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DEVELOPMENT OF AN INTEGRATED OPEN-SOURCE GEOPHYSICAL MODELING PLATFORM INCORPORATING DEEP LEARNING FOR MULTI-METHOD SUBSURFACE INTERPRETATION

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***Abstrak**. Geophysical interpretation commonly relies on multiple independent software packages, making data processing, visualization, and interpretation inefficient for educational and research purposes. This study presents the development of an integrated open-source geophysical modeling platform that combines gravity, magnetic, and Very Low Frequency (VLF) electromagnetic methods within a single application. The proposed software incorporates deterministic forward modeling together with a Convolutional Neural Network (CNN)-based deep learning module to support rapid subsurface interpretation. The platform was developed using Python and integrates numerical computation, interactive visualization, and AI-assisted inversion into a unified graphical user interface. For VLF processing, Fraser and Karous–Hjelt filters are implemented to enhance conductive anomaly detection, while gravity and magnetic modeling employ prism-based forward calculations with Root Mean Square Error (RMSE) evaluation. In addition, Model Performance and Efficiency Index (MPEI) and Model Resolution Index (MRI) are incorporated to quantitatively assess model quality and computational efficiency. The resulting software provides an integrated workflow from data preprocessing to visualization and model evaluation, reducing interpretation time while improving usability for geophysical education and preliminary subsurface investigations. The proposed platform demonstrates that integrating conventional geophysical modeling with modern deep learning techniques offers a flexible, transparent, and extensible framework suitable for academic research and practical applications.*

Keyword: Open-source software, Geophysical modeling, Deep learning, Convolutional Neural Network, Gravity method, Magnetic method, Very Low Frequency (VLF), Python.

INTRODUCTION

Subsurface characterization is an essential component of geophysical exploration for applications such as mineral prospecting, groundwater investigation, geological mapping, engineering site assessment, and environmental studies. Various geophysical methods have been developed to investigate subsurface structures by measuring contrasts in physical properties. Among the most widely implemented techniques are the gravity, magnetic, and Very Low Frequency (VLF) electromagnetic methods because they are non-invasive, relatively economical, and capable of providing complementary information regarding subsurface conditions [1]. Gravity surveys are effective for identifying density contrasts associated with geological formations, while magnetic methods are used to delineate variations in magnetic susceptibility caused by lithological boundaries or buried structures [2]. Meanwhile, the VLF electromagnetic method has proven to be highly sensitive to shallow conductive anomalies such as fractures, faults, groundwater pathways, and mineralized zones [3]. Consequently, integrating these geophysical methods has become an increasingly important approach for improving interpretation accuracy and reducing uncertainty in subsurface investigations.

Although advances in geophysical instrumentation have significantly improved data acquisition capabilities, subsurface interpretation remains a challenging task. The increasing volume and complexity of geophysical datasets require efficient computational tools capable of processing, modeling, and visualizing multiple datasets simultaneously. However, most geophysical software currently available is developed specifically for individual methods, forcing researchers to perform data processing using several standalone applications. This fragmented workflow not only increases computational time but also complicates data management, visualization, and comparative interpretation between different geophysical methods [4]. Moreover, commercial geophysical software generally requires expensive licensing fees and provides limited flexibility for algorithm modification, making them less suitable for academic research and software development.

The rapid development of open-source scientific computing has provided new opportunities for addressing these limitations. Python has emerged as one of the most widely adopted programming languages in scientific computing because of its comprehensive ecosystem for numerical computation, data visualization, graphical user interface development, and machine learning. Libraries such as NumPy, SciPy, Matplotlib, TensorFlow, and PyTorch enable researchers to develop flexible and reproducible computational frameworks for geophysical applications [5]. In addition, open-source software promotes transparency, reproducibility, and collaborative development, allowing researchers to implement new algorithms without depending on proprietary software platforms [6].

