

Review

Deep Learning in Gravity Research: A Review

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ABSTRACT: This study explores the application of deep learning (DL) to gravity research, which is a promising intersection of earth science and information science. DL provides new methods and ideas for exploring and solving problems related to multiple solutions and uncertainty in the study of gravity. We focus on the application of convolutional neural networks, recurrent neural networks, and other DL technologies to gravity data denoising, interpolation, anomaly inversion, field modeling, and geological interpretation. However, importantly, the application of DL to the field of gravity research is still in its initial stage. There is significant potential for development and widespread application in overcoming limitations in sample size, network framework optimization, and generalization ability.

KEY WORDS: deep learning, gravity, research status, development trend.

0 INTRODUCTION

The study of gravity lies at the intersection of geophysics, geodesy, astronomy and geodynamics (Cao, 2020) and is considered one of the four important branches of geophysics, the others being magnetism, electricity, and earthquakes. Gravitational techniques have been utilized since the times of Galileo and Newton (Sun, 2021). Gravity data play a crucial role in various fields, such as earth structure research, resource and energy exploration, geological disaster monitoring, the establishment of national surveying and mapping benchmarks and their dynamic changes, and national military security (Sun et al., 2021; Li, 2012; Zeng, 2005). Since the 16th Century, gravity has made significant strides in theory, equipment, methods and applications (Deng et al., 2022; Huang M T et al., 2022; Luo et al., 2022; Sun et al., 2022; Guo et al., 2021; Zhao et al., 2019; Evstifeev, 2017; Nabighian et al., 2005). However, due to the complexity of the Earth's structure, the increasing accuracy requirements of various applications, the diversification of gravity field observation parameters, and the accumulation of massive observation data, the development of gravity research faces opportunities but also brings great challenges. Moreover, traditional model-driven data processing technologies still encounter many bottlenecks, including noise removal from shallow source small-scale signals, potential field separation issues under the condition of under-

ground field source scale mixing, potential field downwards continuation instability, multisolution problems in 3D inversion, and the problem of high computational cost.

In contrast to traditional model-driven methods, machine learning (ML) is a data-driven approach that trains a regression or classification model through complex nonlinear mapping with adjustable parameters based on a training data set. In the ML community, deep neural networks (DNNs) are at the core of a recently developed ML method, named deep learning (DL) (LeCun et al., 2015). DL has been successfully used to solve image classification problems (Krizhevsky et al., 2017), and since gravity maps can be viewed as images, it is plausible that DL can be used to address the aforementioned bottlenecks in gravity data processing. In this context, DL is an excellent choice.

DL can be considered a way to construct a super-high-dimensional nonlinear mapping from data space to feature space or target space. The nonlinear mapping is represented by a DNN, which has the ability to handle complex nonlinear problems and has strong data expression and mapping capabilities (Yu and Ma, 2021; Bengio, 2009). In recent years, increasing numbers of researchers have focused on using DL for applied research in gravity and have made considerable progress. This paper aims to introduce the current research trends in the field of gravity using DL, focusing on analysing research methods and technological innovations based on DL in gravity data denoising, interpolation, inversion, modeling, and geological interpretation. Specific research work in this field is presented and summarized, and existing problems are identified. Furthermore, the prospects for future research in this field are discussed. This paper tries to provide a reference for scholars to carry out relevant research in this field.

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1 DEVELOPMENTAL STATUS OF DL

DL is a critical branch of ML in the artificial intelligence field. It is based on artificial neural networks and usually involves multilayer networks. DL can be divided into two categories: supervised learning and unsupervised learning, as shown in Figure 1. Compared with traditional artificial neural networks with shallow structures, DL can transform single-level data into higher-level and more abstract data by constructing a deep structure using multilayer neural networks. This enables the extraction of complex features from high-dimensional data (Singer, 2021; LeCun et al., 2015; Bengio, 2009).

DL has demonstrated great potential in learning complex functions with higher-level features. However, effective training strategies for deep architecture were stagnant until deep belief networks were introduced (Hinton and Salakhutdinov, 2006). By integrating numerous hidden layers, this architecture enabled the construction of a DNN capable of extracting abstract features. This can alleviate some of the problems associated with the analysis and recognition of high-dimensional massive data, facilitating more completion of classification, regression, visualization and high-dimensional modelling tasks. Today, DL is a highlight of ML (Li et al., 2021).

Various DL architectures and networks have been developed and applied rapidly in recent years. Convolutional neural networks (LeCun et al., 1998), recurrent neural networks (Hochreiter and Schmidhuber, 1997), stacked autoencoders (Bengio et al., 2007), and generative adversarial networks (Goodfellow et al., 2020) are among the frameworks that have been widely adopted. Based on these frameworks, extensions such as AlexNet (Krizhevsky et al., 2017), ResNet (He et al., 2016), GoogLeNet (Szegedy et al., 2015), GRU (Cho et al., 2014), and VGG (Simonyan and Zisserman, 2014) have been developed, significantly improving the level of audio, video and image recognition capabilities. Moreover, these advanced DL methods have shown exciting results in natural language understanding, including topic classification, emotion analysis, question answering, and language translation (Chen and Zhang, 2022; LeCun et al., 2015).

