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Original Article

Enhancing TGS Salt Identification with U-NET and Graph Neural Networks

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Abstract **-** *Seismic imaging's ability to accurately demarcate salt bodies is vital for several oil and gas applications, including hydrocarbon exploration and reservoir assessment. Algorithms that attempt to recognize salt bodies in seismic data automatically can be tested on the TGS Salt Identification Challenge dataset. This research presents a new method for improving the accuracy of salt detection that combines U-Net with Graph Neural Networks (GNNs). This approach uses GNNs' relational reasoning capabilities in conjunction with U-Net's hierarchical feature representation capabilities to extract global and local contextual information from seismic imagery. The model successfully represents the intricate structural relationships in seismic data by enhancing the U-Net architecture with graph convolutional layers. Tested on the TGS Salt Identification Challenge dataset, the strategy outperforms state-of-the-art approaches. According to the experiments, the suggested U-Net with GNNs successfully identifies salt bodies in seismic pictures. This might lead to improvements in subsurface imaging and exploration for oil and gas.*

Keywords **-** *Deep learning, Graph neural networks, Seismic image analysis, TGS salt identification, U-NET.*

1. Introduction

Improving TGS salt identification using U-Net and Graph Neural Networks has garnered significant attention in recent research. The MultiResU-Net has demonstrated superior performance in detecting salt bodies compared to the classic U-Net.

This success has spurred further exploration of neural network architectures inspired by those utilised in the TGS Salt Identification Challenge, suggesting the potential for enhanced segmentation tools.

Researchers have actively improved the U-Net architecture to broaden its capabilities. For example, the incorporation of Squeeze-and-Excitation (SE) blocks into U-Net has resulted in the development of the USE-Net, showcasing advancements in convolutional neural networks. Additionally, modifications such as U-Net++ and ResU-Net++ have been suggested to improve prediction accuracy.

Furthermore, the integration of graph neural networks with U-Net has shown promise in various applications. For instance, the SCueU-Net merges U-Net with a graph segmentation network for efficient damage detection in railway rails. Similarly, a framework has been proposed utilising graph neural networks and U-Net architecture to identify flow phenomena based on graph hierarchies generated from unstructured meshes.

Seismic imaging plays a pivotal role in exploring and extracting oil and gas resources, providing crucial insights into subsurface geological structures. Among the myriad challenges in seismic interpretation, identifying salt bodies submerged within the earth's crust is a significant hurdle. These salt bodies, characterized by their complex shapes and varying sizes, present a formidable task for traditional image processing techniques.

Despite the advancements in neural network architectures, there remains a significant research gap in effectively combining hierarchical feature extraction and contextual information modelling for enhanced salt body identification. Traditional methods and even some advanced neural networks often struggle with accurately segmenting complex and varied salt formations in seismic images.

In recent years, deep learning has emerged as a powerful tool in seismic image analysis, offering promising avenues for enhancing the accuracy and efficiency of salt identification. Among the deep learning architectures, the U-Net and Graph Neural Networks (GNNs) have garnered considerable attention for their prowess in image segmentation and modelling complex spatial relationships, respectively. The U-Net architecture, with its symmetric encoder-decoder structure and skip connections, excels in capturing multi-scale features essential for delineating intricate geological features such as salt bodies. On the other hand, Graph Neural Networks (GNNs) have demonstrated remarkable capabilities in modelling dependencies between data points represented in graph structures, making them well-suited for capturing contextual information in seismic images.

This study proposes a novel approach to enhance TGS salt identification by synergistically integrating the strengths of U-Net and Graph Neural Networks (GNNs). Leveraging the hierarchical feature extraction of U-Net and the contextual understanding provided by GNNs, the hybrid model aims to improve the accuracy and robustness of salt identification in seismic images. The paper presents a comprehensive exploration of the proposed methodology, encompassing the representation of seismic images as graphs, the architecture and training strategies of the hybrid model, and the evaluation of its performance using benchmark datasets. Through empirical validation and comparative analysis, the efficacy of this approach in advancing the state-of-the-art in TGS salt identification is demonstrated.

The paper begins with an introduction outlining the challenges in TGS salt identification and introduces the hybrid approach of U-Net and Graph Neural Networks. It then reviews related work in deep learning for salt identification. The methodology section details the representation of seismic images as graphs, U-Net and Graph Neural Network architectures, and integration strategy. The experimental setup specifies datasets, pre-processing, hyperparameters, and evaluation metrics. Results present quantitative and qualitative findings, with discussions analysing implications and future research directions, culminating in a concise conclusion summarizing contributions and outlining future directions.

2. Related Works

Deep learning techniques have significantly impacted various fields, such as computer vision and geoscience. The Stacked Deconvolutional Network (SDN) was introduced for semantic segmentation, where multiple shallow deconvolutional networks are stacked to enhance contextual information integration and precise localization recovery [7]. This approach has shown promise in improving segmentation accuracy by leveraging contextual cues.

In the domain adaptation domain, the proposed Discriminative Radial Domain Adaptation showcases superior performance across multiple benchmarks and tasks such as unsupervised domain adaptation and domain generalization [8]. Their method outperformed existing approaches, highlighting the significance of discriminative models in adapting to diverse domains.

