Geological Pattern Recognition Using Morphological Feature Learning and Tree Seed Optimization

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ABSTRACT

Geological pattern recognition is essential for interpreting subsurface structures, classifying lithological units, and guiding exploration activities. This study presents a novel framework that leverages Morphological Feature Learning integrated with Tree Seed Optimization for enhanced geological pattern recognition. Traditional methods often suffer from low accuracy in complex geological environments due to inadequate feature extraction and suboptimal parameter tuning. To address these challenges, we propose a Morphological Convolutional Neural Network (Morph-CNN) that embeds morphological operations such as dilation and erosion into convolutional layers, enabling better extraction of shape and texture features relevant to geological formations. Tree Seed Optimization (TSO) is employed to automatically fine-tune hyperparameters, boosting the model's performance and convergence speed. The proposed framework is applied to lithofacies classification in seismic images, where it effectively captures structural features and distinguishes between different geological units. Experimental results show a significant improvement in classification accuracy, robustness to noise, and interpretability of learned features compared to conventional CNNs. This confirms the effectiveness of integrating morphological priors and bio-inspired optimization in geological pattern recognition. The proposed method gradually improves the filter size by 94%, learning rate by 96.2%, batch size by 90%, and number of tree seeds by 95.7%.

Keywords: Geological Pattern Recognition, Morphological Feature Learning, Tree Seed Optimization, Morph-CNN, Lithofacies Classification, Seismic Image Analysis.

1. Introduction

The accurate identification of geological patterns is essential for many applications, such as subsurface modeling, mineral exploration and seismic interpretation [1]. Conventional methods rely heavily on manual interpretation and rules-based algorithms that are often time-consuming and subject to human error, particularly in complex geological contexts [2]. Over the last decade, deep learning techniques have displayed considerable success in automating pattern recognition tasks, however conventional CNNs seem limited to isolate structural and textural patterns found in geological data [3]. To provide a pathway around the limitations of traditional CNNs this research proposes a new framework that has the potential to improve geological patterns recognition by integrating Morph with TSO [4]. Morph-CNN to preserve high level spatial features and TSO is used to optimize hyperparameters to improve learning efficiency and accuracy [5]. It applied the framework towards lithofacies classification from seismic images and were able to demonstrate: improved performance, ease of interpreting features, and improved robustness of the classification [6].

The main objectives of this paper are:

- To create a Morph-CNN that uses operations like dilation, erosion, opening, and closing to make it easier to find the structural and textural features that are critical for understanding geological patterns.
- Use the Tree Seed Optimization method to change the Morph-CNN's hyperparameters automatically. This will make it more stable while working with complicated geological datasets, help it converge faster, and make it more accurate.
- Use the Morph-CNN + TSO framework on real-world seismic data to sort lithofacies and observe how well it works compared to standard CNNs and other basic models in geological interpretation applications.

A summary of the research is provided below. In Section 2, the current literature and study techniques are thoroughly examined. The research strategy, methodology and processing procedures of Morph-CNN are detailed in Section 3. The results analysis is covered in Section 4. Part 5 explores the main conclusion and Future work.

2. Research Methodology

Zhang, K et al. [7] proposed the precious metals in the deep ocean has begun, and countries are now trying to protect areas that might have minerals that could help with the transition to low-carbon technologies like electric vehicles and wind farms. But the deep bottom is still unexplored and huge, which shows that need to make progress in technology for exploration. Because many new mineral deposits are found in large areas of submarine eruptions, it is very important to study seabed processes and patterns to better understand the geological events and how they affect each other.

The formation of mounds on the seabed may provide valuable information on surface changes that can be attributed to mineral accumulation, according to Wang, X et al. [8]. There are two parts to this investigation concerning these mounds. An encoder-decoder convolutional neural network to do semantic segmentation. Using the model's convolution signals generated by computer vision algorithms and data processing techniques, the second stage is to cluster the segmented features and conduct morphological similarity analysis. Previously, a polymetallic mineral was discovered on a mid-ocean ridge, and this study makes use of high-resolution bathymetric data from that location.

