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Enhancing Seismic Image Analysis: Segmentation-based Detection of Salt Deposits

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ABSTRACT

This study presents a cutting-edge deep convolution neural network (DCNN) segmenting seismic images for subsurface salt detection. Finding the location of the salt is crucial before beginning mining. Therefore, to pinpoint the precise location of salt below the surface of the earth, a seismic picture is used. It is challenging to pinpoint the precise position of salt deposits, though. Therefore, competent human comprehension of salt bodies is still required for professional seismic imaging. This results in renderings that are highly diverse and subjective. Therefore, we require a strong algorithm that can automatically and reliably determine if the surface of the object is salt or not in order to produce the most realistic seismic pictures and 3D renderings. Given DCNN's well-established and well-known performance for identifying objects in images, it is an excellent fit for this specific task and has been successfully utilized to a dataset of acoustic images where each pixel is labelled as either salt or not. This algorithm produces a promising result.

Keywords: Seismic Picture, Image Separation, DCNN, Auto Encoding

1. INTRODUCTION

Imaging the reflection originating from rock boundaries produces a seismic image. The boundaries between various rock types can be seen in the seismic image. Theoretically, the variation in the physical qualities on both sides of the interface directly relates to the strength of reflection. Seismic pictures are useful for identifying borders between rocks, but they don't provide much information about the actual rocks themselves. There are many places on Earth where the subsurface is covered in enormous amounts of salt. Finding the salt-containing portion of the subsurface is one of the difficulties with seismic imaging. On the other hand, from the standpoint of image processing, it is a picture fragmentation issue. The literature contains a wide range of reliable algorithms for this purpose, including physics-based, feature-space, and image-domain methods [1]. These methods have been effectively applied to digital camera colour picture segmentation. The most advanced methods fail at segmenting images because seismic images differ greatly from digital photos. The segmentation of seismic images presents numerous obstacles. Here is a list of a few of them:

1. Technique for taking images.
2. An uneven dispersion of rocks and salt.
3. A rock that is denser than salt.
4. A grayscale image alone indicates incomplete information.
5. irregular reflection is caused by the irregular structure of rocks beneath the surface of the ground.

To address this issue, though, a variety of cutting-edge machine learning strategies are available. For any image-related problem, the deep a convolution neural network technique is the most promising method found in the literature. Object recognition [2], picture segmentation [3], style translation [4], human activity detection [5], segmentation of medical imagery [6], and image denoising [7] are among the applications of this technology. Therefore, the approach has been applied to resolve the current issue. The following are the contributions made to this work:

1 segmented a seismic image using a cutting-edge DCNN to identify salt.
2. automated the seismic picture post-analysis.
3. decreased the price of the examination of seismic images.
4. loosened the requirement for human expertise for segmenting seismic images.

Section II surveys the literature; Section III describes our approach to solving the segmentation problem; Section IV presents the experimental findings of our method; and Section V finishes with a conclusion and suggestions for further work.

2. LITERATURE SURVEY

A essential problem for many computer vision, video analysis, and image processing applications is picture segmentation.

As a result, a large number of research articles have been written about it. The three procedures listed below can be used to group all of the suggested methods [1].

1) Techniques Based on Feature Space
2) Techniques Based on Image Domains
3) Techniques Based on Physics

A. Methods Based on Feature Space

This method assumes that the colour of every object's surface in a picture is a constant. Consequently, each pixel can be aggregated or clustered into a certain area inside the to create the segmented image. Two popular feature-space based approaches include clustering and histogram thresholds [1].

B. Methods Based on Image Domains

The global property of the image is the focus of the feature space-based algorithms, which meet the homogeneity criterion for image segmentation. Nevertheless, those methods disregard the image's spatial characteristics. Researchers discovered the picture domain-based method as a result. These methods simultaneously satisfy spatial compactness and feature-space homogeneity. Either by segmenting and combining picture regions or by gradually expanding image regions, the region's compactness is guaranteed, and the homogeneity is used as a guide to guide these two procedures. These algorithms are typically separated into split-and-merge and region-growing strategies based on the selected strategy for spatial grouping. Image domain-based techniques include neural-network-based classification, divide and merge utilizing region adjacency graph (RAG), and edge-based algorithms [1].

C. Physics Based Techniques

When highlights, shadowing, and shadows are present in the image, the approaches that have been discussed are vulnerable to segmentation errors. By taking into account how light interacts with coloured materials and including models of this physical relationship into the segmentation algorithms, the problem can be resolved. These methods are referred to be physics-based methods for this reason. The fundamental physical model created for the reflection's features of coloured matter is the main distinction between these two types of approaches and the mathematical tools employed in them [1].

