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Salt Segmentation Using UNET

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ABSTRACT:

Salt classification is an important task in image analysis and plays an important role in many applications such as geological exploration, autonomous vehicles and medical imaging. Salt segmentation methods often fail to clearly identify salt bodies in images, especially in difficult cases. In recent years, deep learning has revolutionized image segmentation, and the UNet architecture has become an effective tool to solve this problem. This project performs a general study of salt partitioning using the UNet convolutional neural network. UNet is a popular choice for medical image segmentation tasks, known for its ability to capture fine points and provide boundary objects. The aim of this study is twofold: to develop and train the UNet model for salt separation and to evaluate its performance on various data and scenarios. The approach includes preliminary data, design, and extensive training and evaluation phases. A large database of recorded salt images is used to train and improve the UNet model. The performance of this model is evaluated by measuring the model such as Competition over Union , Dice coefficient and pixel accuracy.The results show that UNet based on the salt segmentation model achieves greater accuracy and performance than traditional methods. In addition, the model is resistant to noise, changes in light conditions and different geological formations.

INTRODUCTION :

Image segmentation, the process of dividing images into useful regions, is an important task in computer vision, with many applications ranging from medical applications to geological exploration and autonomous navigation systems. In many of these applications, it is important to detail specific objects or areas in the image. One of the most difficult and important tasks is salt classification; The aim here is to accurately identify and display salt in the ground in seismic and geological images. Salt deposits are important geological structures in terms of hydrocarbon exploration, geological studies and environmental assessment due to their unique physical properties. Traditional salt partitioning methods, including manual identification and control methods, often fail to capture the complex shape and boundaries of salt bodies. These limitations support the need for advanced techniques that can address the complexity and nuances of salt segmentation with high precision. In recent years, deep learning has made great progress in image segmentation tasks, promising to provide efficient and practical solutions. Among many deep learning methods, the U-Net model has become a powerful tool to solve image segmentation challenges as it can preserve fine details and provide accurate object boundaries. With its unique encoder-decoder structure, the U-Net architecture has proven effective in many medical and non-medical segmentation applications. This project is a comprehensive investigation of salt distribution using the U-Net architecture to solve the problems and limitations of traditional methods while using the capabilities of deep learning. The main aim of this work is to develop a custom U-Net model for salt classification, train it on a large and diverse dataset of salt images, and evaluate its good performance in many situations around the world. Through this effort, we aim to demonstrate the effectiveness of U-Net-based salt segmentation as a state-of-the-art solution to accurately identify and depict salt deposits in photography. The project's findings not only contribute to computer vision studies, but also have the potential to change the way salt deposits and properties are found in geological and geophysical surveys, impacting many business and scientific disciplines. This research brings us one step closer to automatic, precise and powerful partitioning of salt, meeting the need for advanced tools to better understand the Earth's subsurface and support important decision-making.

LITERATURE REVIEW :

Xu Zhifeng; Li Kewen; Ma Chengjie; Feng Deyong; East Yimin; and Yin Ruonan pointed out that the salt body is an important water system, and stated that it is still difficult to interpret the salt body end-to-end from three-dimensional seismic data. It is always difficult for semi-supervised learning to obtain good pseudo labels in the initial stage, which affects the subsequent processing model. In addition, background noise complicates the accuracy of salt mass estimation, and the strategy of feeding training blocks slowly makes the results ambiguous and confusing. To solve these problems and obtain the accurate subsurface salt profile, we propose a new, fully automatic, improved 3D salt interpretation method called 3D Salt-HSM. In this way, we develop a hybrid semi-supervised training paradigm based on fixed pseudo-labels and multilevel inequality. This approach allows us to obtain good pseudo-labels of salt bodies and search for their properties in unlabeled blocks. These models enable the network to obtain global data from seismic images and help interpret salt quality. In our experiments on the SEAM and F3 seismic datasets, we used only 3% of the labels for supervised learning, while the remaining data were used for unsupervised learning and validation.

Arsha PV; Presented by Pillai Praveen Thulasidharan Salt body exploration has been an important area of research in fields related to geophysics and seismic interpretation due to its importance in the oil and gas industry. With the developments in machine learning in recent years; Deep learning models are used to identify and segment salt bodies from seismic images. This paper presents a deep neural network model with segmentation capabilities to detect and classify salt deposits in seismic images. The model accepts seismic images as input, which must be divided into pixels, and produces annotated images to clearly show fragmented salt zones. The model was trained and tested using the seismic image dataset provided by Kaggle. The results obtained were compared with the CNN model known in the field, and experimental results showed that the proposed model was better.