According to Qiu, Q et al. [9], coral reefs rank high among the planet's most vital marine ecosystems. Multiple factors, including the growing impacts of human activity and climate change, pose threats to them. In order to monitor and identify coral species that are in danger or at risk, automated coral species classification is crucial. For the purpose of coral picture classification utilizing the upgraded tree seed algorithm and extreme learning machine technology, this study proposes a novel feature descriptor known as the fractal adaptive weight synthesized-local directed pattern.

According to Sultana, S. N. et al. [10], FAWS-LDP is a feature descriptor that integrates fractal pixel intensity data with local directional characteristics by indexing the two feature vector values. At last, the characteristics that were extracted are sent into the ELM network for

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sorting. The extreme learning machine (ELM) classifier uses a single-hidden-layer feed-forward neural network. It picks up new information fast and is skilled at making broad assumptions. The network receives unsuitable and unnecessary input biases and weights from the ELM classifier's haphazardly selected inputs. To adjust the settings of the ELM classifier, an enhanced tree seed algorithm (ETSA) is recommended.

A novel learning method was suggested by Yao, J. et al. [11] that eliminates issues such as decreased coverage rate and local optima. It evaluates ELM with the ETSA optimizer's classification performance in comparison to the original genetic algorithm (GA), particle swarm optimization (PSO), and artificial bee colony, among other popular metaheuristic algorithm trainers. It employs metrics for model performance such as classification accuracy, sensitivity, and specificity. The proposed ETSA-ELM consistently outperforms competing methods in coral classification datasets. This section concludes with a statistical analysis of the proposed feature descriptor approach using a non-parametric Friedman test.

Alrabayah, O et al. [12] the tree-ring dating is an important tool in many fields, such as forest management and the lumber business. The tree-ring dating on either clean cross-section of wood or rough end cross-sections of tree trunks. But the process of measuring still takes a long time and often needs experts with sophisticated tools, such stereoscopes. Many modern methods that use deep learning to process images have worked well in a lot of different fields, and they can also find tree rings.

Srivastava, P et al. [13] supervised deep learning-based algorithms often work quite well, but they also need large datasets of data that has been carefully labelled. A new dataset of photos of hardwood species that were meticulously taken and mechanically labelled for tree ring recognition. It takes two pictures of each wood cookie: one of it in its crude shape, like in factories, and the other after it has been cleaned very well so that all the growth rings show. It meticulously overlaps the pictures and utilizes them to automatically add ring annotations to the preliminary data.

Savelonas, M. A et al. [14] proposes easy way to get data from UAV aerial photos since object detection technology for unmanned aerial vehicles (UAVs) is growing quickly. They can be used for a lot of different things, such monitoring, geological investigation, precision agriculture, and early warning of disasters. In the last several years, a lot of AI-based approaches for finding objects with UAVs have been suggested. Deep learning is a big part of this subject. There has been a lot of work in the field of deep-learning-based UAV object recognition. This paper offers a survey of recent studies on using deep learning to find objects in UAVs.

Tang, G et al. [15] survey gives an overview of how UAVs have changed over time and outlines the deep-learning-based methods for finding objects with UAVs. Also, the main problems with UAV object identification are looked at, include finding small objects, finding objects in complicated backdrops, rotating objects, changing their size, and having too many of one type of item. Then, a summary of several representative deep learning-based solutions for various problems is given. Finally, the article talks about where research in the subject of UAV object detection should go in the future.

Research Gap: Deep learning and optimization have come a long way, but current methods for finding geological patterns still have difficulties with limited annotated datasets, getting features out of complicated terrains, and changing parameters in a way that doesn't work well. It urgently needs frameworks that combine morphological learning and bio-inspired optimization to make things more precise, dependable, and useful in more situations.