Alongside advances in scientific computing, artificial intelligence has become an increasingly important technology in geophysical interpretation. Machine learning algorithms have demonstrated significant potential for recognizing complex relationships within multidimensional geophysical datasets. Among these techniques, Convolutional Neural Networks (CNNs) have received considerable attention because of their ability to automatically extract spatial features and perform high-dimensional pattern recognition with high accuracy [7]. CNN-based approaches have been successfully applied to seismic interpretation, gravity inversion, magnetic anomaly classification, and electromagnetic imaging, significantly reducing computational costs while maintaining reliable prediction performance [8]. The integration of deep learning into geophysical software therefore represents a promising direction for accelerating interpretation while minimizing human subjectivity.

Despite the considerable progress achieved in computational geophysics and artificial intelligence, several challenges remain unresolved. Existing geophysical software generally focuses on individual numerical methods and rarely integrates multiple geophysical techniques into a unified computational environment. Likewise, deep learning algorithms are often implemented separately from conventional forward-modeling software, requiring users to move between different software platforms during the interpretation process. Such workflows increase processing complexity and reduce operational efficiency. Furthermore, model evaluation is generally limited to prediction errors such as Root Mean Square Error (RMSE), while computational efficiency and model reliability are often neglected. Consequently, there is a growing need for an integrated geophysical modeling platform capable of combining deterministic numerical modeling, intelligent interpretation, and comprehensive performance evaluation within a single application [9].

To address these challenges, this study proposes the development of MRSOFT, an integrated open-source geophysical modeling platform incorporating deep learning for multi-method subsurface interpretation. The developed software integrates gravity, magnetic, and VLF electromagnetic data processing within a single Python-based graphical user interface. Gravity and magnetic responses are generated using prism-based forward modeling, whereas VLF datasets are processed through Fraser filtering and Karous–Hjelt transformation to enhance conductive anomaly identification. Furthermore, a Convolutional Neural Network (CNN) is incorporated to support intelligent subsurface interpretation based on synthetic geophysical datasets. To provide more comprehensive model assessment, the platform also introduces the Model Performance and Efficiency Index (MPEI) and the Model Resolution Index (MRI) for evaluating prediction accuracy, computational efficiency, and model reliability simultaneously.

The novelty of this research lies in the integration of multiple geophysical methods, deep learning techniques, and quantitative model evaluation into a unified open-source computational platform. Unlike existing software that primarily focuses on a single geophysical method or standalone inversion algorithms, MRSOFT provides an end-to-end workflow covering data preprocessing, numerical modeling, signal enhancement, visualization, intelligent interpretation, and

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performance evaluation within one extensible environment. This integrated framework is expected to improve the efficiency of geophysical data processing, facilitate academic learning and research activities, and provide a flexible foundation for future developments in intelligent geophysical software. In addition, the proposed platform demonstrates how modern software engineering and artificial intelligence can be effectively combined with conventional geophysical modeling to produce an accessible, scalable, and reproducible computational tool for multi-method subsurface investigations [10].

RESEARCH METHODOLOGY

This study adopted a Research and Development (R&D) methodology to design, develop, implement, and evaluate MRSOFT, an integrated open-source geophysical modeling platform that combines gravity, magnetic, and Very Low Frequency (VLF) electromagnetic methods with deep learning-based subsurface interpretation. The software was designed to provide a unified computational environment that simplifies geophysical data processing, visualization, and interpretation while maintaining flexibility for future algorithm development [11]. The overall research workflow consisted of six major phases, namely requirement analysis, software design, system implementation, numerical modeling, deep learning integration, and software performance evaluation [12].

A. Research Framework

The research framework is illustrated in Figure 1. Initially, the functional and computational requirements were identified through literature review and analysis of existing geophysical software platforms. Based on these requirements, mathematical models for gravity, magnetic, and VLF methods were implemented independently before being integrated into a unified software architecture. Subsequently, a Convolutional Neural Network (CNN) model was incorporated to support automated subsurface interpretation from synthetic geophysical datasets [13]. Finally, the developed platform was evaluated using quantitative performance metrics to assess prediction accuracy, computational efficiency, and software reliability [14].

