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**Original Research Article**

# Automatic Salt Deposit Identification from Seismic Images

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**ABSTRACT**

*Identifying mineral deposits from seismic data has been receiving a lot of research attention of late most especially salt identification. Attempts have been made to automate this process to phase out its manual identification. To this end, artificial intelligence models have been leveraged, and one of such is the UNET model. This work puts forward an improved UNET model by adding a preprocessing image layer (diffusion filtering) on top of the UNET model. Results on 2011 salt images showed improved performance over the traditional UNET model.*



## 1. INTRODUCTION

Seismic data provides the opportunity of revealing minerals embedded in the earth sub-surface. Therefore, this process could lead to the identification of mineral resources manually or automatically (Milosavljević, 2020). Seismic interpretation through manual means has been the tradition (Guo *et al*., 2020). However, this process is tedious and slow. These limitations have paved the way for the automatic interpretation of seismic data. The advent of deep learning models, such as the convolution neural network (CNN), has provided the opportunity for researchers to carry out automatic object detection evident in the object recognition domain (Hieu *et al*., 2016, Luis *et al*., 2016, Wanli *et al*., 2017), and also for environment recognition (Oyebode *et al*., 2019) with remarkable results. This positive development has led to its deployment in seismic analysis. The CNN is a network of cascaded layers of convolution operations whereby chains of filters are convolved with images to learn unique extracted features.

The U-shaped neural network (UNET) model is a specialized type of CNN that combines the CNN operations with a series of upscaling layers (Ronneberger *et al*., 2015). The objective of these layers is to localize features extracted from the CNN phase. A detailed explanation of the UNET is found in Olaf *et al.* (2015). The UNET, which is famous for medical image segmentation (Leng *et al.*, 2018; Weng *et al.*, 2019) has now been deployed for faults detection in seismic data as observed in Wu *et al.* (2018), Li *et al.* (2019) and Shengrong *et al.* (2019). However, none of these works focused on investigating suitable image enhancing or noise removal methods before invoking the UNET segmentation model.

Seismic images may suffer from perturbation and non-uniform illumination due to their inherent nature of acquisition (Zhang et al., 2019). Therefore, it becomes imperative to deploy a denoising mechanism to filter noise before invoking a suitable deep learning model.

Therefore, the contribution of this work to salt identification in seismic data is to carry out an image preprocessing method using the anisotropic diffusion filter.

## 2. MATERIALS AND METHODS

### 2.1. Proposed Model

The proposed model takes advantage of robust anisotropic diffusion filtering for noise removal. The seismic data are usually perturbed with noise and might be challenging for the UNET model to recognize areas where salt lies accurately. Therefore, preprocessing provides the opportunity to minimize noise from seismic data.

### 2.2. Anisotropic Diffusion Filtering

There are various image prepossessing enhancement techniques in literature, for example, the median, Gaussian, and diffusion filtering. Linear filters such as the Gaussian filter is suitable for smoothening and removing noise. However, they also remove or blur object edges significantly during this process, as seen. The median filter being a nonlinear filter performs better. It does not blur critical structures like object edges; however, it is only useful in removing 'salt and pepper' noise. However, the anisotropic diffusion filtering pioneered by Perona and Malik (1990) provides the opportunity of image denoising at the same time preserving critical object structures like edges. The anisotropic diffusion filtering of an image *I* is given in Equation 1.

$$\frac{\partial I}{\partial t} = div.(g\,\nabla I) \tag{1}$$

where $\mathrm{I}$ gives the diffused image at an instance in time $\mathrm{t}$, $\mathrm{t}$ is the smoothening time, $\mathrm{g}$ controls the smoothening of the image, it provides the diffusivity with which describes the rapidity of diffusion in a given direction and $\nabla\mathrm{I}$ is the image gradient. In Perona and Malik, (1990), $\mathrm{g}$ is a function of the image gradient ($\nabla\mathrm{I}$) given as $\frac{1}{\sqrt{(1+|\nabla\mathrm{I}|^2)}}$. The Perona and Malik's python implementation in Bianco *et al.* (2013) has been used.

