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U-Net-Based Segmentation of Magnetic Lineaments: Application to Aerogeophysical Data

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Abstract

This study applies a convolutional neural network (CNN) based on the U-Net architecture for automatically segmenting geological lineaments in aeromagnetic data. The model was trained using 11,914 synthetic image–mask pairs generated from simulated magnetic anomalies representing lineaments and fault zones. Data augmentation techniques improved model generalization. Real aeromagnetic data from the Rio Maria Project (SGB/CPRM 1129) were used for validation. The model achieved a validation accuracy of approximately 94%, effectively detecting linear magnetic features with high spatial continuity and robustness, even under noisy conditions. The results demonstrate that deep learning techniques are promising tools for automating structural mapping in geophysical data, with potential applications in mineral exploration and geological interpretation.

Introduction

Deep learning (DL) techniques (Bengio et al. (2009); Goodfellow et al. (2016); LeCun et al. (2015)), particularly convolutional neural networks (CNNs), have become powerful tools in automating geophysical data interpretation. In aeromagnetic surveys, detecting lineaments and fault zones is crucial for structural geological analysis and mineral exploration. However, traditional manual interpretation is time-consuming, subjective, and prone to inconsistencies.

Recent research has demonstrated the effectiveness of CNNs for geological feature extraction in geophysical datasets. Architectures like U-Net, initially designed for biomedical imaging, have been successfully adapted for seismic fault detection (Dou et al., 2022; Tang et al., 2023) and aeromagnetic lineament mapping (Lee et al., 2012; Naprstek and Smith, 2022). These models leverage encoder–decoder structures with skip connections to balance global context with local feature preservation, making them highly effective for linear feature segmentation.

This study proposes a U-Net-based CNN framework trained on synthetic aeromagnetic datasets to automate lineament detection. The model is evaluated on real aeromagnetic data from the Rio Maria Project (SGB/CPRM 1129), aiming to improve the efficiency and consistency of structural mapping for geological and mineral exploration applications.

Materials and Methods

This study employed 37 synthetic aeromagnetic images generated using the GravMag Prism software (Bongiolo et al., 2013), simulating magnetic anomalies caused by geological lineaments and fault zones with varying geometries, orientations, and noise levels to represent diverse geological settings.

Data augmentation techniques such as rotation, mirroring, and subdivision into smaller patches were applied to improve model generalization. Each original image yielded 322 variants, totaling 11,914 image–mask pairs for training and validation.

For independent testing, real aeromagnetic images from the SGB/CPRM 1129 – Projeto Aerogeofísico Rio Maria (Costa et al., 2016) were used. These were extracted from the geological–geophysical map of the Carajás Mineral Province, with manually interpreted structural lineaments serving as reference masks.

The deep learning model is based on the U-Net architecture, known for its effectiveness in image segmentation in medical and geophysical applications (Dou et al., 2022; Tang et al., 2023). It adopts an encoder–decoder structure with skip connections, enabling the capture of both global context and fine spatial features, key for detecting linear patterns in geophysical data (Figure 1).

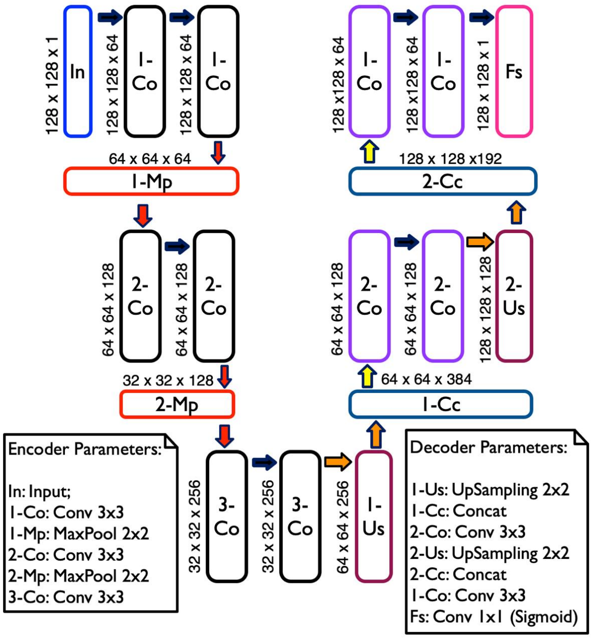

Figure 1: Schematic representation of the U-Net architecture used in this study, with an encoder–decoder structure and skip connections.

The dataset was split into training (80%), validation (16%), and testing (4%) subsets. The model was trained for 40 epochs using the Adam optimizer (initial learning rate: 0.001) and a weighted binary cross-entropy loss to address class imbalance. Training was performed on an NVIDIA GeForce RTX 4060 GPU, and performance was evaluated using accuracy, precision, recall, and loss evolution across epochs.

Results

The U-Net architecture detected geological lineaments and fault zones in synthetic aeromagnetic data. Training was efficient, with rapid convergence and a final validation accuracy of 93.9% and loss of 0.10 after 40 epochs (Figure 2). Learning curves show consistent accuracy gains and steady loss reduction, with no signs of overfitting.

On synthetic test datasets (Figure 3), the model accurately reproduced the spatial patterns of magnetic lineaments. Predicted masks displayed strong spatial continuity and alignment with ground truth, even under noise and variable anomaly geometries.