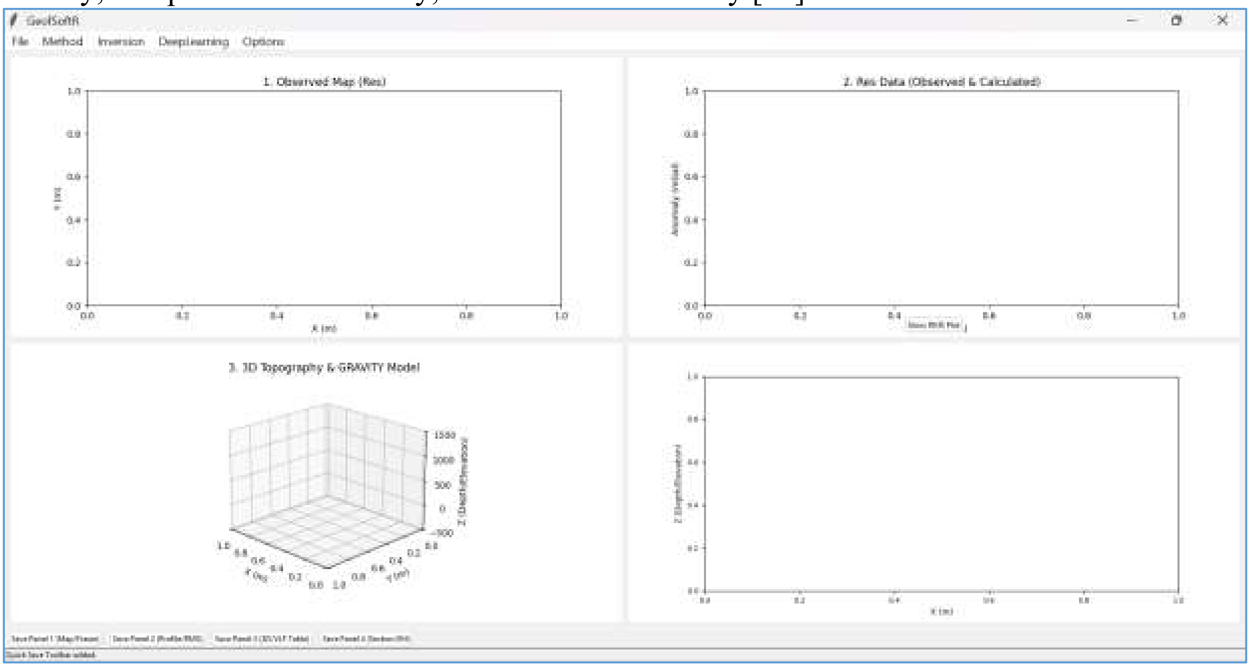

Figure 1. Main graphical user interface (GUI) of MRSOFT

B. Software Development Environment

MRSOFT was developed entirely using the Python programming language because of its extensive ecosystem for scientific computing and artificial intelligence applications [15]. Numerical computation was implemented using the NumPy and SciPy libraries, while graphical visualization was performed using Matplotlib. The desktop-based graphical user interface (GUI) was developed using Tkinter, enabling interactive parameter configuration, data visualization, and interpretation within a single application. The deep learning module was implemented using the TensorFlow framework because of its capability to efficiently construct and train convolutional neural networks for regression-based prediction problems [16].