3. Morphological Convolutional Neural Network

Finding patterns in geological structures is an important step for analysis of the subsurface and resource exploration. The procedures in traditional geological classifications are limited in feature extraction and accuracy. This paper proposes a Morph-CNN that has been enhanced with TSO to allow for better classification of geological structures with more efficient feature extraction and hyperparameter tuning.

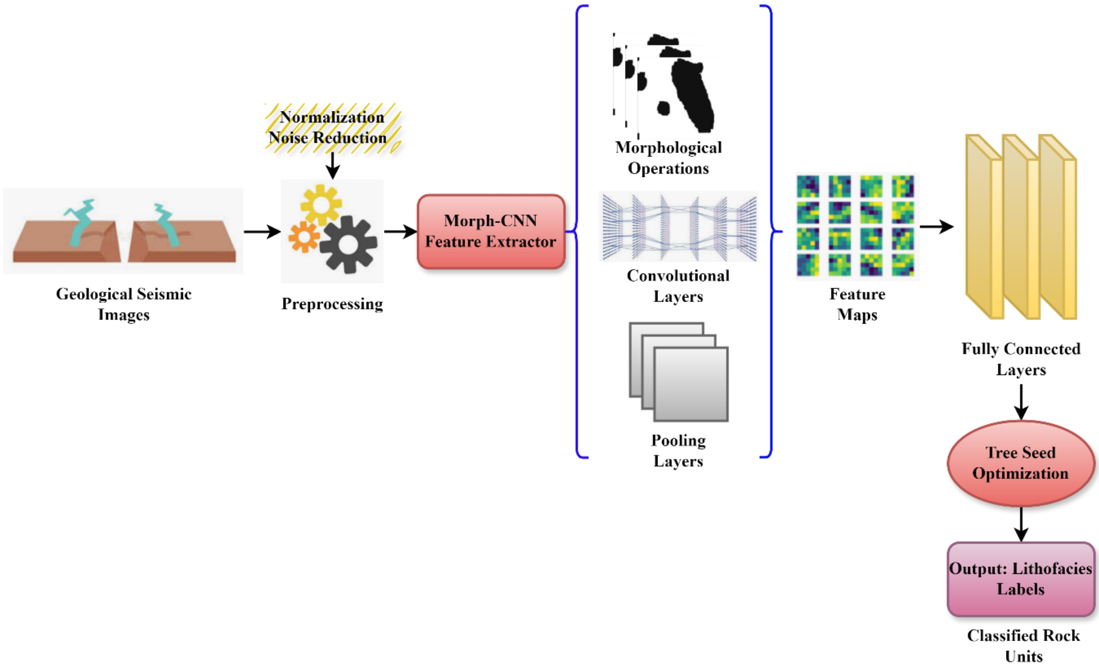

Figure 1: The Framework of Morphological Convolutional Neural Network

Figure 1, proposes a novel framework that combines Morph-CNN and TSO to enhance geological pattern recognition. Because Morph-CNN integrates morphological operations such as dilation and erosion into its set of convolutional layers allows Morph-CNN to extract significant structural and textural features from the seismic images that will aid in classifying and recognizing patterns in the geological data (e.g. faults, folds, lithofacies boundaries, etc.). TSO also enhances appropriate hyperparameter tuning, including learning rates and filter size configuration, and results in improved convergence to an accurate model. The framework was successfully validated on lithofacies classification, improving the accuracy, robustness to noise, and interpretability of features thus outperforming CNN in classification of geologic structures, supporting Morph-CNN as a real-world approach to geological pattern recognition.