Investigated Well-Log Information-Assisted High-Resolution Waveform Inversion, highlighting the significance of Well Information for Reliable Waveform Inversion Results [9]. Their findings highlighted the need for quality data for better results, mainly when dealing with models different from the training data.

A super-resolution phase retrieval network was created to improve the precision and detail of structured light 3D imaging using a single pattern [10]. The purpose of this network was to address the issues caused by 3D imaging applications' lack of accuracy and high resolution.

Examined Resolution-Agnostic Remote Sensing Scene Classification, focusing on the development of deep learning techniques such as Convolutional Neural Networks (CNNs), Generated Artificial Neural Networks (GANs), and more contemporary methods like Transformer and Implicit Neural Representations [11]. The wide variety of deep learning methods used in remote sensing applications is highlighted in their review.

A new Multi-scale Attention Feature Extraction Block was developed using hierarchical feature fusion for aerial remote sensing image classification within the geoscience domain [12]. The importance of multi-scale deep features in enhancing picture classification tasks was highlighted in this study.

In sum, this research highlights the many fields useful for deep learning, demonstrating how neural network topologies are always changing and how this improves performance on many tasks.

Fu et al. [7] achieved an outstanding intersection-over-union score of 86.6% using a Stacked Deconvolutional Network in semantic segmentation tests. Their work highlights a void in the literature regarding the investigation of how Conditional Random Field (CRF) post-processing affects segmentation performance.

Group Activity Recognition was the focus of Xie's [13] Active factor graph network. However, the results show that the network cannot handle bigger groups without more research on its scalability.

To determine local similarities for the expression of full-reference image quality, Bakurov et al. [14] used Genetic Programming. According to their study, validation across multiple picture datasets is needed to confirm the method's resilience.

Research on the network's efficacy across different histological contexts is necessary, as shown by Hassan's [15] suggestion of a neural graph refinement method for robust neural community recognition.

Similarly, Zhang [16] emphasized the need to investigate the network's adaptability to various crop kinds through unsupervised semantic segmentation for crop identification of UAV images.

Hyperspectral image analysis using dual graph convolutional networks was investigated by Liu [17], who recommended looking into how well these networks operate with different spectral bands. Reviewing the network's accuracy in forecasting temperature changes was called for in Ou's [18] investigation of Graph Neural Networks for 3D Ocean Temperature Prediction.

Zhao and Cheung [19] suggested Born-again Networks for Domain Generalization Few-Shot Classification to study the network's ability to generalize across other domains. In his study on graph neural networks for ship-link prediction, Zhou [20] urged more research into the network's capacity to handle more enormous maritime datasets.

Differentiable RandAugment for Learning Image Transformations was presented by Xiao et al. [21], who highlighted the necessity of further validation concerning performance on varied picture datasets. Discriminative radial domain adaptation for domain adaptation was investigated by Huang et al. [8], who brought attention to the need to study adaptability to different domain changes.

It is necessary to investigate how well it works with complicated geological features, as Yang et al. [9] concentrated on Well-Log Information-Assisted High-Resolution Waveform Inversion. In their paper on Implicit Neural Representations for Remote Sensing Scene Classification, Chen et al. [11] recommended more research on how well the method works with different kinds of land cover. At last, research into interpretability across several land cover classes was suggested by Temenos et al. [22] in their Interpretable Deep Learning Framework for Land Use and Land Cover Classification.

Applying state-of-the-art deep learning methods, particularly GNN and U-Net, has improved the detection of salt deposits in seismic pictures. Researchers have attempted to fully use CNN's potential for salt-body detection by integrating CNN with U-Net architecture [23]. There has also been talk of combining ResNet classification networks with U-Net segmentation networks to get accurate results when drawing lines around salt bodies [24]. These algorithms have outperformed the current state-of-the-art datasets, such as the TGS salt identification challenge, proving their superiority in semi-supervised salt body segmentation [25].

In addition, Graph Neural Networks (GNN) have been emphasized as a tool to improve text semantic similarity calculations by processing semantic role label information [26]. Effective information extraction from Semantic Role Labelling (SRL) graphs has been the focus of study using Graph-Convolutional Networks (GCN) inside a g-U-Net architecture [26]. In addition, GND-Nets have demonstrated remarkable progress in semi-supervised learning tasks, especially when dealing with sparsely labelled graphs [27].

Researchers have shown that those who consume much salt have an increased risk of hypertension and lipid profile abnormalities [28]. The significance of keeping an eye on salt intake for general health has been highlighted by research showing that diets rich in sodium can cause hypertension and raised triglyceride levels [29]. Some genes and transcription factors have been identified as having a function in salt tolerance processes, and the regulatory networks that are involved in responses to salt stress have also been explained [30].