Mustafa Alfahan; Muhammed Deriş; Ahmed Maalej suggested that translating seismotectonic tools into the reality of oil and gas reservoirs is a difficult task. After training and expertise, seismic interpreters learn to accurately identify ground structures; This is difficult and time consuming. In this paper, we propose a new semantic segmentation model to identify salt domes and faults in real synchronous scenarios, using a reliable encoder-decoder deep neural network to complement salt domes and fault research. We also present a learning pass to solve the problem of insufficient long-term seismic data collection and develop a good model whose performance is not affected by the consistency of various anomalies in the seismic data, the quality of the situation. We also use the remaining parts of deep neural networks to make them stronger. We conduct extensive validation experiments to demonstrate the validity of our model and test it on real published seismic data from the Dutch offshore F3 block, LANDMASS and TGS datasets. A thorough and comprehensive analysis is provided to ensure the best performance is achieved with our deep learning-based work in the complexity of many events in ground investigations.

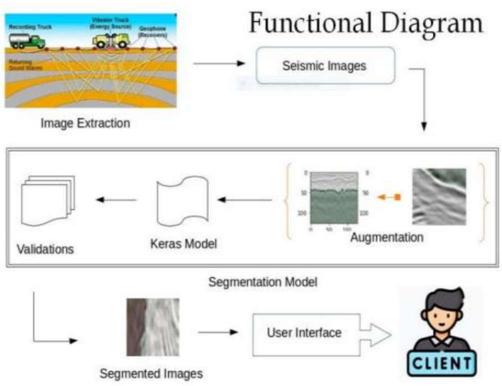
Lu Zhiyong; Zhong Pingdong; Wang Wei; You Zhenzhen; Nicola Falco said that when deep learning training is given without prior knowledge, learning is not satisfactory. In this paper, a multivariate neural network detection method based on transform gradient imaging (CGI) is proposed. First, multi-image information is integrated into the backbone of UNet to realize the multi-information fusion function of two-time images. Secondly, the location channel tracking module (PCAM) is proposed to enable the neural network to pay more attention to the spectral and spatial information in the multi-feature fusion map. Finally, modified gradient guidance module (CGGM) is proposed to improve the performance and eliminate the disadvantage of negative migration. Compared with seven state-of-the-art methods using three pairs of real remote sensing images, this method will smoothly detect salt and water noise in the images and definitely improve your knowledge. The quantitative improvement in overall accuracy (OA) and kappa coefficient are about 1.67% and 3.00%, respectively, which confirms the feasibility and superiority of the proposed method for checking land cover changes from remote sensing images. Program code: https://github.com/ImgSciGroup/MACGGNet.git.

PROPOSED SCHEM :

ProjectGoal: The main aim of the project is to detect and identify saltrich areas in seismic images. Additionally, the project aims to include all salt-related areas in these images.

Modules description and Functional Diagram

U-Net-based salt segmentation projects usually have several modules that control
various aspects of the segmentation process. This is the description of of the project, you can see the work of our project in the picture.



Data Preparation Module:

- **Data collection:** Collect seismic images and corresponding salt facies. This change includes obtaining information from relevant sources or creating your own information.

- **File advancement:** Resize images, normalize pixel values, and perform file enhancements to take advantage of files. Data preprocessing helps ensure that input data is suitable for training models..
- **Model Architecture:** Use UNet architecture using deep learning methods such as TensorFlow or PyTorch. Configure the encoderde coder model with the appropriate number of layers and filter
- **Loss function:**Defines learning parameters such as Dice coefficient, cross entropy or focus loss to measure the difference between predictio n and verbal accuracy.
- **Optimization:** Set up an optimization process using algorithms such as Adam or stochastic gradient descent (SGD). Configure learning rate and other hyperparameters for effective learning.

Training Module:

- **Data Splitting:** Split the dataset into training, validation, and test sets. This module manages the division of data for model training and evaluation.
- **Model Training:** Train the U-Net model on the training dataset. Monitor and log training progress, including loss, accuracy, and other relevant metrics.
- **Hyperparameter Tuning:** Fine-tune model hyperparameters and architecture to optimize performance. This module aims to improve the model's ability to accurately segment salt bodies.
- **Model Evaluation:** Evaluate the trained model's performance using metrics such as Intersection over Union (IoU), F1 score, accuracy, and loss on the validation dataset. This module helps assess the model's ralization capability.
- **Early Stopping:** Implement early stopping to prevent overfitting and save the best model checkpoint based on validation performance.
- **Testing Module:** Use the trained model to segment salt bodies in a separate test dataset. Measure and report the model's accuracy and segmentation results in this module.

Post-processing Module:

Morphological Operations: Use postprocessing techniques such as dilation, erosion, and component analysis to optimize segmentation masks. This module is designed to improve segmentation quality and reduce noise.

Visualization Module:

- **Result Visualization**: Develop tools to visualize the original seismic images, ground truth, and model-generated segmentation masks for qualitative analysis. Visualization is essential for understanding the model's performance.
- **Deployment Module:** Model Deployment: If necessary, deploy the trained model in a deployment environment, such as a web application, using web frameworks like Flask or Django.
- **System Maintenance:** regularly maintains and updates systems to incorporate improvements, resolve issues, and introduce new functionality.
- **Real-World Testing:** A comprehensive and practical test using real seismic data to ensure the system meets the specifications of geological or geophysical investigations. Together, these models form a working framework that supports efficient model design, training, evaluation, and deployment for U-Net based salt segmentation projects. Customize and tailor this template to your project's specific needs and constraints.