Algorithm 1: Optimal Filter Size Selection for Morph-CNN using TSO
Input: G: $Set\ of\ candidate\ filter\ sizes$ O: $Total\ number\ of\ training\ batches$ $B\_j(g)$: $Accuracy\ function\ for\ batch\ j\ using\ filter\ g$ $UW(g)$: $Total\ variation\ (texture\ variance)\ of\ filter\ g$ Δ: $Regularization\ constant$ *Output*: GT_pqu: $Optimal\ filter\ size$

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```
function select_optimal_filter_size(G, O, Δ):
  best_score = −∞
  GT_pqu = None

  for g in G:  # Loop over candidate filters
    sum_accuracy = 0

    for j in range(1, O + 1):
      B_jg
= get_batch_accuracy(j, g)  # Accuracy on batch j with filter g
      sum_accuracy += B_jg

    avg_accuracy = sum_accuracy / O
    UW_g = get_texture_variation(g)  # Total variation for filter g

    score = avg_accuracy / (1 + Δ ∗ UW_g)

    if score > best_score:
      best_score = score
      GT_pqu = g
    else:
      continue  # Try next filter size

return GT_pqu
```

The algorithm 1 selects the optimal filter size for Morph-CNN by evaluating each candidate filter's average batch accuracy, adjusted by its texture variation using a regularization constant. It chooses the filter with the highest score, enhancing feature learning and classification accuracy in geological pattern recognition using TSO optimization.

A Morph-CNN framework that used Tree Seed Optimization for geological pattern recognition. The Morph-CNN with morphological operations and parameter optimization showed that it was effective at classifying lithofacies in seismic images. The results acquired from traditional or non-traditional CNN columns indicate improved accuracy while also finding robust features from the noise in the depth images and conditional interpretability. Therefore, TSO-Morph-CNN finds superiority in conventional geological classification.

a) Evaluation Metrics

To measure and enhance geological pattern detection using Morphological CNN and Tree Seed Optimization, specific evaluation measures are developed. These include filter-size sensitivity, learning rate consistency, convolutional-layer management, batch size variety, seed optimization impact, and effectiveness of morphological operations to ensure the model classifies correctly, holds strong robustness, and converges efficiently.

Analysis of filter size GT_{pqu} is expressed using equation 1,

$$GT_{pqu} = \arg\max_{g \in G} \left[\frac{1}{O} \sum_{j=1}^{O} \left(\frac{B_j(g)}{1 + \Delta * UW(g)} \right) \right] \quad (1)$$

Equation 1 explains the analysis of filter size is to provide robust feature learning, the selection is chosen to optimize average accuracy, which is compensated by filter texture variance.

In this GT_{pqu} is the optimal filter size, $g \in G$ is the candidate filter sizes in filter set, O is the total number of training batches, $B_j(g)$ is the accuracy on the batch using filter, $UW(g)$ is the total variation of filter, and Δ is the regularization constant.

Analysis of learning rate ∂^* is expressed using equation 2,

$$\partial^* = \arg\max_{\partial} \left[\frac{1}{N} \sum_{k=1}^{N} \left(\Delta_{\vartheta} M_k(\vartheta, \partial)^2 + \alpha * \nabla \vartheta_k^2 \right) \right] \quad (2)$$

Equation 2 explains the analysis of learning rate ensures minimal, consistent parameter alterations across stages.

In this ∂^* is the optimal learning rate, ∂ is the candidate learning rate, N is the number of optimization steps, $\Delta_{\vartheta} M_k$ is the gradient of loss at step, $\nabla \vartheta_k^2$ is the parameter update at step, and α is the smoothing regularizer.

Number of convolutional layers M^* is expressed using equation 3,