In recent years, there has been a noticeable increase in the research and application of DL to geophysics (Yu and Ma, 2021). It has been used for data process-

ing, inversion and interpretation of geophysical methods such as seismic, electromagnetic, gravitational and magnetic methods. The effectiveness of many applications has been remarkable. For example, the use of DL on the Stanford seismic dataset improved seismic detection accuracy from 91% using the traditional short time average over long time average (STA/LTA) method to 100% (Yu and Ma, 2021; Mousavi et al., 2020). Another example is the identification of four lithology types of calcareous rock, diabase, shale and siltstone based on a depth residual neural network with an average accuracy of 81.45% using 193 307 data samples in geophysical logging (Li et al., 2021; Valentín et al., 2019).

The progress achieved in DL thus far has been significant, yet it remains in the early stages of development. DL still faces challenges such as processing massive amounts of data, solving complex problems, and improving the levels of intelligence. Despite these challenges, DL has broad prospects for development (Yu and Ma, 2021; LeCun et al., 2015). Although unsupervised learning has been overshadowed by the successful application of supervised learning in recent years, it is expected to become more important in the long run since it is more consistent with unsupervised characteristics of human and animal learning processes (LeCun et al., 2015). Transfer learning, federated learning, and multimodal learning are also important research directions (Yu and Ma, 2021).

2 RESEARCH SITUATION OF DL IN GRAVITY

The integration of DL and gravity presents a promising approach to solve gravity problems, such as the multiplicity of traditional gravity data processing and interpretation methods and the gradual increase in the complexity of geological problems to be solved.

2.1 Trends in Published Papers

Interestingly, there have been more than 80 relevant studies found from 1994 to 2022 in the fields of exploration geophysics, solid geophysics, physical geodesy and other related fields, with the themes of “gravity, deep learning, neural network, deep neural network”. The literature searches covered two information service platforms, Web of Sciences and China National Knowledge Infrastructure (CNKI), and extended the searches based

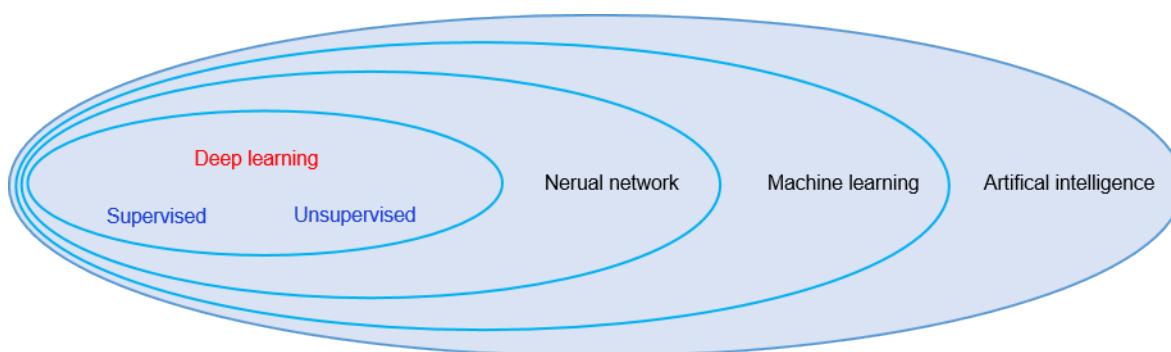


Figure 1. Inclusive relationship of artificial intelligence, ML, artificial neural network and DL.

on the reference links of relevant documents. The addition of the term “neural network” to the search themes was based on the consideration that DL was developed on the basis of neural networks to find the transition and development trend from shallow neural networks to deep neural networks in gravity research. Based on our findings (Figure 2), DL was first applied to gravity research in 2019, prior to which traditional artificial neural networks were employed. The utilization of DL technology in the field of gravity has resulted in significant advancements in addressing challenges that have previously stumped artificial intelligence for many years, which in turn has spurred a new surge in artificial intelligence technology. In recent years, there has been a notable surge in the number of relevant publications (Figure 2). However, its rapid rise appears to trail slightly behind that of the field of geophysics (Figure 3). These observations suggest

that DL is gaining increasing prominence in gravity research, pointing to a promising future for this intersectional application.

Notably, master’s and doctoral theses account for 25% of the total number of studies on the subject of “gravity, deep learning, neural networks, and deep neural network” (Figure 4). Moreover, a significant portion of journal literature and conference papers are based on the extension and summary of the achievements of these master’s and doctoral theses. This observation suggests that the application of DL to the field of gravity is still in the exploratory stage. While there have been significant advances in theoretical research, there remains a gap in the practical application of DL technology to gravity data. In conclusion, it is plausible to predict that the number of published papers will continue to increase as research efforts shift towards bridging this gap.