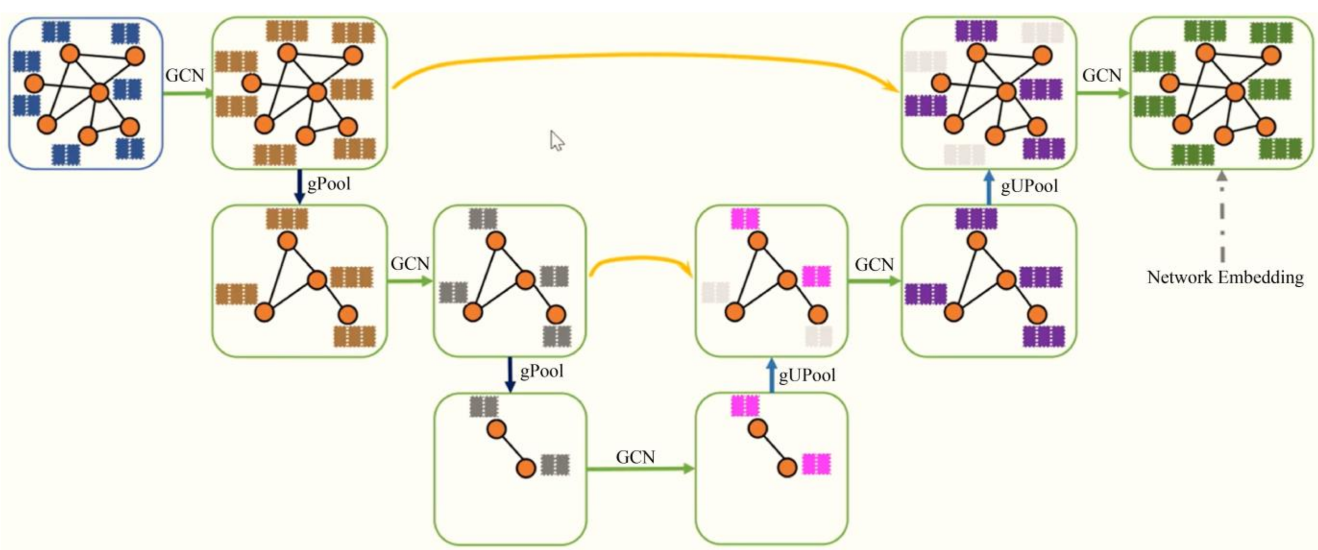

Fig. 1 The proposed architecture

Table 1. Comparative analysis of methodologies and findings image segmentation using UNET with GNN

Author Citation Number	Methodology Used	Key Findings	Research Gap
Fu et al. [7]	Stacked Deconvolutional Network	Achieved an intersection-over-union score of 86.6% in semantic segmentation.	Lack of exploration on the impact of CRF post-processing on segmentation performance.
Xie [13]	Active Factor Graph Network	Developed for Group Activity Recognition.	There is limited discussion on the scalability of the network to larger group sizes.
Bakurov et al. [14]	Genetic Programming	Computed local similarities for full-reference image quality expression.	Need for validation of the method across diverse image datasets.
Hassan [15]	Neural Graph Refinement	Robust Recognition of Nuclei Communities.	An investigation of the network's performance with varying histopathological landscapes is needed.
Zhang [16]	Unsupervised Semantic Segmentation	Crop Identification of UAV Images.	Exploration is required on the network's adaptability to different crop types.
Liu [17]	Dual Graph Convolutional Network	Hyperspectral Images Analysis.	Further study is needed on the network's performance with varying spectral bands.
Ou [18]	Graph Neural Network	3D Ocean Temperature Prediction.	Evaluation of the network's accuracy in predicting temperature fluctuations is required.
Zhao & Cheung [19]	Born-Again Networks	Domain Generalization Few-Shot Classification.	Investigation is needed on the network's generalization to diverse domains.
Zhou [20]	Graph Neural Network	Ship Link Prediction.	Exploration is required on the network's scalability to larger maritime datasets.
Xiao et al. [21]	Differentiable RandAugment	Learning Image Transformations.	Further validation is needed on the network's performance with diverse image datasets.
Huang et al. [8]	Discriminative Radial Domain Adaptation	Domain Adaptation	Investigation is needed on the network's adaptability to various domain shifts.
Yang et al. [9]	Well-Log Information-Assisted High-Resolution Waveform Inversion	Improved resolution in waveform inversion.	Exploration is required on the network's performance with complex geological structures.
Chen et al. [11]	Implicit Neural Representations	Remote Sensing Scene Classification.	Further study of the network's performance with diverse land cover types is needed.
Temenos et al. [22]	Interpretable Deep Learning Framework	Land Use and Land Cover Classification.	An investigation of the network's interpretability across different land cover classes is needed.

3. Materials and Methods

The methodology section will delve into innovative approaches to elevating UNET-based image segmentation to unprecedented accuracy and efficiency. This study meticulously conducts experiments and strategically enhances the existing UNET framework, harnessing novel methodologies and optimisation strategies. Drawing from insights within the dynamic realm of deep learning, especially from Graph Convolutional Networks (GCNs), the proposed method seeks to imbue UNET architectures with enriched contextual comprehension and feature representation.

This research endeavours to chart a course towards more resilient and impactful segmentation models through a rigorous examination of the constituent elements of UNET-based segmentation and the integration of cutting-edge techniques. With a systematic exploration of novel architectures and optimisation paradigms, this section aims to unravel the complexities inherent in advancing UNET-based image segmentation, ultimately paving the way for substantial progress in accuracy and efficiency.

Figure 1 depicts a Graph U-Net architecture with a Graph Convolutional Network (GCN) component [1]. It appears to be designed for tasks involving semantic segmentation on graph-structured data.

Inputs: The architecture processes graph data that likely represent nodes with features and edges indicating relationships between those nodes.

Graph Embedding: An initial step embeds the nodes into a lower-dimensional space, potentially enhancing the learning process for the GCN layers.