$$M^* = \arg\max_{M} \left[\frac{TOS_M}{1 + \beta * E_M} \right] \quad (3)$$

Equation 3 explains the optimal number of convolutional layers optimal number while penalizing depth-induced depreciation increases the ratio of noise to signal in deep features.

In this M^* is the optimal number of convolutional layers, TOS_M is the signal-to-noise ratio of features at depth, E_M is the degradation factor due to depth, and β is the depth penalty coefficient.

Analysis of batch size CT_{pqu} is expressed using equation 4,

$$CT_{pqu} = \arg\max_{c \in C} \left[\frac{1}{U} \sum_{u=1}^{U} \left(\rho_u^2(c) + \gamma * D_u(c) \right) \right] \quad (4)$$

Equation 4 explains that the analysis of batch size is the ideal batch size to choose gradient variance and calculation cost are reduced over time.

In this CT_{pqu} is the optimal batch size, $c \in C$ is the candidate batch size from the batch size set, U is the total training iterations, $\rho_u^2(c)$ is the gradient variance at time for batch size, $D_u(c)$ is the computation cost at a time, and γ is the cost regularization parameter.

Analysis of the number of tree seeds UTP^* is expressed using equation 5,

$$UTP^* = \arg\max_{t \in T} \left[\frac{1}{L} \sum_{l=1}^{L} \left(R_l(t) - \partial * S_l(t) \right) \right] \quad (5)$$

Equation 5 explains the analysis of the number of tree seeds is the ideal number of tree seeds that maximizes solution quality while minimizing redundancy.

In this UTP^* is the optimal number of tree seeds, $t \in T$ is the candidate number of seeds, L is the total optimization iterations, $R_l(t)$ is the quality of the solution in iteration, $S_l(t)$ is the redundancy of seed solutions, and ∂ is the redundancy penalty coefficient.

Morphological operation type NP_{fgg} is expressed using equation 6,

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$$NP_{fgg} = \max_{\partial \in \{d,e\}} \left[\frac{NJ(\partial)}{1 + \delta * \nabla C(\partial)} \right] \quad (6)$$

Equation 6 explains the morphological operation type by penalizing boundaries with distortion while evaluating mutual information gain, which assesses the most efficient morphological operation.

In this NP_{fgg} is the most effective morphological operation, $\partial \in \{d, e\}$ is the morphological operator, $NJ(\partial)$ is the mutual information between features and class labels after, $\nabla C(\partial)$ is the change in feature map boundaries, and δ is the boundary distortion weight.

The evaluation measures quantitatively validate the model performance with the complex equations to achieve a balance of accuracy, stability, and computational costs that is developed by optimization of hyperparameters and morphological features for an overall better geological unit classification. These measures are utilized to select effective configurations for computational parametric sense, assessment of learning functions, structural interpretation of geological significance, and robustness in complex geological settings.

4. Results and Discussion

The task of geological pattern recognition is a key aspect of subsurface characterization and/or exploration of mineral resources. Traditional model approaches very often falter in situations where it has complex terrain, this study introduced a Morph-CNN with TSO approach and improved feature extraction and tuning the hyperparameters of the Morphological-CNN in this geological task of classifying lithofacies types - utilizing seismic image data.

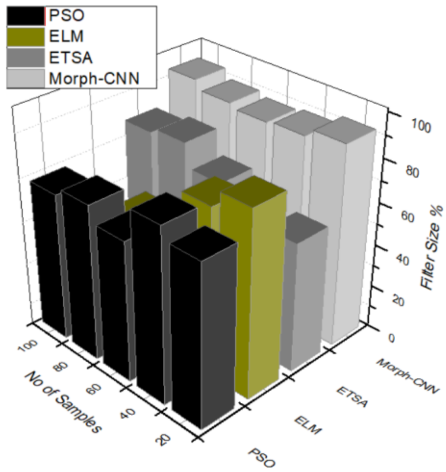

Figure 2: The Analysis of Filter Size