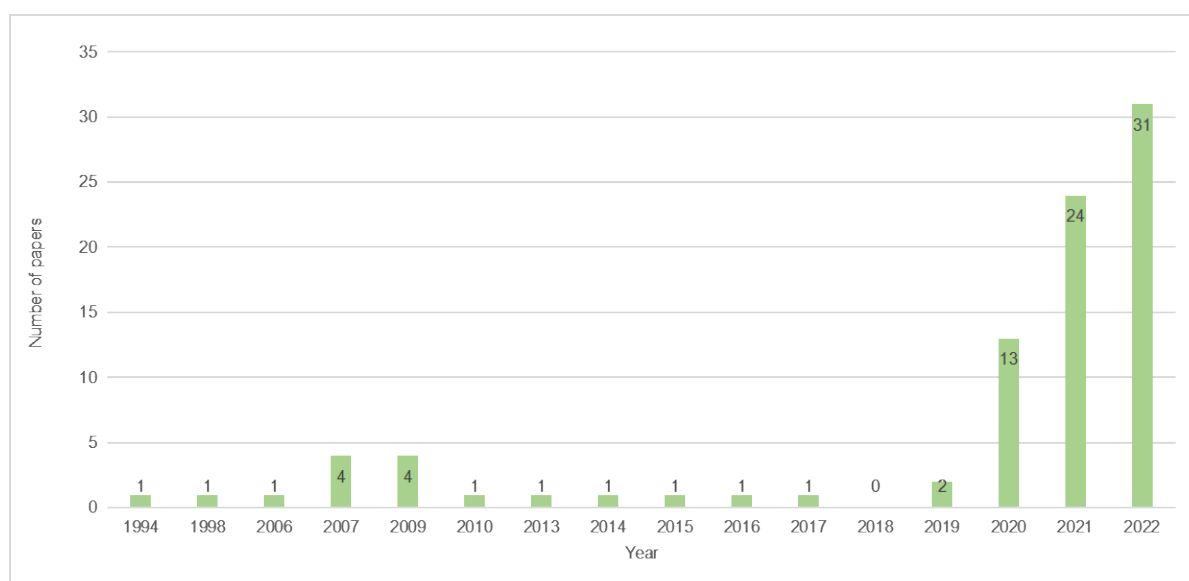


Figure 2. Trend of papers published on neural network topics in the field of gravity application over the years (before 2019: traditional artificial neural network; since 2019: DL).

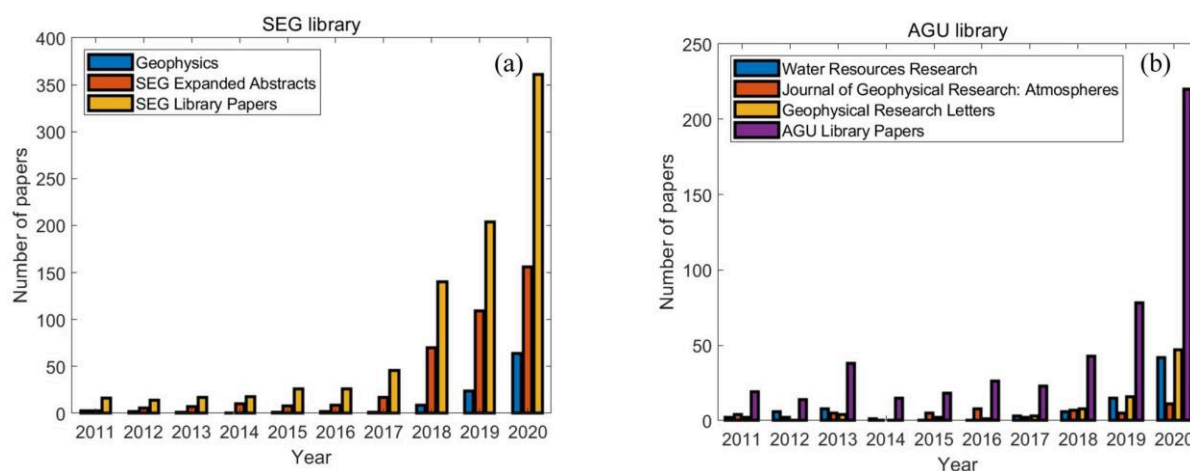


Figure 3. Trends of papers published on AI topics in geophysics over the years (Yu and Ma, 2021). (a) and (b) are the statistical results of relevant papers on artificial intelligence (AI) in the SEG database and AGU database, respectively.

2.2 Publication of Papers by Major Research Institutions

We performed a further analysis of papers published on the theme of “gravity, deep learning, neural network, deep neural network” included in the Web of Sciences and CNKI database, which encompass a range of institutes, including universities, research institutes and other institutions. By the end of December 2022, Jilin University, the China University of Geosciences (Beijing), and the China University of Geosciences (Wuhan) emerged as the top three institutions publishing the highest number of papers (Figure 5). The majority of these research institutions are universities. Notably, the research efforts of domestic scholars are at the forefront of international research in this field.

2.3 Research Hotspot Keywords

The visual analysis results of literature retrieval in the CNKI database indicate that the research hotspots in the field of gravity research concerning the theme “gravity, deep learning, neural network, deep neural network” include gravity inversion, gravity field modelling, noise removal, error compensation, and gravity anomaly fitting, among others. Among these subfields, gravity inversion is the most researched topic.

3 APPLICATION STATUS OF DL IN GRAVITY

Accounting for the academic research status and research hotspots of DL in the field of gravity, we prioritize the analysis of the application of DL to gravity data denoising, interpolation, inversion, modelling, and geological interpretation.

