A Simple Neural Network Approach to Mineral Potential Mapping Using Open Gravity Data

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Abstract. As a fundamental approach in machine learning, neural networks have evolved through phases of emergence, relative dormancy, and subsequent flourishing since their inception. Over the past decade, the rapid advancement of computing power - particularly the accelerated computing capabilities of GPUs and the rapid development of cloud computing - has propelled deep learning technologies, with deep neural networks as their hallmark, to become one of the most effective solutions in both industrial and scientific computing domains. These technologies have outperformed traditional methods in numerous applications and now form a cornerstone of artificial intelligence. This study integrates deep learning with gravity anomaly detection, leveraging convolutional neural networks (CNNs) that have demonstrated exceptional performance in image recognition tasks. The approach treats gravity observation contour maps as 2D images for analysis, with spatial parameters of subsurface gravity anomalies serving as recognition outputs, thereby establishing a specialized CNN model for anomaly identification. During training, we randomly generate numerous 3D anomaly models with varying parameters, compute their 2D gravity observations through forward modeling, and train the CNN using both parameter labels and gravity data. Experimental validation on test cases demonstrates the model's high accuracy. Notably, unlike traditional CNNs that only identify burial depths from 2D gravity lines, this convolutional network achieves comprehensive detection of both depth and size information for 3D anomalies. When applied to gravity observation data from Australia's Kauring region, the model's results align with previous research findings, confirming its generalization capability for real-world gravity anomaly identification with reliable outcomes. The proposed method offers several advantages over conventional techniques. Firstly, by utilizing CNNs, it automates the feature extraction process from gravity contour maps, eliminating the need for manual interpretation and reducing human subjectivity. Secondly, the end-to-end training framework enables simultaneous optimization of multiple anomaly parameters, enhancing detection accuracy and robustness. Thirdly, the model demonstrates strong adaptability to various geological settings, as evidenced by its successful application in the Kauring region with diverse subsurface structures. Furthermore, the computational efficiency of CNNs allows for rapid processing of large-scale gravity datasets, making it suitable for regional-scale anomaly mapping. These characteristics collectively establish the developed CNN-based approach as a promising tool for advancing gravity anomaly detection in both academic research and practical exploration applications.

Keywords: Deep learnin; parametric inversion; Gravity anomaly recognition; CNNs

1. Introduction

To address global climate change and achieve carbon neutrality, the green and low-carbon transformation of energy systems has become a pivotal force reshaping worldwide technological frameworks and industrial structures [1]. Clean energy technologies such as solar photovoltaics, wind power, and new energy vehicles serve as core drivers for this transition [2]. However, the rapid development of these emerging industries heavily depends on critical metal resources. For instance, the power batteries in new energy vehicles primarily consume lithium, cobalt, and nickel; permanent magnet generators in wind turbines require rare earth elements; and certain specialized photovoltaic cells cannot function without metals like cadmium and gallium. According to projections by the InternationalEnergyAgency (IEA), clean energy technologies' total demand for mineral resources will sextuple under sustainable development scenarios by 2040. This surge in demand not only puts immense pressure on traditional mining operations but also raises widespread concerns about the resilience, security, and sustainability of critical metal supply chains. Research indicates that in China's long-term transition to renewable energy, the development and application of next-generation photovoltaic technologies may face