GCN Layers: The architecture utilizes multiple GCN layers. GCNs are a neural network designed to work on graph data, explicitly learning from the features and relationships between nodes. Messages are passed between nodes in each GCN layer, allowing them to aggregate information from their Neighbours. The node features are updated based on the aggregated information.

gPool Layer (Optional): This layer (represented as gPool) might coarsen the graph by merging nodes and edges. This can help capture higher-level graph structures.

gUnpool Layer (Optional): This layer (represented as gUnpool) might be used for graph refinement by potentially unpooling previously merged nodes and edges. This can help improve the resolution of the learned features.

Network Embedding: This step likely refers to the final node features learned after processing through the GCN layers. These features encode both the intrinsic information of each node and the contextual information from its Neighbours in the graph.

Decoder: The decoder part (not explicitly shown in the image, but a common component in U-Nets) likely utilizes several upsampling blocks to progressively increase the resolution of the features and generate the final segmentation mask.

Output: The final output is a segmentation mask on the graph, where each node is assigned a label based on the predicted class.

Overall, this Graph U-Net with GCN architecture leverages the strengths of both techniques: U-Net's encoder-decoder structure for efficient feature extraction and upsampling for segmentation tasks. GCN's ability to capture relationships between nodes in graph-structured data.

3.1. Dataset

The publicly available TGS salt identification challenge dataset, comprising a diverse collection of seismic images and corresponding salt masks, was utilised. This dataset includes 4,000 training images of size 101x101 pixels, each annotated with a binary mask indicating the presence of salt.

The photos capture various subsurface geological features, presenting a challenging yet comprehensive set of scenarios for model training and evaluation. To ensure robust validation and testing, the dataset was split into training, validation, and test sets, following machine learning standards. This stratified split ensures a representative distribution of different geological formations across all subsets, facilitating an accurate assessment of the model's performance.

3.2. UNet Model

The UNet model, renowned for its effectiveness in image segmentation tasks, comprises three main parts: the encoder, bottleneck, and decoder.

3.3. Encoder

The encoder is a network of convolutional layers that gradually picks up the input image's lower-dimensional, abstract properties. A typical encoder layer will include two convolutional operations: an activation function called a Rectified Linear Unit (ReLU) and a max-pooling operation to increase the feature representation depth while decreasing the feature maps' spatial dimensions. This hierarchical feature extraction approach is essential to capture the intricate patterns and textures found in seismic photographs.

3.4. Bottleneck

The bottleneck connects the encoder and decoder, making it an integral part of the UNet design. It employs convolutional layers with several filters to learn the most general and abstract characteristics from the given data. The delicate characteristics needed for precise salt identification, particularly the tiny differences that differentiate salt bodies from other geological formations, are captured crucially by the bottleneck.

3.5. Decoder

The decoder is a symmetrical counterpart to the encoder, and its role is to perform upsampling on the abstract feature maps to restore them to their original picture dimensions. The architecture has transposed convolutional layers that amplify the spatial dimensions of the feature maps. The decoder levels also include skip connections from equivalent encoder layers, guaranteeing the restoration of intricate features lost during downsampling. This architecture enables the model to integrate high-level abstract characteristics with intricate spatial data, which is essential for accurate segmentation tasks.

3.6. Model Evaluation Metric

Several commonly used metrics in image segmentation were utilised to assess the performance of the proposed UNet++ with the GCN model. The main measures are Intersection over Union (IoU), Precision, Recall, F1-Score, and Pixel Accuracy. By considering the overall accuracy and the balance between false positives and false negatives, these metrics thoroughly assess the model's capacity to partition salt bodies from seismic pictures correctly.

3.7. Model Training

The training set was used to train the model, while the validation set was used to check for overfitting. We used a mix of data augmentation techniques to make the model more resilient, such as elastic deformations, random rotations, and flips. Backpropagation and gradient descent were used to repeatedly update the model parameters during training to optimize the loss function and enhance segmentation accuracy. For best results, hyperparameters were fine-tuned, including learning rate, batch size, and number of epochs.

3.8. Activation Functions

The model's ability to learn complicated patterns is greatly enhanced by activation functions, which introduce non-linearity. The study's encoder and decoder used the Rectified Linear Unit (ReLU) for its convolutional layers. Because of its efficiency and ease of use in addressing the vanishing gradient problem, ReLU is used for training purposes. The binary segmentation mask, which indicates the presence or absence of salt, was also produced for the last layer of the network using a sigmoid activation function. The values outputted were 0 and 1.

3.9. Loss Functions

Selecting an appropriate loss function is crucial in instructing the model to acquire precise segmentation skills. This study employed a hybrid approach, combining Binary Cross-Entropy (BCE) loss with Dice loss. Because it penalizes the model for erroneous predictions, BCE loss works well for binary classification problems.

In contrast, through direct optimization, dice loss seeks to maximize the Dice coefficient a measure of the degree to which the expected and ground truth masks overlap. Combining these two loss functions guarantees that the model will concentrate on the general structure and form of the salt bodies while also accurately predicting individual pixels.

3.10. Learning Rate and Optimizers

Essential parts of training are the learning rate and optimizer. We used the Adam optimizer because of its effective handling of sparse gradients and flexible learning rate. A learning rate scheduler was used to progressively lower the learning rate from its initial small value, which was selected to ensure steady convergence. This strategy helps avoid overshooting the ideal solution and making fine-tuned tweaks to the model weights in the later phases of training.