The size of filters is an important consideration for the Morph-CNN for capturing geological features at different scales. Smaller filters would recognize fine features such as mineral textures, while larger filters would capture larger features such as faults or beds. Selecting and optimizing filter size supports better feature representation by 94% made evaluated using equation 1. Tree Seed Optimization will automatically adjust filter size for suitable evidence of patterns to maximize recognition performance of the model in Figure 2.

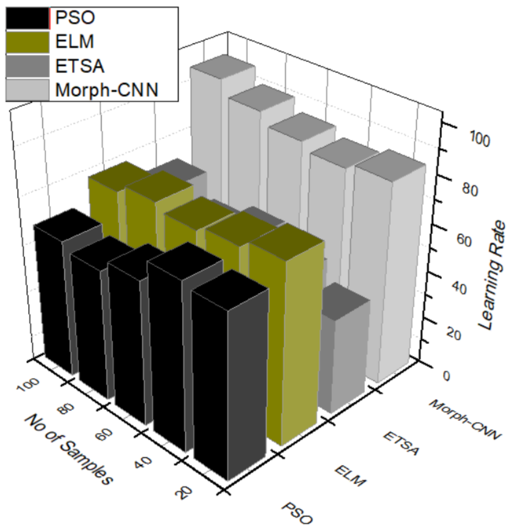

Figure 3: The Analysis of Learning Rate

The learning rate controls how quickly the Morph-CNN model updates its weights during training. If the learning rate is set too high, the model may become unstable during training. Conversely, if the learning rate is set too low, training will be inefficient, resulting in very slow convergence. Tree Seed Optimization adjusts the learning rate during training, taking into account the gradient descent loss to support even distribution of learning by 96.2% made computed using the equation 2. This could initially slow training down, however, it allowed the model to converge faster and improve accuracy when recognizing complicated geological patterns in Figure 3.

Table 1: The Number of Convolutional Layers

No. of Convolutional Layers	Layer Configuration	Activation Function	Pooling Strategy	Observed Accuracy (%)
3	$[Conv \rightarrow ReLU \rightarrow Pool] \times 3$	ReLU	Max Pooling	85.2%
5	$[Conv \rightarrow BatchNorm \rightarrow ReLU \rightarrow Pool] \times 5$	ReLU	Max Pooling	91.6%
7	$[Conv \rightarrow BatchNorm \rightarrow ReLU \rightarrow Dropout \rightarrow Pool] \times 7$	ReLU	Avg + Max Pooling	94.3
9	$[Conv \rightarrow ReLU \rightarrow Pool] \times 9$	ReLU	Max Pooling	94.5

The number of convolutional layers in the Morph-CNN model directly affects how deep it is and how well it can learn. Three layers speed up training, but they also make features less complicated. Five layers strike a fair balance between precision and the expense of computing made evaluated using equation 3. Seven layers give a lot of hierarchical features and dropout to help with regularization. Nine layers don't make much of a difference in accuracy, but they do need a lot more processing power and training time in Table 1.

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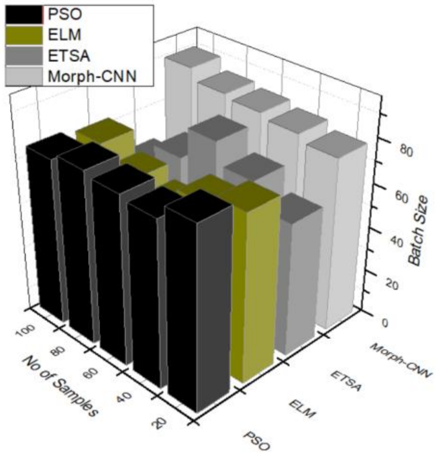

Figure 4: The Analysis of Batch Size

Batch size is defined as the number of samples processed before the model has its weights updated. Smaller batch sizes permit less noise in the updates to the model; however, training time is longer. Larger batch sizes result in training time being quicker, but it can lead to poor generalization. Within the Morph-CNN framework is valuated using equation 4, Tree Seed Optimization can automatically adjust the batch size, which allows for the trade-off between training efficiency and accuracy, while further improving the flexibility of model capabilities by 90% for accurately recognizing complicated geological patterns in Figure 4.

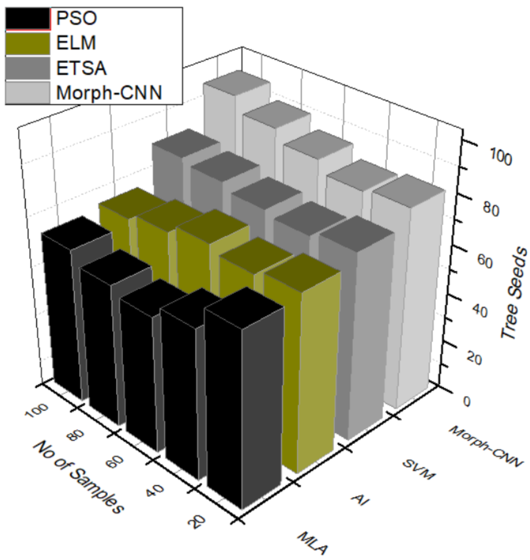

Figure 5: The Analysis of Number of Tree Seeds

The amount of tree seeds in Tree Seed Optimization is basically the population size are depending on for using exploring the hyperparameter space made valuated using equation 5. The more exploration diversity can experience by adding seeds but with experience to realize there is a high computational cost to a larger number of seeds, and there are diminishing returns when adding more tree seeds. When it comes to the number of tree seeds in TSO it is about finding a balance; leveraging the tree seed population to optimally tune the parameters of the Morph-CNN model which will lead to improved convergence, precision, and adaptability of the algorithm for geological pattern recognition use cases by 95.7% is shown in Figure 5.