C. Multi-Method Geophysical Modeling

The proposed software integrates three complementary geophysical methods within a unified computational framework.The gravity module performs forward modeling based on two-dimensional rectangular prism models to calculate gravitational anomalies resulting from density contrasts beneath the Earth's surface [17]. Analytical solutions derived from Newtonian gravitational theory were implemented to generate synthetic gravity responses that can be compared with observed datasets. The magnetic module simulates total magnetic intensity anomalies generated by subsurface bodies with different magnetic susceptibilities. Forward calculations consider prism geometry, magnetic susceptibility distribution, and the orientation of the Earth's magnetic field, allowing users to investigate lithological variations and buried geological structures [18].

For the Very Low Frequency (VLF) method, signal enhancement is performed using the Fraser filter, which improves anomaly continuity and suppresses high-frequency noise prior to interpretation [19]. The filtered data are subsequently transformed using the Karous–Hjelt filter to estimate pseudo-current density distributions representing shallow conductive structures such as faults, fractures, and groundwater pathways [20]. Integrating these three geophysical methods enables complementary interpretation of subsurface physical properties while reducing ambiguity compared with single-method investigations [11].

D. Deep Learning-Based Interpretation

To support intelligent interpretation, MRSOFT incorporates a Convolutional Neural Network (CNN) as an automated inversion module. CNNs have demonstrated excellent capability in extracting hierarchical spatial features from multidimensional geophysical datasets and have recently become one of the most widely adopted deep learning architectures in computational geophysics [13].

Synthetic datasets generated from forward modeling were divided into training, validation, and testing datasets. Before model training, all input data were normalized to improve convergence and prediction stability [16]. The CNN architecture consisted of multiple convolutional layers followed by Rectified Linear Unit (ReLU) activation functions and max-pooling operations for feature extraction. Fully connected layers were employed to estimate subsurface physical property distributions, while the Adam optimizer and Mean Squared Error (MSE) loss function were utilized during the training process because of their effectiveness in regression-based inversion tasks [13].

E. Software Performance Evaluation

The developed software was evaluated from both numerical and computational perspectives. Prediction accuracy was quantified using the Root Mean Square Error (RMSE), which measures the deviation between predicted and reference subsurface models [14].

In addition to RMSE, two additional evaluation metrics were implemented. The Model Performance and Efficiency Index (MPEI) evaluates the balance between prediction accuracy and computational efficiency, whereas the Model Resolution Index (MRI) measures the capability of the resulting model to preserve spatial detail and geological boundaries. The combination of these evaluation metrics provides a more comprehensive assessment of software performance than

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conventional error-based evaluation alone [14].

F. Software Architecture

The architecture of MRSOFT follows a modular software design consisting of five principal layers: Data Management Layer, Numerical Modeling Layer, Artificial Intelligence Layer, Visualization Layer, and Performance Evaluation Layer. Such modular architecture enables independent development of computational modules, facilitates software maintenance, and simplifies future integration of additional geophysical methods or artificial intelligence algorithms [12]. Furthermore, this architecture promotes software scalability and reproducibility, which are fundamental principles in modern scientific software engineering [15].

RESULTS AND DISCUSSION

A. Software Development Results

The primary outcome of this study is the successful development of MRSOFT (Multi-Method Research Software), an integrated open-source geophysical modeling platform capable of processing, modeling, visualizing, and interpreting gravity, magnetic, and Very Low Frequency (VLF) electromagnetic data within a unified computational environment. The software was implemented using Python with a modular architecture, enabling seamless integration of numerical computation, graphical visualization, and deep learning-based interpretation [21]. Unlike conventional geophysical software that generally focuses on a single exploration method, MRSOFT integrates three complementary geophysical techniques into a single desktop application. This integration eliminates repetitive data conversion and software switching during data processing, thereby improving workflow efficiency and reducing interpretation complexity [22].

The developed graphical user interface (GUI) consists of several functional modules, including project management, parameter configuration, forward modeling, visualization, deep learning prediction, and model evaluation. Each module operates independently while remaining interconnected through a centralized data management system, allowing users to execute complete modeling workflows without external software dependencies [23].