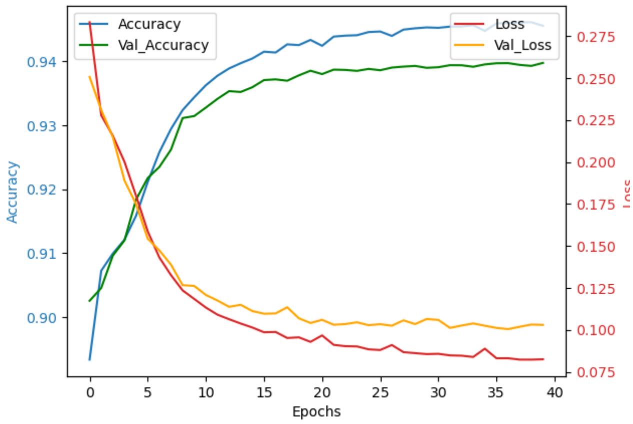

Figure 2: Accuracy and loss curves during training and validation over 40 epochs, showing performance improvement and convergence.

Applied to real aeromagnetic data from the Rio Maria Project (SGB/CPRM 1129), the model maintained robust performance (Figure 4). It detected major structural lineaments, including subtle features often obscured by noise, demonstrating strong generalization from synthetic to real-world data.

Overall, the U-Net model captured magnetic lineaments' geometry, continuity, and orientation. The high validation accuracy and strong agreement between predictions and reference masks validate the approach and highlight its applicability to structural mapping and mineral exploration.

Conclusions

This study demonstrates the effectiveness of convolutional neural networks, particularly the U-Net architecture, in automatically detecting and segmenting geological lineaments in aeromagnetic data. The model achieved high accuracy (94%) on synthetic datasets and generalized well to real data from the Rio Maria region.

The integration of synthetic data, augmentation techniques, and an optimized training strategy enabled robust identification of lineament patterns, even under noisy conditions. Results confirm U-Net's ability to generate accurate segmentation masks, supporting structural interpretation and potentially accelerating mineral exploration workflows.

Future work should aim to expand the training dataset with more real examples, enhance post-processing for mask vectorization, and explore alternative architectures to improve performance in geologically complex areas.

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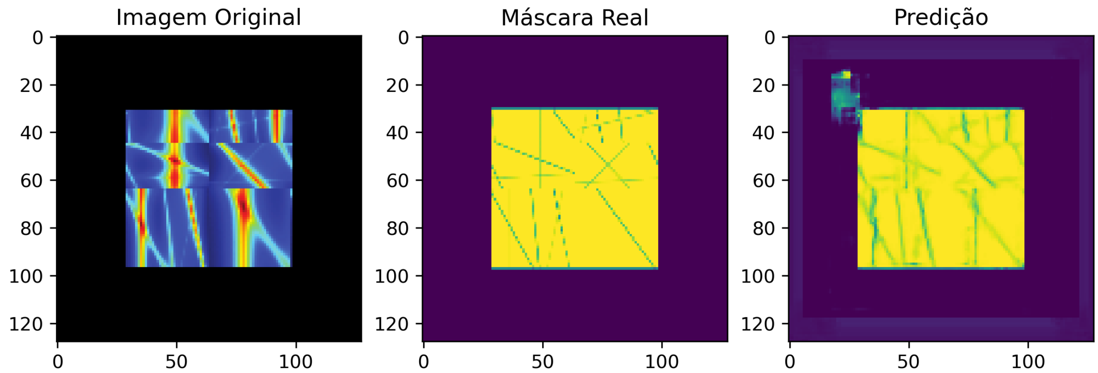

Figure 3: Prediction result on a synthetic aeromagnetic dataset simulating a lineament anomaly. The predicted mask is compared to the reference mask.

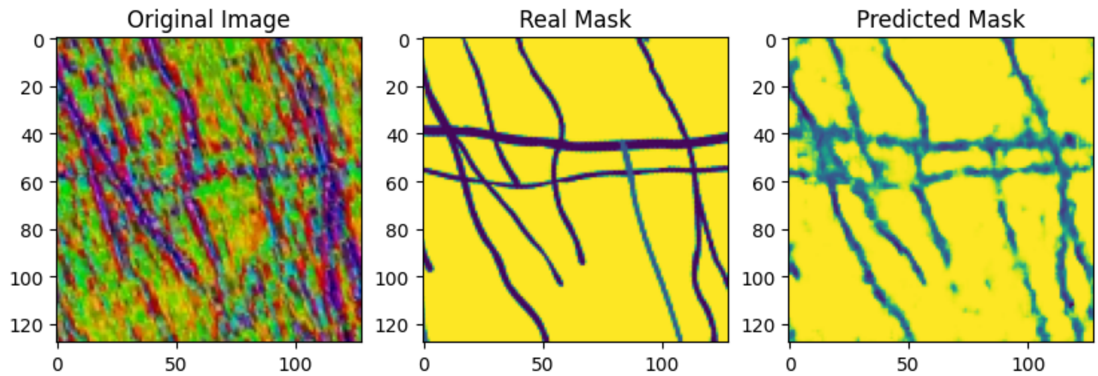

Figure 4: Prediction result on real aeromagnetic data. The model output is compared to a manually interpreted reference mask.

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