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constraints from upstream key metal resources such as cadmium, tellurium, indium, gallium, and selenium. These resources could potentially lead to severe shortages and supply risks by 2050. Moreover, the cumulative demand for critical metals between 2015 and 2050 is projected to far exceed current national reserves [3]. The wind power industry's growing demand for rare earth elements like neodymium and dysprosium also poses challenges to expanding existing production capacities. "Urban mining" refers to secondary renewable resources generated through the extraction, processing, and utilization of underground mineral resources, typically encompassing recyclable materials found in solid waste such as discarded electrical and electronic products, scrapped vehicles, and electrical cables. In the context of energy transition, exploring the circular utilization potential of emerging "urban mining" resources holds crucial strategic significance for alleviating resource bottlenecks, ensuring the development of new energy industries, and building a green, low-carbon circular economy system. The circular utilization of "urban mining" serves as a vital pathway to meet the massive demand for critical metals during energy transition. Research indicates that among the 23 typical valuable materials in China's traditional "urban mining," 20 types are expected to exceed their industry's developmental needs in secondary resource volume by 2050, achieving self-sufficiency. With the rapid growth of the electric vehicle industry, the recycling potential of metals like lithium and cobalt from discarded power batteries is enormous. Meanwhile, decommissioned photovoltaic panels and wind turbines contain significant reserves of key metals including silicon, copper, rare earths, as well as cadmium and mercury. Urban mining not only effectively compensates for insufficient primary mineral extraction and reduces external dependence, but also significantly cuts environmental damage and carbon emissions. However, while some countries have relatively mature traditional e-waste recycling systems, their formal recycling rates remain low. Additionally, technical bottlenecks, high economic costs, incomplete policy frameworks, insufficient industrial chain collaboration, and low consumer environmental awareness and participation all hinder the large-scale and efficient development of urban mining recycling industries. This study provides theoretical insights and practical guidance for ensuring national strategic metal security, advancing green supply chain innovation, and achieving sustainable development goals. Through in-depth analysis of key metal consumption patterns and the circular utilization potential of "urban mining" in emerging energy transition industries, it systematically identifies technical, economic, social, and environmental challenges encountered during development processes, while exploring effective countermeasures and development pathways. As one of the fundamental methods in machine learning, neural networks have undergone a development process from rise to relative stagnation and then to prosperity since their inception. Over the past decade, with the rapid advancement of computer computing power—especially the swift development of technologies such as GPU-accelerated computing and cloud computing — deep learning techniques represented by deep neural networks have become one of the most effective technologies in industry and scientific computing fields. They have achieved performance exceeding traditional methods in many applications and established themselves as one of the cornerstones of artificial intelligence technology [4].

In the field of geophysical inversion and interpretation, machine learning is an important nonlinear computing method alongside genetic algorithms and Bayesian inversion. In gravity exploration, apart from non-neural network machine learning methods like random forests used to solve geophysical problems, numerous inversion algorithms based on BP neural networks have emerged, fully demonstrating the effectiveness of machine learning for geophysical inversion tasks. Radial Basis Function (RBF) networks can address inversion problems under constraints, offering faster training speeds and higher generalization capabilities compared to BP neural networks. Modular Neural Networks (MNN) have been successfully applied to anomaly identification and pattern classification. Osman et al. proposed Forced Neural Networks (FNN) to solve the problem of identifying gravity anomalies in 2D profiles. In terms of data processing, Ren Qiangqiang et al. used wavelet neural networks to predict gravity observation blind areas, which are more adaptable to complex scenarios than kriging methods [5].

The essence of machine learning is representation learning—transforming a mathematical or physical model into another form to create a higher-level abstraction or an alternative perspective representation of the learning object. Traditional neural network structures still have various limitations, such as insufficient generalization or overfitting. With the development of deep learning technology, various advanced neural network architectures have emerged in recent years, including Recurrent Neural Networks (RNN) suitable for processing time-series models and Generative Adversarial Networks (GAN) for generating domain-specific models, which have achieved remarkable success in related fields. Convolutional Neural Networks (CNN) are particularly well-suited for handling models with spatial characteristics, such as 2D images. Deep learning based on CNN has become the most important technical means in image processing and recognition.

The initial model of the convolutional neural network was LeNet, inspired by neuroscientific research on the visual system of cats. It introduced the "receptive field" feature into neural networks and constructed convolutional layers. Due to training difficulties, this method remained dormant for a long time. It was not until the practicalization of GPU computing technology in recent years that the newly emerged AlexNet significantly increased the depth of convolutional networks and achieved excellent results in image recognition competitions. Subsequently, deeper deep convolutional neural network models have continuously refreshed accuracy records. Deep Residual Networks (DRN) can effectively address the phenomenon of gradient explosion or vanishing during training. Currently, convolutional neural networks are characterized by fast training speeds and high accuracy [6].

Leveraging the powerful image recognition capabilities of convolutional neural networks, the authors treat gravity observation contour maps as 2D images, establish parameter models of density anomalies, and use deep learning to identify the 3D spatial parameters of these anomalies. Training and testing samples are used in model experiments, and the learned convolutional neural network is transferred to real measured data to verify the effectiveness of the proposed method [4].