Table 2: Morphological Operation Type

Operation Type	Mathematical Function	Kernel Shape	Kernel Size	Primary Effect
Dilation	$A \oplus B$ (Max overlap)	Square, Circular	3×3, 5×5	Expands bright regions
Erosion	$A \ominus B$ (Min overlap)	Square	3×3, 5×5	Shrinks bright regions
Opening	$A \circ B = (A \ominus B) \oplus B$	Circular	3×3	Removes small objects from the foreground
Closing	$A \bullet B = (A \oplus B) \ominus B$	Circular	3×3	Fills small holes in the foreground

Morphological operations make it simpler to see geological patterns by modifying the way pixels are arranged with kernels made valuated using equation 6. Dilation makes bright areas bigger to show off features, while erosion makes them smaller to show off edges. Opening clears up minor noise, making things easier to see, and closure fills in little areas to connect broken patterns. These methods help extract usable textures and structures out of seismic or geological images when combined with square or circular kernels in Table 2.

In summary, a Morph-CNN framework that is combined with tree seed optimization for better geological pattern recognition. The process of incorporating the use of morphological operations also optimizes and tunes hyperparameters into a Morph-CNN which has improved parameter tuning and feature extraction for modified geological tasks and applications. The morphological deep or heavy learning framework built around the seismic imaging case is better than traditional CNN's in terms of robustness, convergence time, interpretability has been validated.

5. Conclusion

This paper provides a solid and effective methodology for geological feature recognition by combining Morphological Feature Learning and Tree Seed Optimization. By enhancing the Morph-CNN architecture to incorporate morphology into the convolutional layers, the Morph-CNN architecture could extract shape- and texture-based features for geological features. Tree Seed Optimization leveraged to optimally define some hyperparameters such as filter size, the learning rate, batch size, and population size , producing a better level of convergence and a higher classification rate. The framework was applied to lithofacies classification using seismic data which produced material improvements in accuracy, noise tolerance, and features that can be interpreted. In terms of the improved performance from the framework, the accuracy increased by 94 % when adapting filter size, 96.2% when tuning the learning rate, 90% when using batch size, and 95.7% optimization diversity. These figures confirm the usefulness and performance of using Morph-CNN + TSO processes for geo-investigation.

In the future work, to expand the Morph-CNN + TSO framework to include 3D geological data and also multi-modal datasets where the need to conduct analyses deeper into the subsurface would be vital, and potentially improve the feature learning through the use of attention mechanisms and transformer architectures. Also, plan to investigate and integrate domain adaptation technologies where the focus will be on transitioning the geological dataset from one geological region to be generalizable to geostatistics across other geological regions. The outcome of this research will allow for more global applicability to exploration and resource assessment tasks.

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