3. SYSTEM ANALYSIS

A. EXISTING SYSTEM

Although the summary you gave gives a broad overview of the project and its goals, it doesn't go into specifics about how the deep convolutional neural net (DCNN) employed in the current system is implemented or built. Usually, you would need to consult the entire article, project manual, or source code to gain a deeper comprehension of the current system. The

"Methodology" or "implementing" portion of a project report or paper would normally go into great detail about the design, training, and evaluation of the DCNN. It would contain specifics such:

Architecture of the DCNN: The specific layers, nodes, and activation functions used in the neural network.

Training Process: Details on how the DCNN was trained using the seismic image dataset. Information on the loss function, optimization algorithm, and training parameters.

Evaluation Metrics: Metrics used to assess the performance of the DCNN, such as accuracy, precision, recall, F1 score, etc.

Dataset Details: Information about the seismic image dataset, including the size, diversity, and any preprocessing steps applied.

Results and Discussion: Specific results obtained from applying the DCNN to the seismic images

DISADVANTAGES OF THE EXISTING SYSTEM

Dataset Limitations: The performance of the deep convolutional neural network (DCNN) is highly dependent on the quality and diversity of the training dataset. If the dataset is limited in size or not representative of all possible scenarios, the model may struggle to generalize well to new, unseen data.

False Positives and False Negatives: Image segmentation models, including DCNNs, may produce false positives (misclassifying non-salt areas as salt) or false negatives (missing actual salt deposits). The balance between precision and recall is crucial, and achieving both high precision and high recall can be challenging.

Interpretable Results: Deep learning models, particularly complex ones like DCNNs, are often considered "black boxes" due to their complexity. Understanding why the model makes a specific prediction or which features it focuses on can be challenging, limiting the interpretability of the results.

Computational Complexity: Training and deploying deep learning models can be computationally intensive. If the existing system requires significant computational resources, it may limit its scalability or accessibility, especially in resource-constrained environments.

Generalization to Different Seismic Conditions: The model's ability to generalize across various geological and seismic conditions may be a limitation. If the model is trained on a specific type of seismic data, its performance may degrade when applied to data from different environments.

Robustness to Noise: Seismic images can be subject to noise and artifacts. The model's robustness to such noise may affect its performance. If the existing system is not robust to variations in the input data, it may produce less reliable results.

Dependency on Preprocessing Techniques: The abstract does not mention specific preprocessing techniques applied to the seismic images. Depending on the preprocessing steps, the model's sensitivity to these steps and the effectiveness of preprocessing in enhancing features could be a limitation.

B. PROPOSED SYSTEM

"In order to overcome the limitations of the existing salt detection system using seismic image segmentation, we propose an enhanced framework that leverages advanced techniques for improved accuracy and generalization. Our proposed system aims to address issues related to dataset limitations by incorporating transfer learning strategies, enabling the model to leverage knowledge gained from pre-trained neural networks on diverse datasets.

To enhance interpretability, we plan to integrate explainability methods, allowing users to better understand the model's decision-making process. Additionally, the proposed system will focus on refining the model's robustness to noise in seismic images through the integration of sophisticated preprocessing techniques. We also aim to introduce an ensemble learning approach to mitigate false positives and false negatives, promoting a more balanced trade-off between precision and recall. Furthermore, our proposed system will consider the scalability and efficiency of the solution, exploring optimizations to reduce computational complexity while maintaining or improving performance. By addressing these aspects, our proposed system strives to achieve a more robust, interpretable, and scalable solution for accurate salt detection in seismic images, contributing to advancements in mining exploration.".

ADVANTAGES OF THE PROPOSED SYSTEM

Improved Generalization with Transfer Learning: The incorporation of transfer learning techniques enhances the model's ability to generalize by leveraging knowledge from pre-trained neural networks on diverse datasets. This allows the system to adapt more effectively to different geological and seismic conditions, contributing to increased accuracy across varied scenarios.

Enhanced Interpretability through Explainability Methods: The integration of explainability methods provides users with insights into the decision-making process of the model. This increased transparency enables better understanding of how the system identifies salt deposits in seismic images, fostering trust in the model's predictions and facilitating easier interpretation of results.

Robustness to Noise with Advanced Preprocessing Techniques: The proposed system focuses on refining the model's robustness to noise in seismic images through the incorporation of advanced preprocessing techniques. This ensures that the model can effectively filter out irrelevant information and artifacts, leading to more reliable and accurate salt detection even in the presence of noise.

Balanced Precision and Recall with Ensemble Learning: The introduction of ensemble learning techniques aims to mitigate false positives and false negatives, striking a better balance between precision and recall. By combining multiple models, each trained with different aspects of the data, the proposed system is designed to improve the overall accuracy and reliability of salt detection results.