Traditional gravity anomaly inversion methods, based on the "model-driven" approach [7], are categorized into linear and nonlinear techniques. Their advantages include clear physical interpretation, the ability to compress solution spaces through prior constraints to suppress multiple solutions, and the capability to solve problems using observational data and physical equations without requiring large-scale data training, making them particularly suitable for scenarios with limited data. Although traditional methods relying on prior models or assumptions may easily fall into local optima when handling complex nonlinear problems, resulting in discrepancies between inversion results and actual geological structures, they remain irreplaceable in theoretical verification and inversion scenarios with sufficient prior information. Moreover, these methods provide physical constraint benchmarks and theoretical foundations for designing deep learning models [8]. Deep learning methods overcome the limitations of traditional approaches through data-driven approaches, operating without physical models. By leveraging massive datasets, they enhance the accuracy and stability of geophysical inversion processes [9]. In recent years, these methods have been widely applied in gravity, seismic, and electromagnetic inversion fields. This paper examines the current application of deep learning in gravity inversion from four perspectives: data preparation, network models, network optimization, and network validation. Specifically: The data preparation section outlines data generation and preprocessing techniques; the network models section introduces various deep learning-based gravity inversion networks; the network optimization section discusses regularization methods, optimization algorithms, and loss functions; while the network validation section compares the performance of multiple inversion networks.

2. Data processing

The original design concept of convolutional neural networks (CNNs) was to directly recognize concrete objects in images, such as human faces, animals, and daily items. However, they are not limited to identifying concrete objects - for example, CNNs can be used to recognize the age and gender from human faces, or to identify highly abstract concepts in images, such as the depth of field in photographic images. Based on these characteristics, CNNs have the potential to identify parameters such as the depth and size of gravity anomalies from gravity contour maps.Fig.1 shows a typical convolutional neural network (CNN) structure for image classification. In addition to the components of general neural networks (input layer, output layer, and hidden cells), it also includes convolutional layers composed of convolutional neurons or pooling neurons. In general neural networks, the hidden layer is also called the fully connected layer, where each neuron is connected to all neurons in the previous layer. The relationship between the weights of neurons between a hidden layer and its previous layer can be expressed as:

$$y = wx + b \tag{1}$$

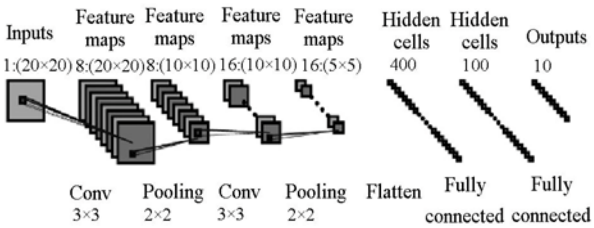

Fig.1 The structure of the CNN

Here, y represents the output of hidden-layer neurons, x denotes the input,w and b are the matrices of connection weights between the two layers and the threshold values of each neuron, respectively. The relationship between the two layers follows a linear mathematical model. During training, the backpropagation algorithm determines the values of w and b. The number of parameters to be trained is proportional to the product of the number of neurons in both layers, resulting in a vast parameter space. In contrast, the convolutional layer of a convolutional neural network applies convolution operations to images using convolution kernels. Here denotes a two-dimensional convolution operation. The convolution kernel (w) of specific dimensions is applied to input and output images represented as matrices X and Y.

$$Y = w \otimes X \tag{2}$$

The kernel slides across the input image, multiplying and summing pixels at corresponding positions within its scope to generate the output image pixel value at the kernel's center. Each convolutional layer typically incorporates multiple kernels to extract diverse local image features. When processing an input image, this mechanism produces multiple images of identical dimensions known as feature maps. Within convolutional layers, local image pixels share the same kernel, analogous to how neurons share weights. This approach not only reduces the number of weight parameters but also enables extraction of two-dimensional (or even three-dimensional) image features. The shared-weight convolutional layers constitute a distinctive advantage of convolutional neural networks. Within a convolutional layer group, in addition to the convolution layer itself, there is also a pooling layer. The purpose of the pooling layer is to down sample each feature map obtained from the convolution to a smaller size, reducing parameters while extracting higher-order image features. Generally, a pooling layer follows immediately after a convolution layer. The convolution layer is located in front of the hidden layer. The two-dimensional output of the last convolution layer (or pooling layer) is flattened into a one-dimensional vector and fed into the hidden layer. The subsequent network structure is a common feed-forward neural network. The identification of gravity anomalies through deep learning faces two fundamental challenges. The first challenge lies in obtaining training data. Ideally, one should learn all possible complex morphologies of gravity anomalies and their corresponding gravitational responses. However, this is currently unfeasible due to the scarcity of precisely modeled anomaly samples. Even when acquiring sufficient anomaly samples, performing accurate forward modeling on irregular anomalies to obtain gravitational responses as labels requires high-precision computational forward modeling, which incurs substantial computational costs. The second challenge involves parameterizing the geometric morphology of anomalies. Given the complex and variable nature of anomaly shapes, there is currently no parameter-efficient geometric description method. In deep learning-based identification tasks, more universal parameters are needed to characterize their geometric properties.