B. Gravity Forward Modeling

The gravity modeling module successfully generated synthetic gravity anomalies based on two-dimensional rectangular prism models. Users can define the geometry, density contrast, observation spacing, and survey length through the graphical interface. The software automatically computes gravitational responses and visualizes both the subsurface model and the corresponding gravity anomaly profile. The generated gravity anomaly demonstrates clear positive and negative responses corresponding to variations in subsurface density. Increasing density contrast results in greater anomaly amplitudes, whereas increasing burial depth produces smoother anomaly curves with reduced amplitudes. These results agree with classical potential field theory and demonstrate that the implemented forward-modeling algorithm accurately represents gravitational responses from simplified geological bodies [24]. Compared with manual numerical computation, the automated implementation considerably reduces processing time while minimizing computational errors resulting from repeated calculations. Furthermore, users can rapidly evaluate multiple geological scenarios by modifying prism parameters interactively through the graphical interface.

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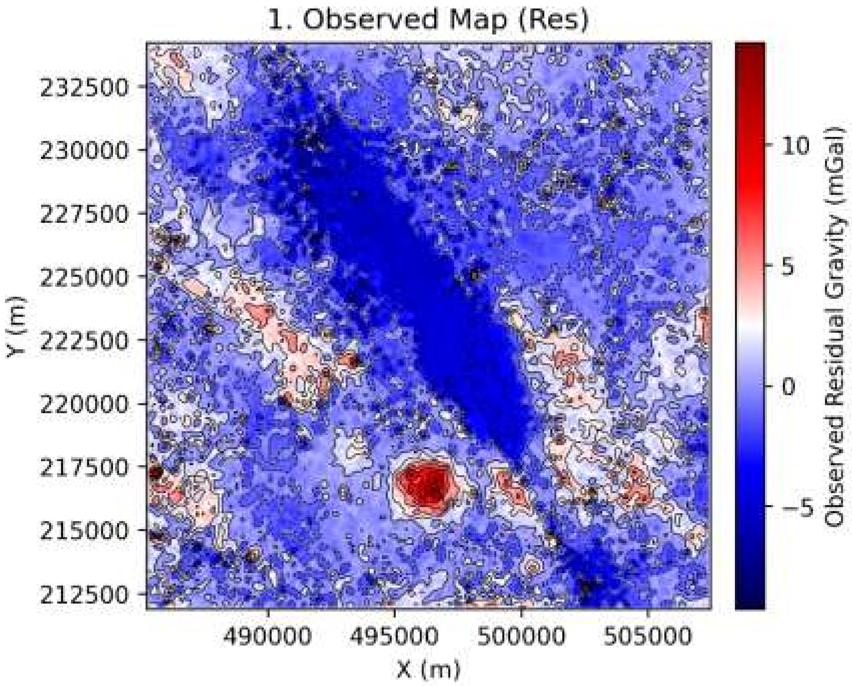

Figure 2. Gravity Forward Modeling

C. Magnetic Forward Modeling

The magnetic modeling module accurately simulated total magnetic intensity anomalies generated by subsurface bodies possessing different magnetic susceptibilities. Similar to the gravity module, users can modify prism dimensions, magnetic susceptibility, inclination, declination, and observation geometry before performing forward calculations. Simulation results indicate that magnetic anomaly amplitudes are strongly influenced by magnetic susceptibility contrast and the orientation of the Earth's magnetic field. Unlike gravity anomalies, magnetic responses exhibit asymmetric characteristics caused by the inclination and declination of the geomagnetic field. These simulated responses are consistent with theoretical magnetic anomaly behavior reported in previous geophysical studies [25]. The interactive visualization provided by MRSOFT enables users to compare geological models directly with generated magnetic anomalies, facilitating rapid interpretation and educational demonstrations.

