by the operating system at this stage are more complex, so the improvement rate should be reduced to ensure steady convergence. If the gradient is small, it means that the model is already familiar with the current task and can speed up learning. β is a moderating parameter that controls the effect of the gradient on the improvement rate. β The effect is to balance the magnitude of the gradient change to the improvement rate. If β the setting is larger, the improvement rate will be more sensitive to changes, which will help the model to respond more quickly in the face of complex marine geological environments. If the setting is small, it can prevent the operating system from being overly sensitive to short-term gradient fluctuations to avoid significant changes in the improvement rate unnecessarily. Based on the adaptive improvement rate adjustment strategy, the operation system can adapt to the dynamically changing marine environment, and gradually converge in the area with complex geological structure and unstable characteristics, so as to better identify anomalies and improve the accuracy of prospecting prediction.

4 RESULTS AND DISCUSSION

4.1 Marine Geological Area Testing

In order to more efficiently identify marine geological anomalies and predict the possible enrichment of mineral resources in a deep-sea mineral exploration project, this study introduces this self-designed deep learning integrated platform, hoping to effectively cope with the limitations of traditional exploration methods in complex seabed environments. The area has a typical multi-layered geological structure, and after many surveys, it has been found that the area may contain abundant polymetallic nodules and natural gas hydrates, which provides an important strategic reserve potential for the development of marine resources, the test area results are shown in Table 1.

Table 1: Distribution of Multimodal Data by Region.

Region	Seismic Wave Data Volume (GB)	Magnetic data volume (GB)	Gravity data (GB)	Number of geochemical samples
A	120	30	25	500
B	150	40	30	600
C	100	20	15	300

Table I shows the distribution of the amount of multimodal data collected in each region. Among them, the seismic wave and magnetic data of area B are large, reflecting its active geological movements.

This exploration mission covers three areas of sea area A, B and C, and the geological characteristics of each area are obviously different. Area A is located in a sedimentary basin and is mainly composed of fine-grained sediments; Zone B is an area with a significant history of volcanic activity with active fault zones; Area C is located in a deep-sea basin and initial exploration indicates possible enrichment of gas hydrates, the structure of the testing area is shown in Figure 1.

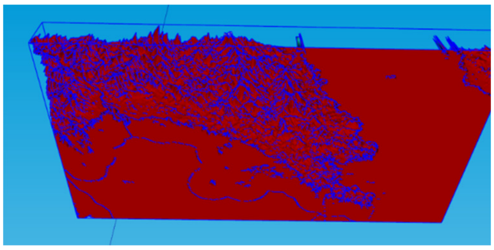

Figure 1: Model construction of marine geological anomalies.

This exploration mission covers three areas of sea area A, B and C, and the geological characteristics of each area are obviously different. Area A is located in a sedimentary basin and is mainly composed of fine-grained sediments, with 120 GB of seismic wave data and 500 geochemical samples. Region B is an area of significant volcanic activity, with 150 GB of seismic wave data and 600 geochemical samples. In order to perform more accurate anomaly identification and mineral prediction, the design of a comprehensive platform in this study integrates multi-modal data fusion, adaptive feature extraction, and dual-branch prediction network.

4.2 Abnormal Ocean Address, Testing the Mining Area

Based on the automatic extraction and fusion of key features from multi-modal data such as seismic waves, magnetism, and gravity, the integrated platform can accurately identify the spatial distribution of geological anomalies and predict the mineral enrichment in them, the test results are shown in Table 2.

Table 2: Feature extraction results after data processing.

Region	Seismic Wave Extraction Features (Weights)	Magnetic Characteristics (Weights)	Gravity Feature (Weights)	Geochemical characteristics (weights)
A	0.45	0.30	0.15	0.10
B	0.50	0.35	0.10	0.05
C	0.40	0.25	0.20	0.15

Table 2 shows the features extracted from the different modal data and their importance weights. It can be seen that seismic waves and magnetic characteristics dominate the identification of anomalies, Determine the range of regional structure, as shown in Figure 2.