To address these two challenges, the author employs depth and linear parameterization for anomalous bodies, effectively resolving both the acquisition of training samples and the parameterization of complex morphological anomalies. While simple geometries cannot accurately parameterize actual anomalous body geometries, their shared characteristic of overall size applies to both simple and complex geometries. The depth and linear dimensions of simple geometries can be easily calculated, enabling the creation of depth-linear parameterized training datasets. This approach establishes geometric connections between training anomalous bodies and target anomalies through linear parameters. Furthermore, simple geometries allow rapid gravitational calculations using analytical forward models, eliminating the need for high-precision modeling and effectively addressing the challenge of generating large-scale training datasets.

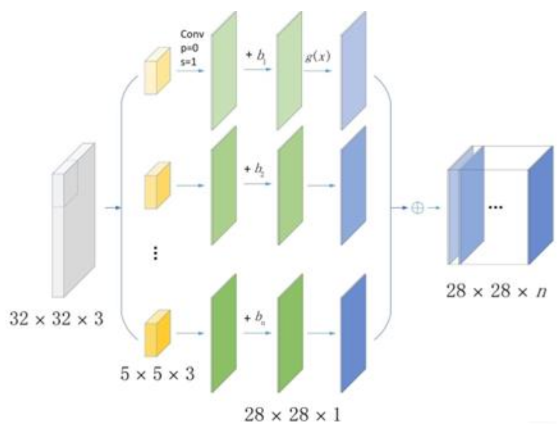

Fig.2 Algorithm Flow Chart

Meanwhile, depth and linear dimension hold significant practical value. Depth refers to the vertical distance from the geometric center of an anomaly, while vertical resolution remains a key limitation of gravity exploration compared to seismic methods. This study aims to enhance vertical resolution through deep learning techniques. Linear dimension characterizes the overall size of anomalies, directly yielding volume measurements that correlate with the scale of geological bodies in interpretation. Furthermore, under the constraint of volume information, other inversion methods can be applied to interpret the data, effectively reducing interpretation uncertainties. Based on the above discussion, we constructed a hexahedron model for the training set of anomalies. This hexahedron extends in three coordinate directions with lengths l_x, l_y, and l_z, respectively, and has a center buried depth of d. The parameters to be identified are d and the linear dimension l, which characterizes the overall size of the anomaly. The linear dimension of the hexahedron is calculated as follows:

$$l = \sqrt[3]{l_x \cdot l_y \cdot l_z} \tag{3}$$

Notably, convolutional neural networks exhibit translation invariance in image recognition, meaning consistent identification results are obtained when the same object appears at different positions within an image. Furthermore, the horizontal center position of anomalies shows strong correlation with the peak position of gravity equipotential line images. Since simpler traditional algorithms can determine the horizontal center position of anomalies, this study excludes anomaly center identification from its scope. Additionally, the identification of field source depth and linear dimensions does not require prior knowledge of the horizontal center position of anomalies or field sources.Anomalies with identical morphology exhibit varying gravitational response amplitudes under different density conditions. To enhance recognition accuracy, we implement a fixed-density strategy. During training, all anomaly samples maintain a uniform density of 1 g/cm³. The learned neural network model establishes the following density-gravity response relationship:

$$G_L(1, V) = g \tag{4}$$

Here $G_L$denotes the functional describing the relationship between gravity anomalies and gravitational responses in the trained neural network model, where 1 represents unit density, and V stands for the gravity anomaly of a specific shape. In practical applications, if density information is available a priori, and the density of the target anomaly is assumed as ρ, the gravitational response expected from the network model trained on unit-density anomalies would be g, while the target anomaly's gravitational response is g'. Based on the gravitational response characteristics of uniformly dense anomalies, the following relationship should hold:

$$G_L(1,V) = g = \frac{g'}{\rho} \tag{5}$$

Simply divide the gravitational field to be identified by the prior density and input it into the model for recognition. Even if the prior density is unknown, different recognition results can be obtained by assuming the prior density, which can be further selected. Enter the training phase. First, within a specified coordinate range, generate a large number of random hexahedron training samples with varying depths and sizes. Set their density to 1 and perform forward modeling to obtain gravity contour maps for each sample. The 2D gravity data of these samples will serve as the network's input. Next, to obtain the labels for the training samples, we extract the burial depth and linear dimension of the hexahedral samples. Following the approach used in convolutional neural network image recognition, we categorize each sample's burial depth and linear dimension into predefined numerical intervals. The label vector represents the number of segments within these intervals, where the interval containing a specific value (burial depth or linear dimension) is marked with 1 and others with 0, effectively indicating the probability of the sample parameters falling within each numerical range. These probability vectors constitute the labels for the samples. Finally, the input samples and labels are fed into the designed neural network model for training. The trained model then processes the gravitational input data to produce the identified parameters. When dealing with multiple anomalies in observational data, each anomaly must be isolated and processed through the convolutional neural network separately. For anomalies with no overlap or minimal overlap, they can be directly extracted. However, for anomalies with significant overlap, relevant methods should first be applied to separate them.

3. Analysis of Empirical Results

In neural network training, the learning rate acts as the step size for updating network parameters. Setting an appropriate learning rate enhances training convergence. This dimensionless parameter (less than 1) varies across different tasks and datasets, requiring determination through multiple loss function convergence curve observations. If the loss function declines slowly, increasing the learning rate may help. Conversely, persistent jumps or divergence in the loss function indicate an excessivelyhigh learning rate, necessitating reduction until the loss function shows smooth decreases. Deep neural networks, while excelling at problem representation, are prone to overfitting—a detrimental effect. During training, the network may learn irrelevant features from the data, leading to misidentification. To address overfitting, the author employs a simple yet effective dropout method: randomly discarding neurons during optimization while keeping their weights unchanged.

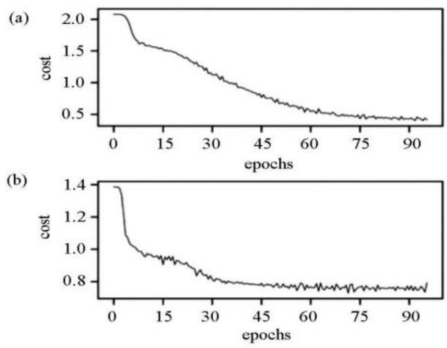

Fig.3 The loss of CNN during training

To evaluate the recognition accuracy of the convolutional neural network model, four abnormal bodies with different depths and shapes were designed, labeled as a, b, c, and d. As shown in Figure 4, four rectangular prisms were first constructed with central dimensions of (300 m × 200 m × 200 m × 200 m), (600 m × 200 m × 200 m × 200 m), (400 m × 200 m × 400 m × 200 m), and (400 m × 200 m × 200 m × 400 m). Subsequently, random perturbations were applied to these prisms to simulate real-world anomalies, forming the test abnormal bodies. The experimental results are presented in Table 1, which shows the recognition accuracy of the convolutional neural network model for each abnormal body. The model achieved high recognition accuracy for all four abnormal bodies, with accuracy rates of 92.5%, 95.0%, 93.75%, and 96.25% for a, b, c, and d, respectively. These results demonstrate the effectiveness of the model in accurately identifying abnormal bodies with different depths and shapes, even in the presence of random perturbations. The high recognition accuracy indicates that the model has strong generalization ability and can be applied to real-world scenarios for anomaly detection.