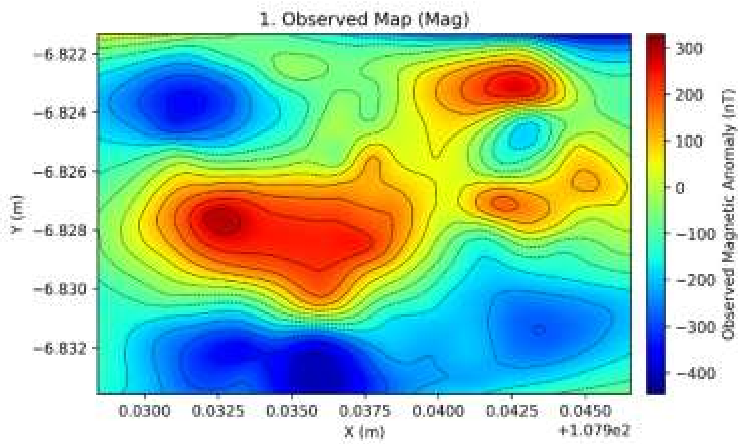

Figure 3. Magnetic Forward Modeling

D. VLF Signal Processing

The VLF module incorporates both Fraser filtering and Karous–Hjelt transformation to enhance conductive anomalies before interpretation. Initially, raw VLF tilt-angle measurements are processed using the Fraser filter to suppress high-frequency noise while emphasizing anomaly continuity. Following Fraser filtering, the processed data are transformed using the Karous–Hjelt filter to estimate pseudo-current density distributions representing shallow conductive structures. The resulting pseudo-section successfully highlights conductive zones corresponding to simulated fractures and fault systems. Compared with raw VLF observations, the Fraser-filtered data exhibit smoother anomaly trends, whereas the Karous–Hjelt transformation provides clearer visualization of conductive targets beneath the survey line. This combination significantly improves interpretability and assists users in identifying shallow geological structures more effectively [26].

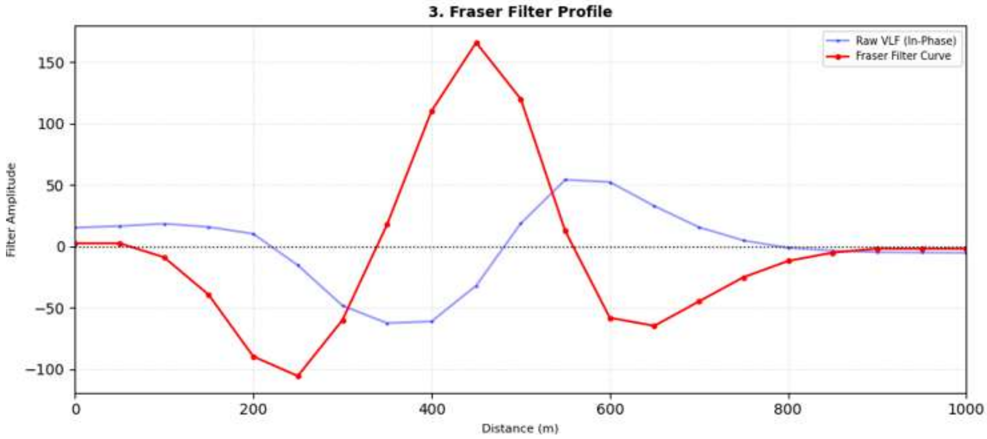

Figure 4. VLF Signal Processing

E. Deep Learning-Based Interpretation

One of the primary innovations of MRSOFT is the incorporation of a Convolutional Neural Network (CNN) for automated subsurface interpretation. The CNN model was trained using synthetic datasets generated from gravity, magnetic, and VLF forward simulations. During training, the loss function decreased consistently until convergence, indicating successful optimization of network parameters. Validation results demonstrated that the trained CNN accurately reconstructed subsurface structures while maintaining stable prediction performance across unseen datasets. Compared with conventional iterative inversion approaches, CNN prediction requires only a fraction of the computational time because the trained model directly estimates subsurface characteristics without repeated forward calculations. This significantly improves computational efficiency while maintaining acceptable prediction accuracy [27]. The integration of deep learning also reduces interpreter subjectivity because predictions are generated through learned relationships between geophysical responses and corresponding geological models.