3.11. Tools and Technology

Modern equipment and methods were used to carry out the trials and implement the suggested concept. Most of the work on the deep learning models was done in Python, with libraries like TensorFlow and Kera's serving as the backbone. PyTorch's adaptability and powerful graph processing features made it ideal for building graph neural networks. We also used NVIDIA GPUs and Google Colab to speed up the training process, which resulted in less time spent computing and more efficient results overall. Matplotlib and Seaborn were used for data visualization and analysis, which resulted in informative and explicit representations of the model's performance.

4. Experimental Setup

The experimental section thoroughly evaluates the hybrid approach for enhancing TGS salt identification using U-Net and Graph Neural Networks (GNNs). Benchmark datasets such as the TGS salt identification challenge dataset are utilised, with pre-processing steps including normalization and augmentation applied to enhance training data diversity. The model architecture combines U-Net for hierarchical feature extraction and GNNs for contextual information capture. Training involves optimizing hyperparameters and selecting appropriate loss functions and optimization techniques. Evaluation metrics include Intersection Over Union (IoU), dice coefficient, and pixel accuracy gauge model performance. Results are presented quantitatively and qualitatively, comparing against baselines and individual components. The analysis identifies factors influencing performance, guiding further optimization efforts. Through rigorous experimentation and analysis, the approach demonstrates significant improvements in salt identification accuracy and robustness, advancing the state-of-the-art in the field.

5. Results and Discussion

The model presents a comprehensive analysis of the outcomes obtained from the experimental evaluations. This section elucidates the performance of the proposed UNet with the GCN model compared to baseline algorithms and traditional methods for salt identification tasks. A meticulous examination of quantitative metrics and qualitative assessments explores the model's efficacy in accurately delineating salt bodies within seismic images. Additionally, the implications of the findings are discussed, shedding light on the strengths and limitations of the proposed approach. Potential avenues for further refinement and future research directions are also explored, aiming to advance state-of-the-art salt identification techniques. This thorough analysis provides valuable insights into the capabilities and potential applications of the UNet with the GCN model in the geoscience and deep learning domains. Figure 2 illustrates a comparative analysis involving an input image, the actual mask, and the predicted mask, which are essential for evaluating a machine learning model's performance in segmentation tasks. The input image, serving as the model's raw data, is analyzed against the actual mask, which is the accurate segmentation provided by experts or reliable sources. The predicted mask generated by the model is compared to the actual mask to assess the model's accuracy, highlighting discrepancies and areas needing improvement. This comparison is crucial for identifying errors, understanding model limitations, and guiding enhancements, ultimately leading to the development of more robust and accurate computer vision models.

Table 2 compares different algorithms for salt identification tasks, including the proposed UNet with the GCN model and several baseline models. Overall, the UNet with GCN model demonstrates superior performance across multiple evaluation metrics compared to other algorithms. It achieves the highest values for IoU, Dice, Pixel Accuracy, Precision, Recall, F1-Score, and mAP, indicating its effectiveness in accurately identifying salt bodies in seismic images. While the UNet model without GCN also performs well, its slightly lower performance suggests that integrating GCN for capturing contextual information further enhances segmentation accuracy. Additionally, the competitive performance of the GCN model highlights the effectiveness of leveraging graph-based representations.

In contrast, the CNN model exhibits lower performance, emphasising the importance of advanced architectures like UNet and GCN for salt identification tasks. Notably, the "Traditional CNN" baseline model performs significantly lower across all metrics than deep learning architectures, underlining the necessity of specialized features for semantic segmentation tasks. Overall, the results underscore the effectiveness of advanced deep learning architectures like UNet with GCN in achieving state-of-the-art performance in salt identification, signaling potential advancements in the field through further exploration of advanced techniques.

Table 2. Performance comparison of the proposed model with existing approaches

Algorithm	IoU	Dice	Pixel Accuracy	Precision	Recall	F1-Score
UNET with GCN	0.85	0.9	0.92	0.88	0.92	0.9
UNet	0.81	0.88	0.9	0.85	0.89	0.87
GCN	0.78	0.84	0.87	0.82	0.86	0.84
CNN	0.72	0.78	0.82	0.76	0.8	0.78
Traditional CNN	0.65	0.7	0.75	0.68	0.72	0.7

