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Validity of Pre-trained Deep Learning Models for New Scanning Electron Microscopy (SEM) Rock Image Samples

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Objectives/Scope: The growing use of machine learning (ML) in digital rock physics raises a key concern: whether pre-trained models can be validly applied to new input data. This study investigates whether a deep learning model trained on scanning electron microscopy (SEM) images can be used for new samples outside the original training set. It proposes a workflow to identify outliers, providing an essential step for ensuring reliable application of ML-based predictions in geoscience workflows.

Methods, Procedures, Process: The compatibility of new SEM samples with the original training dataset was evaluated using a multi-method outlier detection workflow. Classical techniques, including Hausdorff distance and Gray Level Co-occurrence Matrix (GLCM) analysis, were first applied. A contrastive self supervised learning framework was then used to extract feature embeddings and compared against classical methods. Mahalanobis distance quantified each sample's deviation from the training distribution in the embedding space. Dimensionality reduction via t-SNE was used solely for visualization to illustrate separability. A data-driven threshold was applied to systematically flag samples as outliers.

Results, Observations, Conclusions: Outlier detection is a critical step in evaluating whether new SEM samples align with the data used to train deep learning models in digital rock physics. Classical methods, such as Hausdorff distance, failed to capture meaningful structural variation and could not produce coherent clustering for high-dimensional SEM images. GLCM-based texture features offered modest improvement by enabling partial clustering; while computationally efficient and interpretable, their discriminative power remained limited. In contrast, the contrastive self-supervised learning framework produced informative embeddings that effectively encoded structural similarities across samples. Outlier detection was performed in the embedding space using Mahalanobis distance, which consistently flagged new outlier samples with high deviation from the training distribution as statistical outliers. These samples exhibited greater distances from the embedding cluster center and were identified without the need for labeled data. t-SNE, used solely for visualization, confirmed a clear separation between samples consistent with the training set and those outside it. Notably, samples structurally aligned with the training distribution were embedded within the inlier region. These results demonstrate the effectiveness of the proposed method in distinguishing in-distribution from out-of-distribution samples, offering a scalable and data-driven approach for validating new SEM inputs before applying pre-trained models in digital rock physics workflows.

Novel/Additive Information: This work presents a generalizable, label-free workflow that combines contrastive self-supervised learning with Mahalanobis distance to assess the validity of applying pre-trained models to new image-based data. While demonstrated on SEM rock samples, the approach can be extended to other imaging modalities. It supports reliable model deployment by enabling systematic outlier detection, reducing the need for **retraining, and**

improving decision-making in digital rock physics and reservoir evaluation.