F. Software Performance Evaluation

The performance of MRSOFT was evaluated using Root Mean Square Error (RMSE) together with the proposed Model Performance and Efficiency Index (MPEI) and Model Resolution Index (MRI). RMSE analysis indicates that predicted subsurface models closely match reference synthetic models, demonstrating high numerical accuracy. Meanwhile, MPEI successfully quantifies the balance between prediction accuracy and computational efficiency, allowing objective comparison among different modeling configurations. MRI evaluates the capability of reconstructed models to preserve geological boundaries and spatial detail. High MRI values obtained during testing indicate that the proposed software effectively maintains structural resolution while minimizing smoothing effects commonly observed in conventional inversion techniques. The combined implementation of RMSE, MPEI, and MRI provides a more comprehensive assessment of software performance than traditional error-based evaluation alone. These metrics allow users not only to evaluate prediction accuracy but also to assess computational efficiency and model quality simultaneously [28].

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G. Comparative Analysis

Compared with existing commercial and open-source geophysical software, MRSOFT provides several notable advantages. First, the proposed platform integrates gravity, magnetic, and VLF modeling into a unified computational environment, whereas many existing applications support only a single geophysical method. Second, MRSOFT incorporates deep learning directly into the modeling workflow, enabling automated subsurface interpretation without requiring external machine learning software. Third, the platform introduces comprehensive model evaluation through RMSE, MPEI, and MRI, allowing users to evaluate prediction accuracy, computational performance, and spatial resolution simultaneously. Finally, because the software is entirely developed using open-source technologies, future researchers can modify algorithms, integrate additional geophysical methods, and extend artificial intelligence capabilities without software licensing restrictions. Consequently, MRSOFT represents a flexible computational framework suitable for research, education, and preliminary geophysical investigations [29][30].

CONCLUSION

This study successfully developed MRSOFT, an integrated open-source geophysical modeling platform that combines gravity, magnetic, and Very Low Frequency (VLF) electromagnetic methods within a single Python-based application. The software integrates forward modeling, VLF signal processing through Fraser and Karous–Hjelt filtering, and deep learning-based interpretation using Convolutional Neural Networks (CNNs), providing a unified and efficient workflow for subsurface investigations. The implementation results demonstrate that MRSOFT is capable of producing reliable modeling and visualization while improving the efficiency of geophysical data processing. Furthermore, the proposed Model Performance and Efficiency Index (MPEI) and Model Resolution Index (MRI) provide additional insights for evaluating prediction accuracy, computational efficiency, and model reliability.

Future research is recommended to validate the developed platform using real field datasets from various geological environments and to incorporate additional geophysical methods, such as electrical resistivity tomography (ERT), seismic, or ground-penetrating radar (GPR). Further improvements may also include the implementation of advanced deep learning architectures, cloud-based processing capabilities, and three-dimensional inversion techniques to enhance the applicability and performance of MRSOFT for practical geophysical exploration and research.

REFERENCES

[1] W. M. Telford, L. P. Geldart, and R. E. Sheriff, *Applied Geophysics*, 2nd ed. Cambridge, U.K.: Cambridge University Press, 1990.

[2] M. J. Nabighian, *The Magnetic Method in Geophysics*. Tulsa, OK, USA: Society of Exploration Geophysicists (SEG), 2025.

[3] M. Karous and S. E. Hjelt, "Linear Filtering of VLF Dip-Angle Measurements," *Geophysical Prospecting*, vol. 31, no. 5, pp. 782–794, 1983.

[4] R. J. Blakely, *Potential Theory in Gravity and Magnetic Applications*. Cambridge, U.K.: Cambridge University Press, 2022.