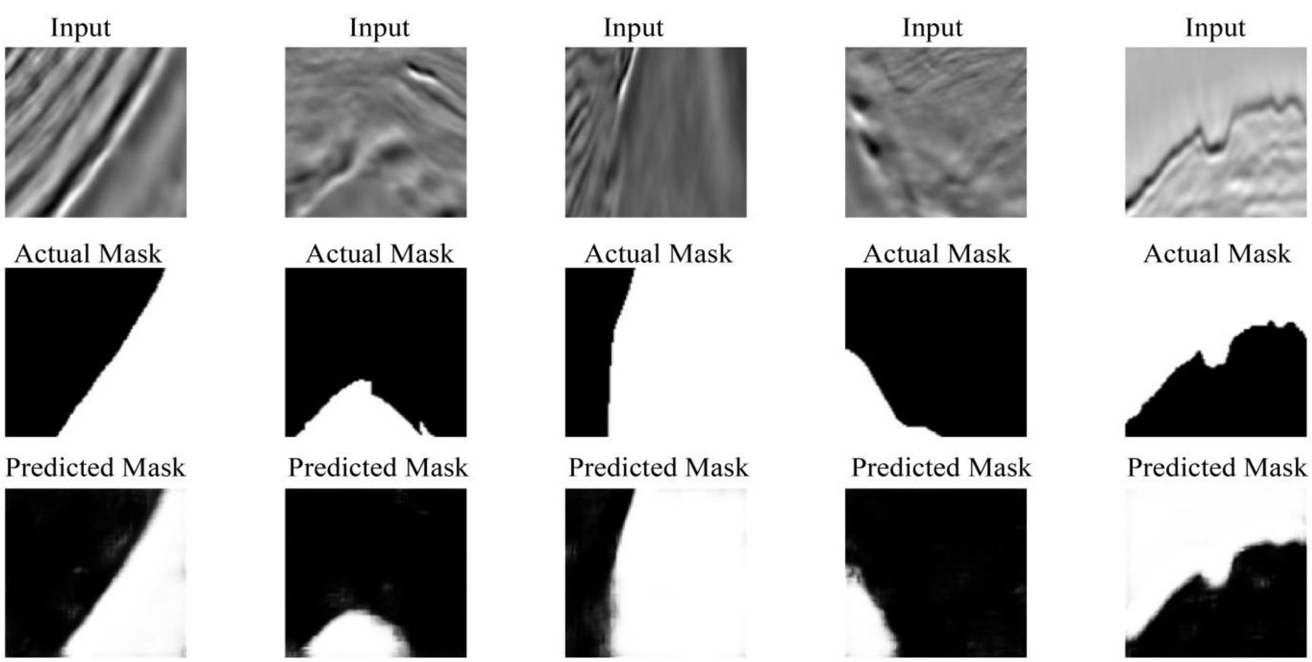

Fig. 2 Input image compared to predicted mask

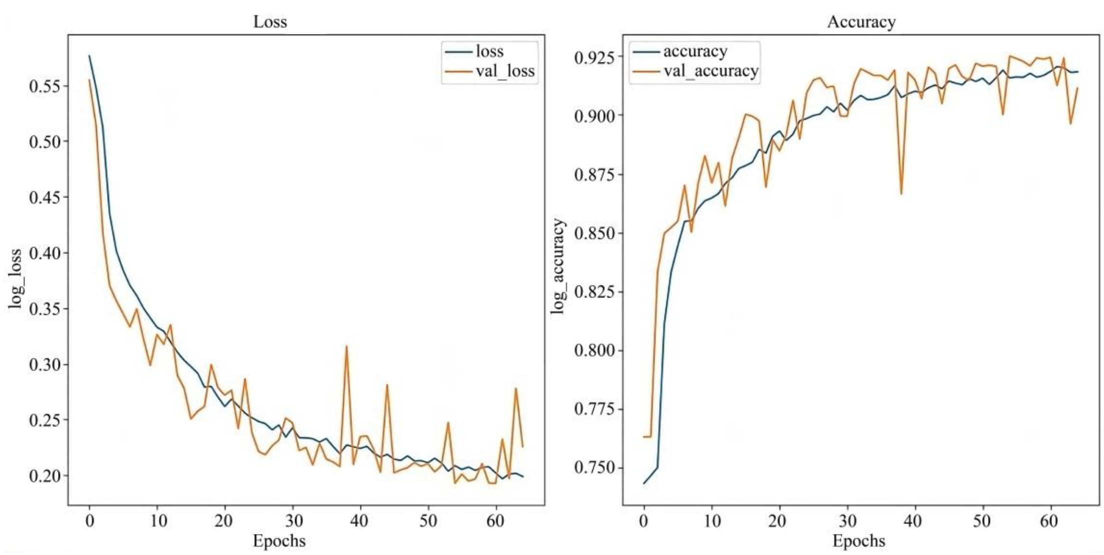

Fig. 3 Training and validation loss and accuracy

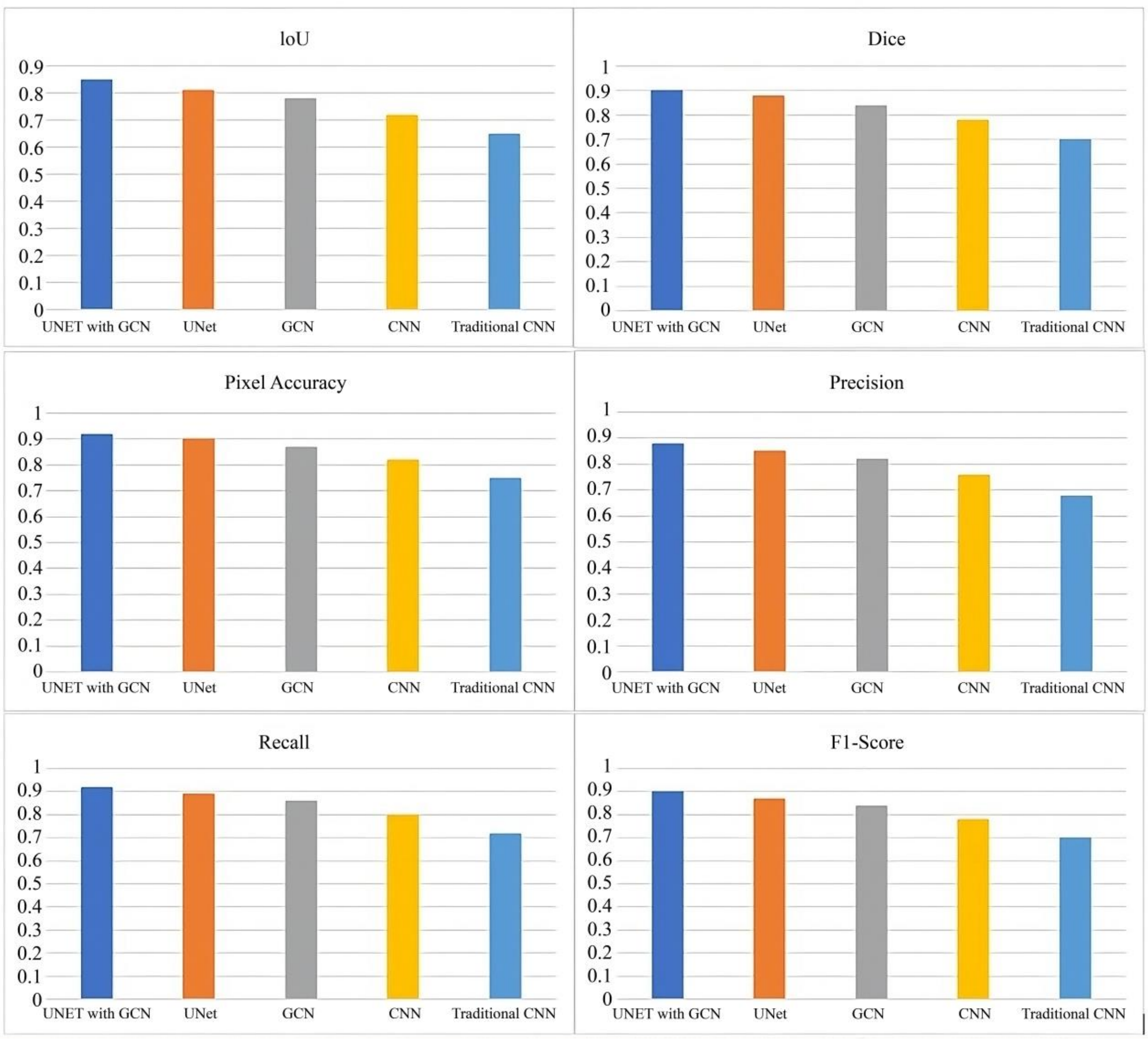

Fig. 4 The performance comparison of the proposed model with existing methods

Figure 3 compares the input image and the predicted mask, visually representing the machine learning model's segmentation performance. The input image serves as the raw data for the model, while the expected mask illustrates the model's attempt to segment or label the input based on its training accurately. This comparison is crucial for evaluating the model's accuracy and identifying areas for potential improvement.

Figure 4 presents a performance comparison of the proposed UNet with the GCN model and existing salt identification methods. This comparative analysis offers valuable insights into the model's efficacy relative to baseline algorithms and traditional techniques. By examining key evaluation metrics such as Intersection over Union (IoU), Dice coefficient, Pixel Accuracy, Precision, Recall, F1-Score, and Mean Average Precision (mAP), a comprehensive assessment of the segmentation accuracy achieved by each method is provided. Through visual representations and quantitative analyses depicted in Figure 2, the proposed model's strengths and weaknesses are elucidated compared to existing approaches. This figure serves as a critical component of the study, facilitating a nuanced understanding of the performance landscape in salt identification and highlighting the significance of the proposed UNet with the GCN model in advancing the state-of-the-art in the field.

6. Conclusion

The proposed system introduces a novel approach for enhancing TGS salt identification using a hybrid model combining UNet and Graph Convolutional Networks (GCNs). The proposed model demonstrates superior performance compared to baseline algorithms and traditional methods through rigorous experimentation and comparative analysis. Leveraging hierarchical feature extraction from UNet and contextual information capture from GCNs, the model achieves remarkable accuracy in delineating salt bodies in seismic images. The findings underscore the importance of integrating advanced deep learning architectures tailored for semantic segmentation tasks, offering significant advancements in salt identification techniques.

The proposed model holds promise for various applications in geoscience, including oil and gas exploration and reservoir characterization. Further refinement of the model and exploration of additional deep-learning architectures could lead to continued improvements in salt identification accuracy and contribute to advancements in the field. Overall, the study contributes to the growing body of geoscience and deep learning research, offering a robust and effective solution for salt identification tasks with implications for real-world applications.