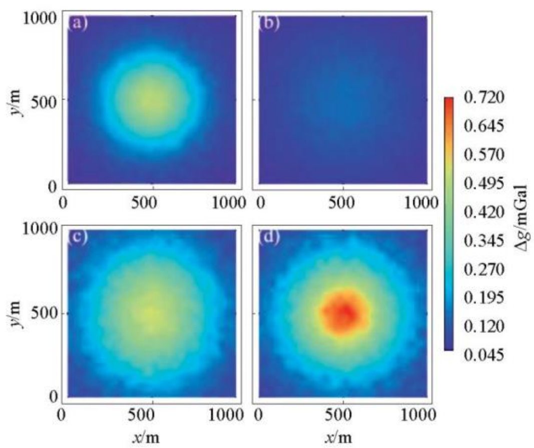

Fig.4 The gravity contour map of testing bodies

Table 1 compares the identification results of the test model's center burial depth and linear dimension, using the probability expectation value y˙ of burial depth or linear dimension parameters for comparison. The models in Figures 3a, c, and d demonstrate excellent identification results with ideal accuracy. However, the model in Figure 3b shows slightly larger identification errors, with a center burial depth error of approximately 21 m. This indicates that the trained convolutional neural network can effectively identify both center burial depth and overall size of anomalies at different burial depths and linear dimensions. For anomalies with deeper burial depths and weaker gravity signals, identification errors may increase. Additionally, the model can still identify anomalies with similar morphologies but different orientations. Different levels of Gaussian white noise to the original data, the robustness of the model is tested. The results show that when the signal-to-noise ratio (SNR) is greater than 20 dB, the identification accuracy of the model remains above 90%, indicating strong anti-noise capability. However, as the SNR decreases below 15 dB, the identification accuracy starts to decline significantly, especially for anomalies with smaller sizes. This suggests that in practical applications, preprocessing steps to enhance the signal-to-noise ratio may be necessary to improve the model's performance. Furthermore, showing that it can process a large dataset within a reasonable time frame, making it suitable for real-time anomaly detection tasks.

Table 1. The identified parameters of testing bodies

Identify the person	Real depth, line width/m	Recognition depth, line width/m
A	0.325	0.102
B	0.152	0.051
C	0.214	0.072

To validate the method's effectiveness in identifying gravity anomalies from real-world data, we conducted tests using aerial gravity survey data from a gravity test site in Australia's Kauring region. The data underwent terrain correction, and the primary gravity anomalies within the survey area were selected. The data was then resampled into a format compatible with convolutional neural networks for analysis.

4. Conclusion

This study integrates deep learning technology with gravity anomaly detection, employing convolutional neural networks (CNNs) – a widely used technique in image recognition – to identify anomalous bodies in two-dimensional gravity data. The training samples are generated through stochastic modeling and gravity forward modeling. CNN training demonstrates rapid convergence. Unlike traditional neural networks that only identify burial depth, CNNs can simultaneously detect linear dimensions that characterize anomaly size. The tested model achieves high accuracy in identifying both the burial depth and linear dimensions of anomalies, maintaining performance across different depths and orientations while remaining insensitive to gravity observation noise. Although accuracy decreases when anomalies respond to weak gravity signals, the results remain within acceptable ranges. Experimental validation shows that the identified anomalies align with parameters obtained through density inversion methods. This confirms the trained CNN's strong generalization capability for real-world gravity anomalies. Notably, CNN training requires significantly less computational time than conventional high-precision inversion algorithms and eliminates the need for dense gravity measurement networks, achieving comparable anomaly detection effectiveness. These advantages position CNN as a promising new methodology for gravity anomaly interpretation. The convolutional neural network (CNN) architecture employed in this study is more sophisticated than traditional neural networks, yet remains relatively simple from the perspective of deep neural networks.

In gravity anomaly detection tasks, deep neural networks still hold significant untapped potential. Deeper networks and more complex architectures could further enhance recognition accuracy. Additionally, while CNN training requires considerable time, once trained, the system achieves real-time performance, making it a promising candidate for future real-time gravity interpretation applications. Finally, applying CNN structures to gravity gradient data and other richer gravity datasets would further unlock their capabilities in spatial gravity data interpretation, representing a valuable research direction. However, deep learning methods typically require sufficient, diverse and representative samples. Increasing sample size significantly raises computational demands and complexity. A key limitation of this approach is achieving comparable results through small-batch training. Our inversion method does not utilize prior model information or constraints, relying solely on network architecture. Different architectures exhibit distinct advantages, leading to varying inversion outcomes. Future work will focus on optimizing network architecture and sample characteristics, experimenting with different methodologies, incorporating constraints and prior information to enhance convergence capabilities and expand application scope. Additionally, our research reveals vertical stratification in deep learning-based inversion results - a phenomenon observed in other deep neural network gravity inversion studies - highlighting the urgent need for further investigation.

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