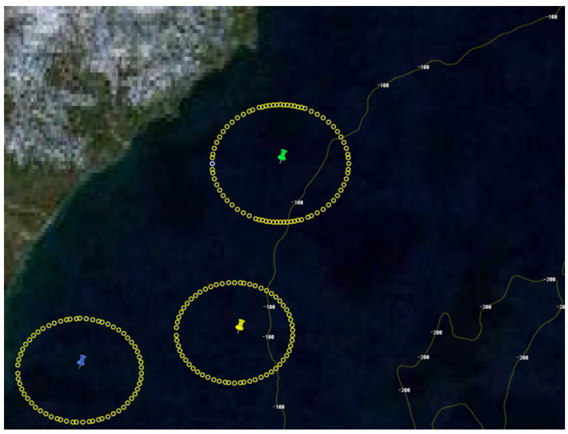

Figure 2: Identification of marine geological anomalies.

From the data analysis in Figure 2, it can be found that there are certain anomalous points in the process of determining the range of anomalous structures in the ocean. Mainly distributed in the left and right parts of the graph.

4.3 Abnormal Ocean Address, Test Results for Predicting Mining Areas

Based on the research and analysis of the above three table data, it can be seen that the seismic wave reflection layer in region B has obvious anomalies, corresponding to the traces of volcanic activity in this area. In the magnetic data, the magnetic anomalies in this area are strong and show potential mineralisation. In contrast, the seismic wave reflection in region C is relatively uniform, but the local anomalies in the magnetic data indicate that it may have a small-scale gas hydrate enrichment zone. Combined with these features, the integrated platform successfully identified anomalies in the volcanic region and speculated on their possible mineral distribution. The identification areas of different outlier points are shown in Table 3.

Table 3: Predictions of mineral enrichment by region.

Region	Copper Ore Enrichment Forecast (%)	Nickel Ore Enrichment Forecast (%)	Gas Hydrate Enrichment Forecast (%)	region
A	2.5	1.5	0.8	A
B	3.8	2.0	0.5	B
C	1.2	0.9	4.5	C

Table 3 shows the projections of mineral enrichment in each region from the integrated platform. Zone B is prominent in copper forecasts, while Zone C shows high enrichment in gas hydrates. In the gravity data of regions A and B, it can be observed that the gravity anomalies in region A are relatively uniform, while the gravity anomalies in region B are obvious, which indicates that the area has a dense rock structure, which is consistent with the enrichment of copper and nickel elements in its geochemical data. Geochemical data indicate that area B has a high content of copper and nickel ore, which confirms the impact of volcanic activity on mineral enrichment. In the mineral enrichment prediction, the copper enrichment in Zone B is 3.8%, which is much higher than that of other regions, indicating that this area is a key area for future exploration. In contrast, Region C has the highest gas hydrate enrichment of 4.5%, indicating that this region has some potential for energy development. Based on the above analysis, the comprehensive platform designed in this study can effectively combine multi-modal data to accurately predict mineral enrichment in complex geological environment, and provide a reliable basis for actual exploration.

5 CONCLUSIONS

Based on the designed integrated platform for the identification and prospecting prediction of marine geological anomalies based on deep learning, this paper successfully realizes the efficient identification and mineral enrichment prediction of marine geological anomalies. Based on the integration of multi-source geological data, the integrated platform significantly improves the accuracy of anomaly identification in complex seabed environments, and shows strong prospecting and prediction capabilities in different regions. In short, the comprehensive performance of this comprehensive platform can provide important technical support for future marine resource exploration, and at the same time, it can also provide a strong and scientific basis for the development of marine minerals. This study is fully reliable, but it has some limitations in terms of data, and it can be expanded in the future. There are limitations in this study, mainly the deep learning dataset and the incomplete collection of marine geological anomaly identification and selection, which will be analyzed in the future.

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