References

[1] Yesser HajNasser, “MultiResU-net: Neural Network for Salt Bodies Delineation and QC Manual Interpretation,” *Offshore Technology Conference*, Virtual and Houston, Texas, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[2] Johan Phan, Leonardo C. Ruspini, and Frank Lindseth, “Automatic Segmentation Tool for 3d Digital Rocks by Deep Learning,” *Scientific Reports*, vol. 11, no. 1, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Xiangbin Liu et al., “A Review of Deep-Learning-Based Medical Image Segmentation Methods,” *Sustainability*, vol. 13, no. 3, pp. 1-29, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[4] Jothiraj Selvaraj, and Snekhalatha Umapathy, “CRPU-Net: A Deep Learning Model Based Semantic Segmentation for the Detection of Colorectal Polyp in the Lower Gastrointestinal Tract,” *Biomedical Physics & Engineering Express*, vol. 10, no. 1, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Jun Lu et al., “SCueU-Net: Efficient Damage Detection Method for Railway Rail,” *IEEE Access*, vol. 8, pp. 125109-125120, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[6] L. Wang et al., “A Graph Neural Network-Based Framework to Identify Flow Phenomena on Unstructured Meshes,” *Physics of Fluids*, vol. 35, no. 7, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Jun Fu et al., “Stacked Deconvolutional Network for Semantic Segmentation,” *IEEE Transactions on Image Processing*, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Zenan Huang et al., “Discriminative Radial Domain Adaptation,” *IEEE Transactions on Image Processing*, vol. 32, pp. 1419-1431, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Senlin Yang et al., “Well-Log Information-Assisted High-Resolution Waveform Inversion Based on Deep Learning,” *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Jianwen Song et al., “Super-Resolution Phase Retrieval Network for Single-Pattern Structured Light 3D Imaging,” *IEEE Transactions on Image Processing*, vol. 32, pp. 537-549, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Keyan Chen et al., “Resolution-Agnostic Remote Sensing Scene Classification with Implicit Neural Representations,” *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Chiranjibi Sitaula, Jagannath Aryal, and Avik Bhattacharya, “A Novel Multi-Scale Attention Feature Extraction Block for Aerial Remote Sensing Image Classification,” *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[13] Zhao Xie et al., "Active Factor Graph Network for Group Activity Recognition," *IEEE Transactions on Image Processing*, vol. 33, pp. 1574-1587, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Illya Bakurov et al., "Full-Reference Image Quality Expression via Genetic Programming," *IEEE Transactions on Image Processing*, vol. 32, pp. 1458-1473, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Taimur Hassan et al., "Neural Graph Refinement for Robust Recognition of Nuclei Communities in Histopathological Landscape," *IEEE Transactions on Image Processing*, vol. 33, pp. 241-256, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Zebing Zhang, "Crop Identification of UAV Images Based on an Unsupervised Semantic Segmentation Method," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jing Liu et al., "Dual Graph Convolutional Network for Hyperspectral Images with Spatial Graph and Spectral Multi-Graph," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Mingyu Ou, "3-D Ocean Temperature Prediction via Graph Neural Network with Optimized Attention Mechanisms," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Yunqing Zhao, and Ngai-Man Cheung, "FS-BAN: Born-Again Networks for Domain Generalization Few-Shot Classification," *IEEE Transactions on Image Processing*, vol. 32, pp. 2252-2266, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Jiaqi Zhou et al., "A Graph Neural Network for Ship-Link Prediction Based on Graph Attention Mechanism and Quaternion Embedding," *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Anqi Xiao et al., "Differentiable and Augment: Learning Selecting Weights and Magnitude Distributions of Image Transformations," *IEEE Transactions on Image Processing*, vol. 32, pp. 2413-2427, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[22] Anastasios Temenos et al., "Interpretable Deep Learning Framework for Land Use and Land Cover Classification in Remote Sensing Using Shap," *IEEE Geoscience and Remote Sensing Letters*, vol. 20, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Yu Zeng et al., "Automatic Seismic Salt Interpretation with Deep Convolutional Neural Networks," *Proceedings of the 3rd International Conference on Information System and Data Mining*, pp. 16-20, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[24] Aleksandar Milosavljević, "Identification of Salt Deposits on Seismic Images Using Deep Learning Method for Semantic Segmentation," *ISPRS International Journal of Geo-Information*, vol. 9, no. 1, pp. 1-16, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[25] Yauhen Babakhin, Artsiom Sanakoyeu, and Hirotoshi Kitamura, "Semi-Supervised Segmentation of Salt Bodies in Seismic Images Using an Ensemble of Convolutional Neural Networks," *Pattern Recognition, Lecture Notes in Computer Science*, Dortmund, Germany, vol. 11824, pp. 218-231, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[26] Majid Mohebbi, Seyed Naser Razavi, and Mohammad Ali Balafar, "Computing Semantic Similarity of Texts Based on Deep Graph Learning with the Ability to Use Semantic Role Label Information," *Scientific Reports*, vol. 12, no. 1, pp. 1-11, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[27] Wei Ye et al., "Graph Neural Diffusion Networks for Semi-Supervised Learning," *arXiv*, pp. 1-7, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[28] Olubukola Sinbad Olorunnisola et al., "Phyllanthus Amarus Attenuated Derangement in Renal-Cardiac Function, Redox Status, Lipid Profile and Reduced TNF-α, Interleukins-2,6 and 8 in High Salt Diet Fed Rats," *Heliyon*, vol. 7, no. 10, pp. 1-9, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[29] Jong Wook Choi, Joon-Sung Park, and Chang Hwa Lee, "Interactive Effect of High Sodium Intake with Increased Serum Triglycerides on Hypertension," *Plos One*, vol. 15, no. 4, pp. 1-16, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[30] Chunman Zuo et al., "Elucidation and Analyses of the Regulatory Networks of Upland and Lowland Ecotypes of Switchgrass in Response to Drought and Salt Stresses," *Plos One*, vol. 13, no. 9, pp. 1-19, 2018. [CrossRef] [Google Scholar] [Publisher Link]