### 2.3. Evaluation of the Proposed Algorithm

Kaggle's seismic dataset was used for the evaluation process (Kaggle, 2018). The dataset contains 4000 images with 4000 ground truths. The dataset was split into a training dataset (1989 images) and a test dataset (2011 images). The evaluation metric used is shown in Equation 2.

$$\mathrm{A}(\%) = \frac{(\text{True positive})}{(\text{True positives} + \text{False positive} + \text{False negative})} \tag{2}$$

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True positive is the total number of pixels that the algorithm predicts as foreground pixels, and indeed they are foreground pixels as observed from the ground truth. False-positive is the total number of pixels that the algorithm predicts as foreground; however, they are background pixels seen from the ground truth. Lastly, false negative is the total number of pixels predicted by the proposed algorithm as background pixels, but they are foreground pixels observed from the ground truth.

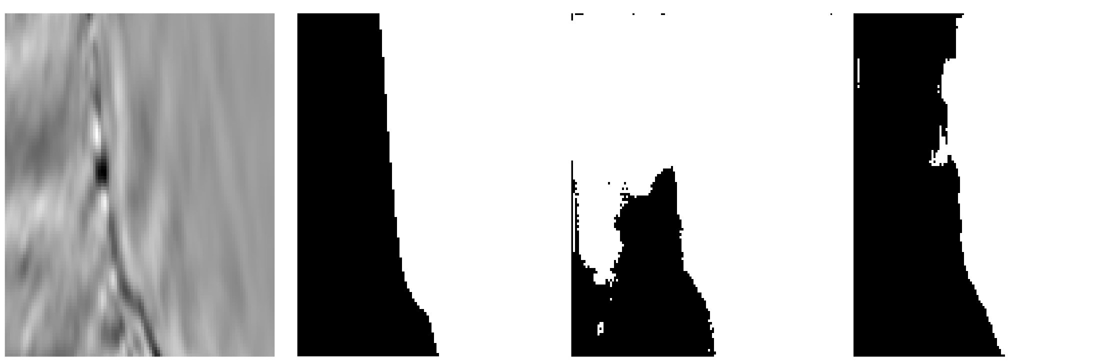
## 3. RESULTS AND DISCUSSION

Table 1 shows the performances of two variants of UNET. The traditional UNET has an accuracy performance of 65% while the proposed has a score of 66 %. This improvement is a result of the preprocessing layer added to the existing model. This layer removes noise as well as preserves critical structures of seismic data.

Table 1: Segmentation output

| Models | A(%) |
|---|---|
| UNET | 65 |
| Proposed model | 66 |

Figure 1 shows the performance of the proposed model. The ground truth image shows how salt is delineated from the seismic image. The white part indicates the salt region, while the dark parts are the non-salt region that is not of interest. The performance of the traditional UNET is seen to have identified areas that do not contain salt. This development tends to increase its false-positive value thereby hampering its segmentation performance A(%). The segmentation output of the proposed model is seen to have fewer false positives as compared with the latter. Also, in Figure 2, the proposed model seems to have done a better job compared to the UNET.



a b c d

Figure 1: Segmentation outputs of various models. (a). Original image (b). Ground truth (c). UNET segmentation (d). Segmentation via proposed model


Figure 2: Segmentation outputs of various models. (a). Original image (b). Ground truth (c). UNET segmentation (d). Segmentation via proposed model

## 4. CONCLUSION

This paper proposed an improved segmentation model on salt images. The introduction of a preprocessing layer had improved the segmentation output of the proposed model. Segmentation results from 2011 images showed enhanced performance over the traditional UNET model.

## 5. CONFLICT OF INTEREST

There is no conflict of interest associated with this work.

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