SAMPLE OUTPUT :

Raw seismic data includes measurements not made by seismometers that detect ground motion during seismic events. It includes amplitude, frequency and noise and is essential for seismic analysis and survey as well as salt segmentation and identification. You can see the results in the picture.

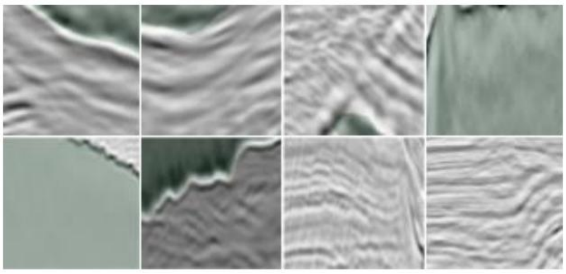


Figure: raw seismic data

Augmented Data:

Developmental data are continuous data created by introducing changes or modifications to existing data. These changes may include adding noise, rotating images, or creating new patterns through processes such as data binding or aggregation. Augmented data is often used in machine learning to improve model performance, increase diversity, and reduce competition, ultimately improving the model's ability to generalize to new information. You can see the results in the picture.

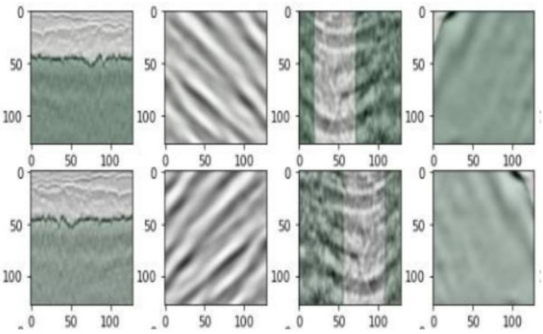


Figure: augmented data

Segmented Data :

Segmented data is data that is divided into different chunks or chunks based on certain patterns or characteristics. Each chapter contains similar or related topics that allow analysis of a particular aspect of larger data. Segmentation can help identify patterns, trends, or inconsistencies in data and is often used in marketing, customer analysis, and other research to gain insight into pressure from specific groups or groups of data. You can see the results in the picture

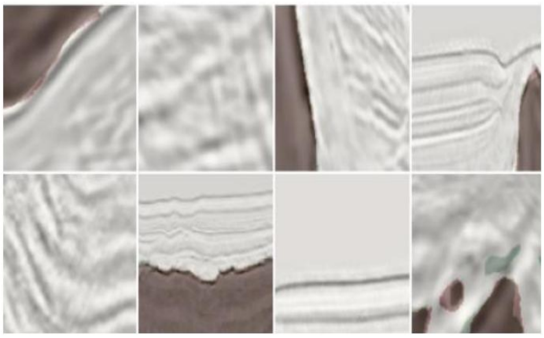


Figure: segmented data

RESULT & DISCUSSION :

CONCLUSION :

In summary, this project focuses on salt classification using the U-Net model, which provides a good and effective solution for the identification and description of salt deposits in seismic images. This project uses deep learning and U-Net architecture to solve problems associated with traditional segmentation techniques..

FUTURE ENHANCEMENT :

- **Improved Accuracy:** The U-Net model and its encoder-decoder model show the best results in classifying salt bodies, making it better than traditional methods. The model's ability to capture fine details and provide clear boundaries leads to more effective segmentation.
- **Prior Data**: Data preprocessing such as resizing, normalization and data augmentation are used to improve the quality of the training process and thus increase model performance.
- **Higher Order Loss Function:** This project supports accurate segmentation by using appropriate loss functions such as Dice coefficient and cross entropy to measure the difference between prediction and reality.

  Hyperparameter Tuning: Careful tuning of model hyperparameters and architecture has resulted in an optimized U-Net model, improving segmentation accuracy and reducing the risk of overfitting.
- **Real-World Testing:** The model has been rigorously tested with real seismic data, ensuring that it meets the specific requirements of geological exploration and geophysics, and it demonstrates its applicability in practical, real-world conditions.
- **Post-Processing:** Postprocessing techniques, including morphological operations, have been used to improve mask segmentation and improve results.

- **User-Friendly Interface:** A user-friendly visualization interface has been developed to facilitate easy interaction with the model, making it accessible to a broader audience. This project represents a significant advancement in the field of salt segmentation, offering a reliable, accurate, and user-friendly tool for geological exploration, geophysics, and related applications. The successful integration of deep learning, U-Net architecture, and best practices in data preprocessing and post-processing has resulted in a valuable asset for professionals in these domains, enabling more precise and efficient analysis of subsurface salt bodies.

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