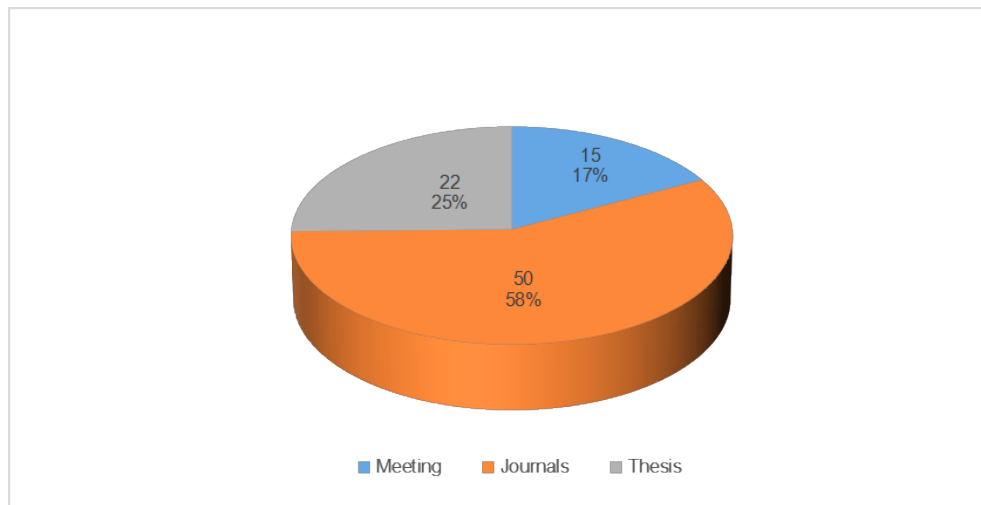


Figure 4. Types of papers published on neural network topics in the field of gravity application.

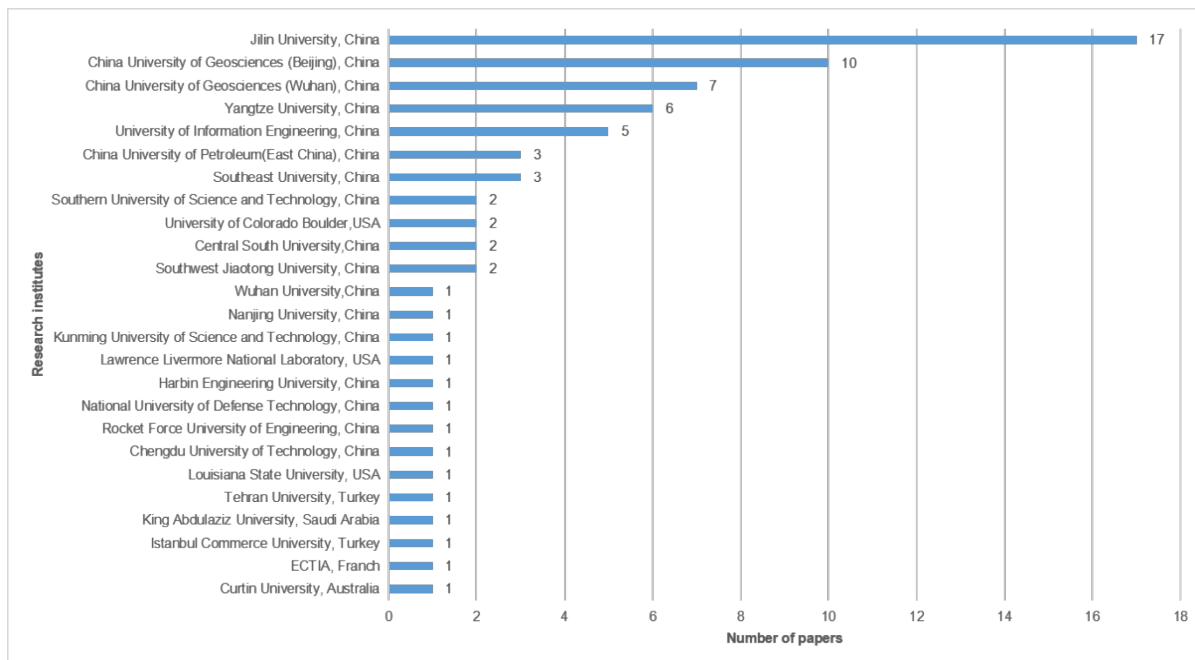


Figure 5. Main institutions delivering papers concerning neural network topics in the field of gravity application.

3.1 Gravity Data Denoising

Noise in gravity measurement data poses a significant challenge to gravity interpretation and application, and the removal of noise from gravity data is crucial to extract useful signals. Removing the noise and improving the signal-to-noise ratio of gravity signals is one of the long-standing problems in the field of gravity data processing. Over the years, traditional methods for gravity data denoising, such as preferential filtering (Guo et al., 2012), Kalman filtering (Wang et al., 2012), and wavelet analysis (Liu and Xu, 2004), have been widely used. However, the effectiveness of these methods has been limited when the noise is complex or has a similar scale to the useful signal. The application of DL presents a novel approach to address this challenging problem of gravity data denoising. Currently, DL-based gravity data denoising mainly is performed using convolutional neural networks (Wang et al., 2023; Zhou Z W et al., 2023; Chen, 2020), multilayer perceptron networks (Cheng et al., 2022), self-attention neural networks (Ma et al., 2022), convolutional autoencoders (Wang et al., 2022), and deep residual networks (Huang et al., 2021a). These methods learn discriminative features of gravity data and effectively differentiate between gravity signals and noise signals, thus minimizing the filtering of useful gravity information and leading to improved results.