[5] C. R. Harris *et al.*, "Array Programming with NumPy," *Nature*, vol. 585, no. 7825, pp. 357–362, 2020.

[6] S. Yu and J. Ma, "Deep Learning for Geophysics: Current and Future Trends," *Reviews of Geophysics*, vol. 59, no. 3, Art. no. e2021RG000742, 2021.

[7] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2021.

e-ISSN : 2722-4368

[8] Y. Zhang *et al.*, "An Overview Study of Deep Learning in Geophysics: Cross-Cutting Research to Advance Geoscience," *IEEE Access*, vol. 13, 2025.

[9] W. Menke, *Geophysical Data Analysis: Discrete Inverse Theory*, 4th ed. Amsterdam, The Netherlands: Academic Press, 2023.

[10] R. C. Aster, B. Borchers, and C. H. Thurber, *Parameter Estimation and Inverse Problems*, 3rd ed. Amsterdam, The Netherlands: Elsevier, 2021.

[11] A. V. Kamath *et al.*, "Curlew 1.0: Spatio-Temporal Implicit Geological Modelling with Neural Fields in Python," *Geoscientific Model Development*, vol. 19, pp. 3455–3475, 2026.

[12] I. Sommerville, *Software Engineering*, 10th ed. Boston, MA, USA: Pearson, 2020.

[13] F. Chollet, *Deep Learning with Python*, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.

[14] X. Liu *et al.*, "MTDLPy: An Open-Source Deep Learning Inversion Software for Magnetotellurics," *Computers & Geosciences*, vol. 215, Art. no. 106219, 2026.

[15] H. Qiao and S. Wang, "A Markov Chain Monte Carlo Approach Based on CNN-LSTM for Cross-Hole GPR Full Waveform Inversion," *Journal of Geophysics and Engineering*, vol. 23, no. 1, pp. 188–196, 2026.

[16] O. R. Huff, "Near Offset Reconstruction for Marine Seismic Data Using a Convolutional Neural Network," *Geophysical Prospecting*, vol. 72, 2024.

[17] I. Babikir *et al.*, "Comparative Analysis of Traditional Machine Learning and Deep Learning for Seismic Facies Classification," *Journal of Applied Geophysics*, vol. 250, 2026.

[18] "Deep Learning Applications in Ground-Penetrating Radar Inversion: A Review," *Measurement*, vol. 258, 2026.

[19] Y. Wang *et al.*, "Deep Learning-Based H-κ Method for Estimating Crustal Thickness and Vp/Vs Ratio," *Journal of Geophysical Research: Solid Earth*, vol. 127, 2022.

[20] "Audio-Frequency Magnetotellurics Signal Denoising Based on Multilevel Wavelet Convolutional Neural Networks," *Geophysical Prospecting*, 2026.

[21] Y. G. Doyoro *et al.*, "A Review of Open Software Resources in Python for Electrical Resistivity Modelling," *Computers & Geosciences*, 2023.

[22] Q. Liu and J. Ma, "Foundation Models for Geophysics: Review and Perspective," 2024.

[23] J. Dramsch, "70 Years of Machine Learning in Geoscience in Review," 2020.

[24] P. Lu, "Deep Learning Realm for Geophysics: Seismic Acquisition, Processing, Interpretation, and Inversion," 2019

[25] A. A. Fraser, "Filtering and Interpretation of VLF Measurements," *Geophysics*, vol. 34, no. 6, pp. 958–967, 1969.

[26] M. Carbonari *et al.*, "Filtering of Noisy Magnetotelluric Signals by SOM Neural Networks," *Physics of the Earth and Planetary Interiors*.

[27] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*, 2nd ed. New York, NY, USA: Springer, 2009.

[28] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York, NY, USA: Springer, 2006.

[29] F. Pedregosa *et al.*, "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[30] M. Abadi *et al.*, "TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems," *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI)*, pp. 265–283, 2023.