Scalability and Efficiency Optimization: The proposed system prioritizes scalability and efficiency by exploring optimizations to reduce computational complexity. This ensures that the model can be deployed in resource-constrained environments without compromising performance, making the salt detection solution more accessible and applicable across a broader range of scenarios.

4.SYSTEM DESIGN

SYSTEM ARCHITECTURE

Below diagram depicts the whole system architecture.

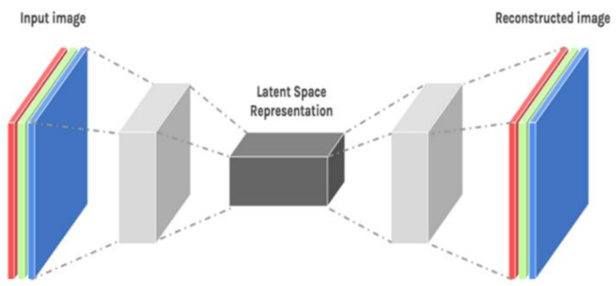

Fig 1. Methodology followed for proposed model

5. SYSTEM IMPLEMENTATION

MODULES

Data Preprocessing Module:

This module focuses on preparing and enhancing the seismic image data for effective model training and testing. It includes tasks such as data normalization, noise reduction, and feature extraction. The goal is to optimize the input data for the subsequent stages of the system, improving the overall robustness and quality of the model.

Transfer Learning Module:

The transfer learning module incorporates pre-trained neural network architectures, leveraging knowledge gained from large and diverse datasets. This module enables the system to extract relevant features from seismic images, enhancing the model's ability to generalize across different geological conditions. It facilitates efficient training even with limited labeled data specific to the target problem.

Model Training and Ensemble Learning Module:

This module involves the training of the deep convolutional neural network (DCNN) using the preprocessed data. Ensemble learning techniques are applied to combine multiple models, each trained with a unique perspective on the data. By integrating diverse models, the system aims to achieve a more robust and balanced salt detection algorithm, minimizing both false positives and false negatives.

Explainability Module:

The explainability module is responsible for incorporating techniques that enhance the interpretability of the model. It includes methods such as attention mechanisms or saliency maps, allowing users to understand which regions of the seismic images contribute most to the model's decisions. This transparency aids in building trust and facilitating the interpretation of results by domain experts.

Scalability and Optimization Module:

This module addresses the scalability and efficiency of the system. It involves optimizations to reduce computational complexity, making the model more resource-efficient and suitable for deployment in various environments. Additionally, considerations for scalability ensure that the system can handle larger datasets or be easily adapted for use in different mining exploration scenarios.

6. RESULTS AND DISCUSSION

Four thousand seismic images and four thousand labelled mask images make up the dataset utilized in this study. The mask photographs are in black and white, whereas the vibration images are in grayscale. The mask image's white pixel signified the existence of salt within the initial image. Every image has a dimension of 102 by 101. To expedite processing, the input pictures are resized to 128*128; nevertheless, the mask images remain unaltered. Fig. 2 displays a few samples tectonic and mask pictures. The source of the information set is [14]. These are the software tools that were utilized on this project:

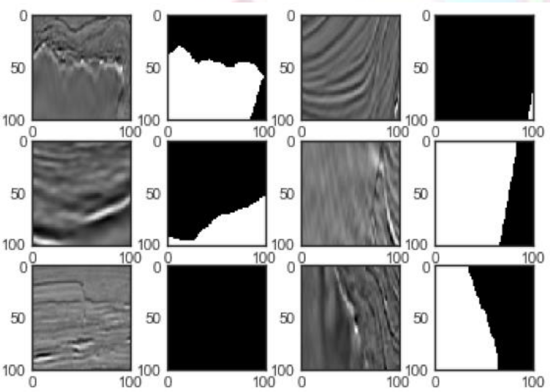

Fig 2. Sample seismic images and corresponding mask images

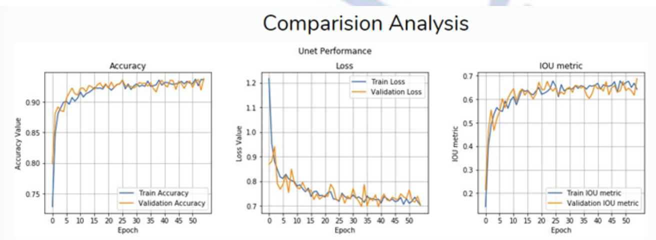

Fig 3. Comparison Analysis

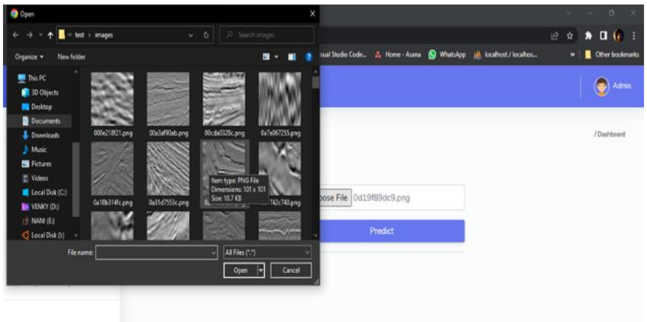

Fig 4. Uploading Soil Images

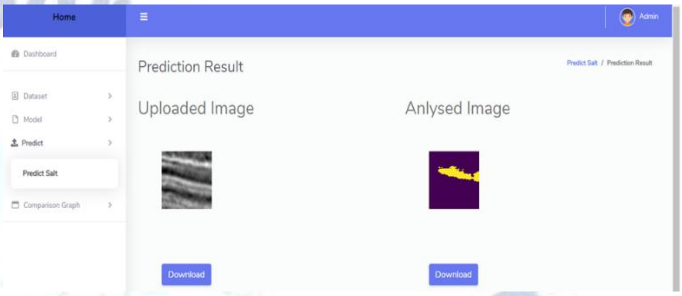

Fig 5. **Analysed Images Data**

7.CONCLUSION

In this project, I have successfully used the auto-encoder architecture of CNN to detect each pixel in a seismic image as a salt pixel or other rock. The developed technique can be used for detecting other valuable rocks embedded below the earth surface. With a proper number of epochs, the designed system can reduce the prediction error as low as 10% main drawback of the proposed system is that it takes a significant amount of time to train the network. The reason is that the computational complexity of the system is very high. However, by using GPU accelerated implementation, the training time can be reduced to a reasonable time. On the other hand, the prediction operation of the trained model is very fast. Therefore, the trained model can be used for real-time detection of a scanned seismic image which will accelerate the total processing time of mining location detection. In the future, I will investigate how the training process can be accelerated with limited computing resources. The results of the developed technique will be compared with other existing algorithms. To conclude, I can say, the obtained result from the developed system is promising, and the trained model can be used for other seismic image analysis. The developed system is not limited to only salt detection problem.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] L. Lucchese and S. K. Mitra, Proceedings of the Indian National Science Academy Part A, vol. 67, no. 2, pp. 207–222, 2001. "Colour image segmentation: a state-of-the-art survey."

[2] Faster r-cnn: Towards real-time object detection using region proposal networks, S. Ren, K. He, R. Girshick, and J. Sun, Advances in neural information processing systems, 2015, pp. 91–99.

[3] "Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 40, no. 4, pp. 834–848, 2018. L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy and A. L. Yuille.

[4] Arya and S. A. Etemad, "3D human action recognition and style transformation using resilient backpropagation neural networks," ICIS 2009, [4]. IEEE International Conference on, 2009, Pages 296-301, Volume 4.

[5] "3D convolutional neural networks for human action recognition," by S. Ji, W. Xu, M. Yang, and K. Yu, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 35, no. 1, 2013: 221-231.

[6] F. Milletari, N. Navab, and S.-A. Ahmadi, "V-net: Fully convolutional neural networks for volumetric medical image segmentation," in Proceedings of the Fourth International Conference on 3D Vision (3DV), IEEE, 2016, pp. 565–571.

[7] In IEEE Transactions on Image Processing, vol. 26, no. 7, pp. 3142–3155, 2017, K. Zhang, W. Zuo, Y. Chen, D. Meng, and L. Zhang, "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising."

[8] "Deep learning components - autoencoders," autoencoders-deep-learning-bits-1-11731e200694, available at https://hackernoon.com.

[9] "Convolution in two dimensions," The link is https://github.com/PetarV-/TikZ/tree/master/2D% 20Convolution.

[10] "Relu: Not a differentiable function: Why is it utilized in optimization based on gradients? and more relu generalizations. The link is bit.ly/2uPTxNx.

[11] "An understanding of convolutional neural networks through intuition," intuitive-explanation-convnets (https://ujjwalkarn.me/2016/08/11/).

[12] "Image scaling methods and matlab implementations," https://aditharajakaruna.wordpress.com/2013/07/12/ image-scaling-methods-and-matlab-implementations/.

[13] M. D. Zeiler, "Adadelta: an adaptive learning rate method," arXiv preprint arXiv:1212.5701, 2012.

[14] "Tgs salt identification challenge," https://www.kaggle.com/c/ tgs-salt-identification-challenge.