Striped interference and Gaussian noise are two of most common types of noise in gravity data, and recent research has compared the filtering effects of the DL-based method and traditional median filtering method on these noise types (Ma et al., 2022). It was found that the

traditional median filtering method is inadequate in completely removing Gaussian random noise and strip interference. However, the DL-based method, which combines a self-attention neural network and convolution self-coding, could accurately identify and remove strip interference and effectively eliminate Gaussian distributed noise (Figure 6). A nonlinear mapping network model based on a deep residual network was used to press measured gravity data with 80% standard deviation amplitude noise (Huang et al., 2021a). The results demonstrate that the standard deviation of the DL-based denoising method result is 37.1%, 32.7% and 13.4% lower than that of IIR filtering, FIR filtering and wavelet filtering, respectively, which suggests its excellent denoising ability and generalization ability (Figure 7).

Contrary to the ground static gravity measurement method, gravity or gravity gradient data collected on mobile measurement platforms, such as airborne or shipborne platforms, often contain significant dynamic noise. For instance, the vertical motion acceleration of the carrier in airborne gravity gradient measurements can cause errors of thousands of the useful signals, completely obscuring gravity gradient signals produced by underground geological bodies (Yang and Li, 2017). The multilayer perceptron network (Cheng et al., 2022) is the first DL-based attempt to address the removal of such noise in gravity data. In the application of actual airborne gravity gradient measurement data, the results show that the method achieves a noise suppression degree of over 98%, thus verifying its practicality and effectiveness in actual data processing. Furthermore, considering the influ-

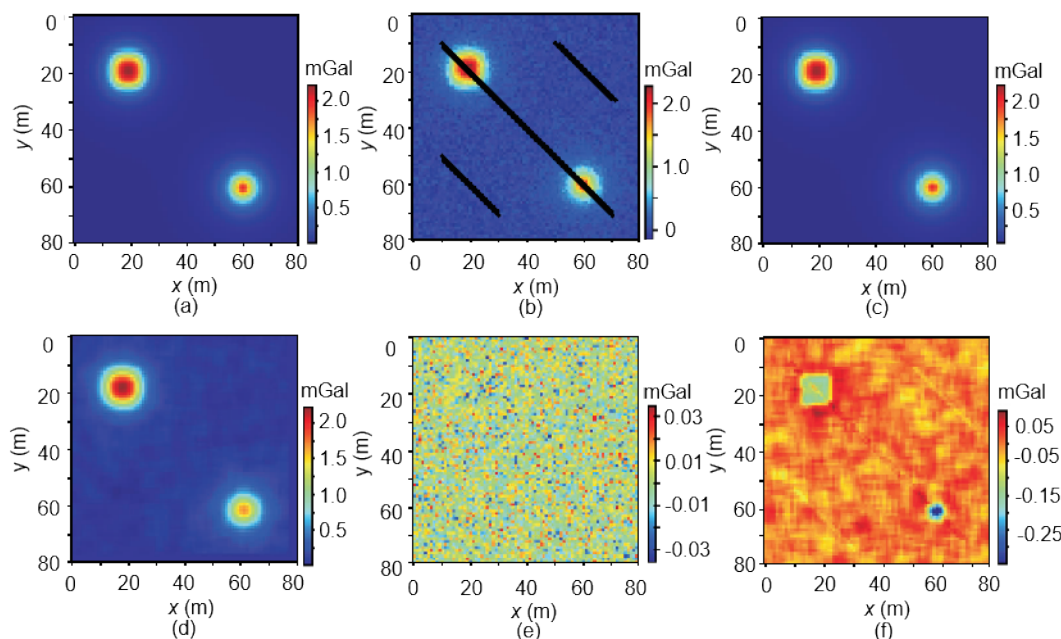


Figure 6. Comparison of filtering results between depth learning of gravity anomalies in strip-shaped areas and traditional filtering methods (Ma et al., 2022). (a) Original gravity anomaly; (b) gravity anomaly with banded interference and Gaussian random noise; (c) the self-attention neural network is used to process the stripe interference, and the convolution self-encoder is used to remove the filtering results of Gaussian random noise; (d) the median filtering method is used to deal with stripe interference, and the mean filtering method is used to deal with Gaussian random noise; (e) the difference between Figure 6c and Figure 6a; (f) difference between Figure 6d and Figure 6a.

ence of external measurement environments such as magnetic fields and temperature in the construction of sample sets and optimizing the network are anticipated to help further improve the denoising effect.

3.2 Gravity Data Interpolation

Gravity data interpolation refers to the process of estimating the gravity value of unknown points using the gravity value of known measuring points. This method is used to fill the blank areas of regular grid data or expand the edges of data. Common interpolation methods for gravity data include the kriging method (Hansen, 1993), equivalent source method (Cordell, 1992), and minimum curvature method (Wang et al., 2009). However, these methods have limitations (Ma et al., 2022). To improve the precision of gravity data grids, the K-means RBF neural network has been proposed, but this is a shallow learning method (Huang et al., 2021b). Compared with shallow learning methods, DL methods simplify the workflow and achieve better results. Currently, the DL frameworks for gravity data interpolation include deep convolutional neural networks (Wang et al., 2019), recurrent neural networks (She and Fu, 2021), and DL networks based on self-attention mechanisms (Ma et al., 2022). These DL frameworks achieve superior interpolation effects compared to traditional methods such as the kriging method.

A deep learning network with 22 convolution layers was designed and tested in a ground gravity survey area, and its performance was compared to that of the inverse distance power method, the minimum curvature method and the kriging method (Wang et al., 2019). The convolutional neural network method achieved optimal results, although a few false anomalies were present. In the estimation of the blank area of the free-air gravity anomaly on the southwest edge of Ordos, a recurrent neural network based on long- and short-term records was employed (She and Fu, 2021), adding the constraint of elevation data. The results were superior to those of the kriging method, but the calculation efficiency was lower. For gravity data gridding, a deep neural network based on the self-attention mechanism was developed (Ma et al., 2022). The self-attention mechanism layer processed the two-dimensional position coding. After the full connection layer, the anomaly of the grid node was finally output. By comparison, the calculation accuracy and speed were superior to those of the kriging method and the minimum

curvature method (Figure 8). It is evident that different DNN structures have achieved good interpolation effects of gravity data upon proper training. Targeted optimization of the network structure in the future can further enhance the interpolation effect and network training efficiency.

3.3 Gravity Anomaly Inversion

Geophysical inversion is the inverse problem of reconstructing the Earth's internal structure using geophysical observation data (Zhdanov, 2015). Gravity anomaly inversion is one of the primary methods used to estimate the spatial and density distribution information of underground geological bodies. Gravity anomaly inversion is generally classified into linear and nonlinear inversion techniques. Linear inversion is model-driven with the objective function minimized through optimization technology (Li and Oldenburg, 1998). Although the inversion speed is relatively fast, it is sensitive to the initial model and tends to fall into a local minimum. The genetic algorithm (Zhang et al., 2004), simulated annealing (Nagihara and Hall, 2001), ant colony algorithm (Liu et al., 2014) and particle swarm optimization (Pallero et al., 2015) are global optimization nonlinear inversion methods that are less dependent on the initial model but are computationally intensive, particularly for 3D inversion problems. Recent studies have shown that DL is a new driver for promoting gravity anomaly inversion towards a more robust and effective direction.

In recent years, various inversion strategies utilizing frameworks such as U-Net, 3D U-Net, 3D U-Net++, and V-Net have successively emerged for the 3D inversion of gravity anomalies, and the complexity of training models has gradually increased (Lv et al., 2023; Zhou X Y et al., 2023). The first application of the U-Net framework to the 3D inversion of gravity anomalies was in 2021 (Yang et al., 2021). Then, based on the U-Net structure, the joint inversion of gravity anomalies and gravity gradient anomalies was realized (Zhang et al., 2021). However, the depth information in their work was expressed by the number of output channels, which essentially resulted in a pseudo-3D inversion method with limited ability to extract 3D information. To achieve true 3D inversion, a convolutional neural network composed of a gravity encoder, a dimension converter and a density decoder was designed (Zhang L Z et al., 2022). The model test showed that the inversion accuracy of the gravity anomaly in the

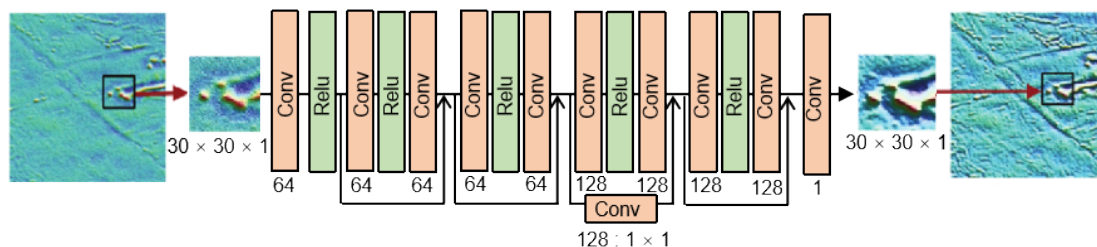


Figure 7. GraResNet network structure (Huang et al., 2021a).

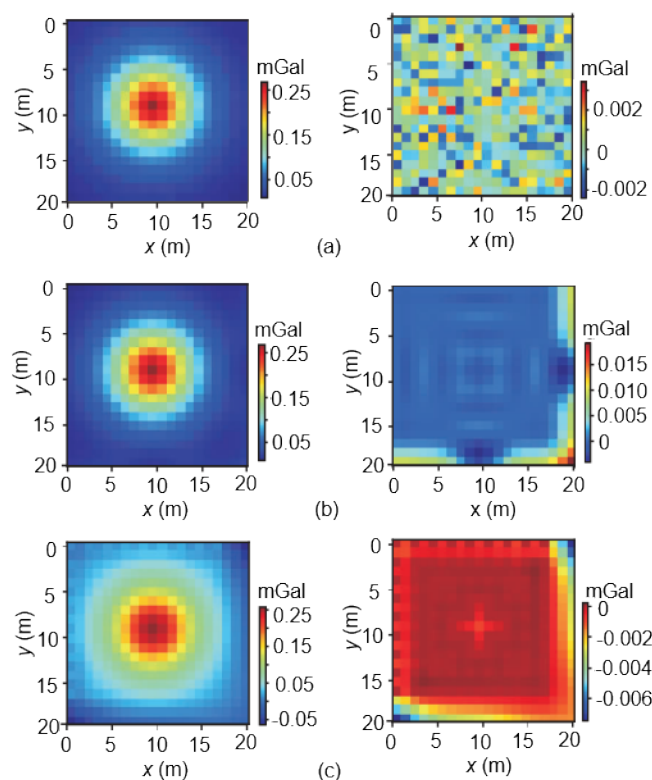


Figure 8. Gravity anomaly map and its difference from the theoretical gravity anomaly. (a) DL method; (b) kriging method; (c) minimum curvature method (Ma et al., 2022).

entire area reached 97%. Moreover, compared with the regularized inversion, the speed was increased by 20 times, and the boundary of the anomaly body and density amplitude obtained were more accurate. However, the network training mentioned above utilized isolated cubes, a small number of cube combinations (2–4) or simple slope combinations (2–3), which cannot meet the inversion requirements of underground geological bodies with complex morphology. To address this, relatively complex underground body models were designed (Zhang S et al., 2022), and 3D U-Net++ and full convolutional neural network architectures were constructed (Huang R et al., 2022). These complex models were incorporated into the network training, and the test results of simple models were given in the network test, demonstrating exceptional generalization ability. For the three-dimensional inversion of large-scale gravity data, the V-Net architecture was constructed (Huang R et al., 2022), and the complex model was composed of six density bodies with different sizes, shapes and depths. The test results showed that the relative error of the inversion density model was 57.44%, and the entire inversion time only took 36 minutes (including training time). With acceptable inversion results obtained in a short time, the increment in calculation time was negligible even with a significant increase in the amount of measured point data. Despite only two years of development, 3D gravity inversion based on depth learning has yielded remarkable inversion effects, with future potential for further advancements.

Regarding the identification of gravity anomaly

source bodies, constructing appropriate training samples and building fully connected neural networks, convolutional neural networks, U-Net and other architectures have been used to realize the centre position and boundary identification of anomalous bodies (Li et al., 2023). This demonstrates the advantages of DL in calculation speed, and the inversion effects were close to or even better than those of traditional methods. The recognition accuracy of the anomalous body with different burial depths and postures was good (Wang et al., 2020). Nevertheless, the existing algorithms still have issues, such as simple network structures and nonuniqueness of inversion results. The idea of building a fully connected neural network based on the gravity and magnetic gradient ratio was proposed to acquire the centre position of the field source (Ma et al., 2021). This approach has been demonstrated to have good anti-noise performance, avoiding the complex process of screening the results required by traditional linear inversion methods. However, the network structure contains only two hidden layers, which belongs to a simple network structure, and the optimization of the structure should further improve the inversion effect. In comparison, a relatively complex network architecture was proposed (Figure 9) (Zhang Z H et al., 2022). The backbone network used an improved U-Net, including a standard convolution module, dense skip connections module, attention module and other modules. The theoretical model tests suggested that this approach was significantly better than the traditional methods. Nevertheless, due to the limitations in label labelling methods and

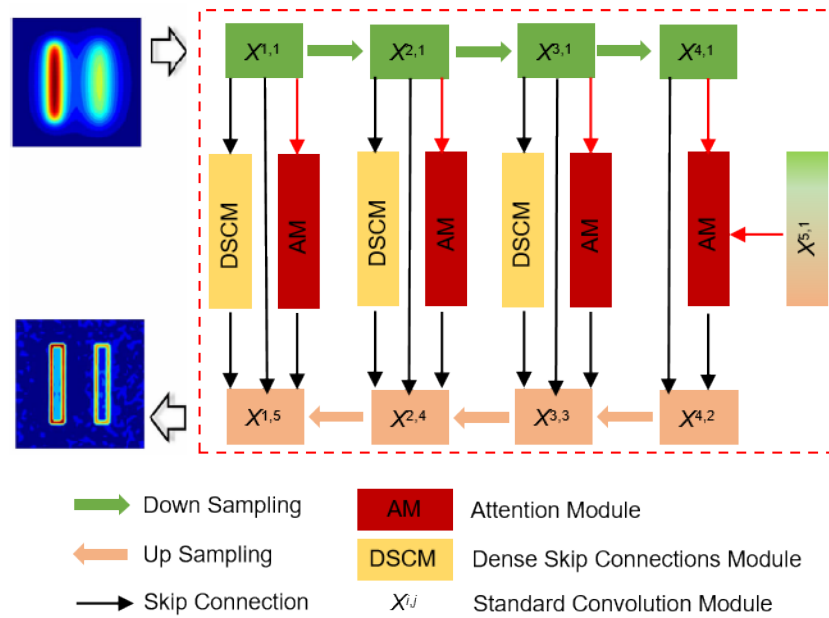


Figure 9. Overall structure of PFD-NET for potential field boundary recognition (Zhang Z H et al., 2022).

numbers, there are still problems with multiple solutions and low computing efficiency. DL provides a new solution for the identification of gravity anomaly sources, with significant achievements during the initial stage of development. Although there is still room for improvement in network optimization and other aspects, these studies have demonstrated the potential for significant advancements in this field.

3.4 Gravity Field Modelling

A gravity field model is a critical set of parameters used to describe and represent the approximation gravity field of celestial bodies such as the Earth. Gravity field models are an important research subject and are applied to the geophysics, geodesy, astrodynamics, geology, earthquakes, oceans, national defence and military (Luo et al., 2022; Martin and Schaub, 2022; Yang et al., 2012). Classical methods for constructing gravity field models involve spherical harmonic analysis (Martin and Schaub, 2022), spherical cap harmonic analysis (Li, 1993) and moment harmonic analysis (Jiang et al., 2014). However, the calculation cost associated with these methods is directly related to the order of the model coefficients. Therefore, there is a need to balance precision and efficiency in practical applications (Martin and Schaub, 2022). Traditional model-based methods and traditional machine learning algorithms based on artificial neural networks (Furfaro et al., 2021; Gao and Liao, 2019; Bayram, 2016) have limitations such as limited generalization ability and lack of a physical foundation. To address this, a DNN gravity field modelling method based on physical knowledge constraints was proposed (Martin and Schaub, 2022). It was applied to earth gravity field modelling and demonstrated outstanding advantages in simulating the high-frequency disturbance sig-

nals of the earth. Then, the method was extended to solve the problem of gravity field modelling of irregular asteroids (Martin and Schaub, 2022). At the same time, a further improved DNN was used in the modelling of the asteroid gravity field (Cheng et al., 2020). According to the articles we gathered, compared with the application of DL in gravity inversion and other fields, gravity field modelling has led the way in realizing the combination of fundamental physical principles and DL. This integration provides modelling results that can be interpreted with a physical basis.

3.5 Geological Interpretation of Gravity Data

The geological interpretation of gravity data is a critical tool for deep structure research, mineral resource prediction, oil and gas exploration, seismic monitoring and other fields. In the traditional geological interpretation of gravity data, human-computer interactive interpretation based on expert knowledge is commonly used for delineating metallogenic prospects, dividing fault structures, and studying deep geological characteristics. However, traditional geological interpretation entails a large workload, and interpretation results depend on the expert's geological knowledge of the working area. Different experts may lead to different or even opposite geological interpretation results. To address these issues and promote the intelligence of geological interpretation of gravity data, solutions based on DL are being formulated (Yang, 2022). A DL-based gravity and magnetic geological interpretation method based on the characteristics of spatial structure changes has been proposed, allowing for preliminary achievement in scientific research on regional geology, deep geological feature mining, and intelligent recognition of fault structures, such as in Benxi Xiuyan. Based on the Noddy modelling platform, 1 million

3D geological models were generated, which provides a publicly accessible training set for geological interpretation of gravity and magnetic data (Jessell et al., 2022). Based on a U-Net deep neural network, an innovative ML method was proposed to determine salt structures directly from gravity data (Chen et al., 2020). However, due to the complexity of geological interpretation of gravity data, the application of DL to this area still needs further improvements.

4 DISCUSSION

This study provides an overview of the application of DL to various gravity data tasks, including denoising, interpolation, inversion, modelling, and geological interpretation. The theoretical model and the measured data demonstrate that DL has achieved the same or even improved results compared to traditional gravity data processing methods. Nevertheless, several challenges remain prevalent in the field of DL for gravity data processing.

4.1 DL Models

After conducting a literature review, we found that previous studies have focused on developing DL models for specific gravity problems, resulting in limited portability. Therefore, there is a need to construct a comprehensive model that enhances the universality and generalization. This can be achieved by using adequate, diverse, and representative high-quality sample datasets. Additionally, DL models should be designed to efficiently handle the varying complexities of geological models, including complex multilayer structures.

4.2 Prior Constraints

The interpretation of gravity data cannot be separated from prior constraints, as their inclusion can significantly enhance the reliability of gravity data processing results. While three possible strategies for integrating geological constraints into DL have been proposed (Wu et al., 2023), much current research attention is directed towards seismic data processing and interpretation. More prior constraints should be added to DNNs to solve gravity problems more effectively.

4.3 Multiple Solutions

The nonuniqueness problem of inversion is one of the main problems in gravity data interpretation in traditional inversion methods. Although there have been numerous studies utilizing DL three-dimensional gravity inversion, our research indicates that the problem of multiple solutions in DL-based inversion techniques has not been fully addressed at its core.

Therefore, we need to be clear that although DL has made notable advancements in improving the effectiveness and efficiency of gravity data processing, there are still significant challenges that need to be addressed through further research.

5 CONCLUSION

This review paper introduced the basic concepts and development status of DL approaches, presented a wide range of applications of DL to gravity research with the associated pros and cons, and discussed the problems of DL applications in gravity research. Based on the above mentioned aspects, the application of DL to gravity research is rapidly growing, but it is still in the early stages of development. There is still much work to be done, and future research should focus on the following aspects. First, there is a need for further model simplification and compression, as well as enhancements in the speed and efficiency of network training. Second, it is crucial to advance the development of more optimized and effective deep learning frameworks, such as transfer learning, semisupervised learning, or unsupervised learning. Third, there should be focused research on combining deep learning with other multisource data, such as seismic data, to enhance the analysis of gravity data. Fourth, it would be beneficial to integrate traditional methods with deep learning to improve the application results that adhere to the principles of gravity and geological conditions. Finally, expanding the application fields of gravity, including potential field extension, potential field separation, and other aspects, could lead to further advancements in the field.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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