Salt Segmentation on Seismic Images using Deep Learning

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***Abstract*—This document is the result of the elaboration of a project about the segmentation of seismic images, specifically the segmentation of salt, in the oil industry sector, through research and analysis, it was founded and the development was carried out of the project based on deep learning.**

***Index Terms*—Salt Segmentation, Neuronal Network, U-net**

I. Introduction

The project is aimed at the exploration and extraction of hydrocarbons, which are a very important source for power generation. In the extraction and exploration process there is a thread called "Seismic image reading and interpretation" which is essential to meet its main objectives. This allows to delimit the bodies of the different characteristics of the subsoil obtained in the seismic images, in the case of the project to delimit the bodies of salt.

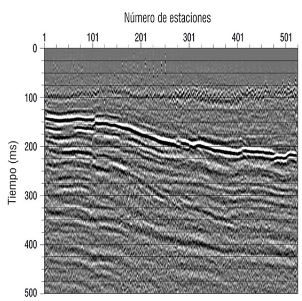

Fig. 1. Seismic image

We will call the result of this thread "image segmentation", this field of study has already been approached by other sectors of science such as medical images, which consist of a set of techniques and processes to analyze images of the human body for scientific and medical purposes. The nature of the problem that led to the application of image segmentation in this sector is very similar to the project presented in this article.

Segmentation is one of the general problems in the field of artificial vision and consists of dividing a digital image into several regions (groups of pixels) called segments. More specifically, segmentation is a pixel classification process that assigns a category to each pixel of the analyzed image. This general problem is divided into specialized problems, giving rise, for example, to color targeting, texture targeting, super pixel, semantic targeting

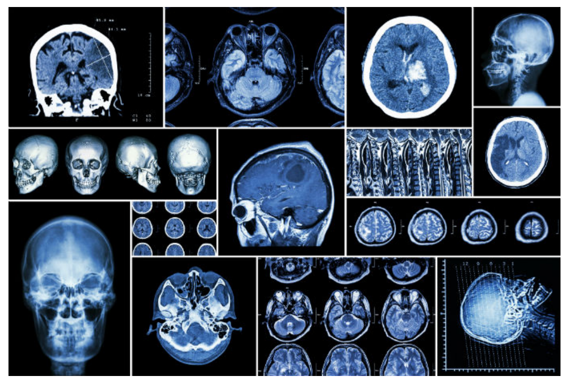

Fig. 2. Medical Imaging Segmentation

In the development of the image reading and interpretation thread there are certain mechanisms that are not very efficient to achieve the objectives. One of them is the high demand for time to analyze the images by the experts, as well as the interpretive variety that they can have. Despite the fact that everyone works in the same field of study, the human factor does not exempt the possibility of making mistakes, bringing with it a certain rate of error.

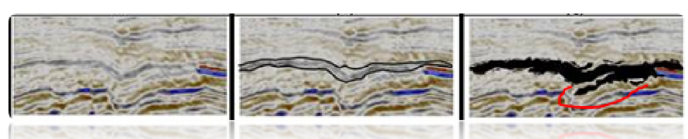

Fig. 3. Interpretive variety

Likewise, it becomes difficult to make a decision, which means more time is required in this process. This can mean risks at the time of exploration and extraction, since an erroneous interpretation generates risks ranging from the economic to the physical integrity of the personnel who work there. Next, in the following image you can see a seismic image that illustrates the characteristics of a subsoil that can be analyzed.

As you can see, if an inaccurate interpretation is made at the drilling stage, the entire operation can be jeopardized. This project is based on this criterion. This was essential to establish the objectives of the project, since it allowed laying the foundations for carrying out the project.

Fig. 4. Oil rig explosion

Based on this situation we have to figure out how to implement a deep neural network model that allows the segmentation of salt in seismic images in an efficient and effective way, which allows an easy interpretation of them. This with the objective of pointing out the places in which there is a greater probability of finding the presence of hydrocarbons.

Fig. 5. Graphical deep neural network model

II. METHODOLOGY

A. Research

To carry out the stated objectives, the need arises to know the general panorama around the general theme. For this reason, different queries are made about the segmentation of salt, its applications in the industry, the repercussions it can have on the finances of a company and the problems to which it is exposed from making a wrong interpretation.

On the other hand, based on the challenge ”TGS Salt Identification Challenge”, published on the Kaggle portal, the choice of 3 types of algorithms based on U-net networks and Autoencoder networks is made. This provides a dataset with 4,000 images with their respective masks for training and 18,000 images for the network test. All with a size of 101x101 pixels.

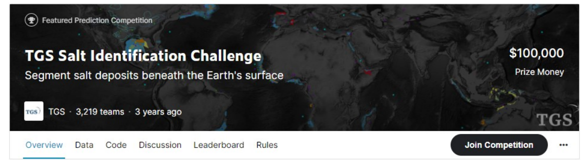

Fig. 6. Kaggle Portal Competition

B. Evaluation and Choice

At this point, several quantitative tests were carried out between the proposed models, following different parameters such as time and precision. From this, one based on the U-net network was chosen, since it was the most efficient and the one that best adjusted to the needs raised. In addition, the network was chosen complies with some didactic aspects, in which the structure of the code was considered, that it be clear, concise and that allows adequate learning on the subject.

C. Adaptation and Optimization

A code adaptation process is carried out, in which the way in which the images are prepared to be used in the network, as well as their sizes and the default values of the model, was taken with great relevance, thus modifying different sections and metrics. used to optimize the neural network. The original dataset for training was reduced to 3500 images in order to reduce the network training time.

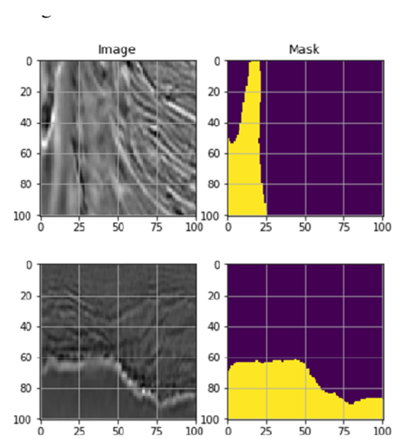

Fig. 7. Graphic example of the dataset. Original image with his mask by his side

D. Analysis and Conclusion

Following the output images thrown by the network, each one of the results is analyzed to verify if the network meets the requirements, in terms of segmentation, which lead to an approximate conception of the most appropriate place to find salt. This stage of analysis implies that depending on the results obtained, it is necessary to resort to modifying parameters to improve the results.

III. U-NET

As previously mentioned, the network chosen to develop the segmentation model is of the U-Net type. This is a convolutional neural network (CNN) characterized by having a "U" shape in the scheme that represents the structure of the network.

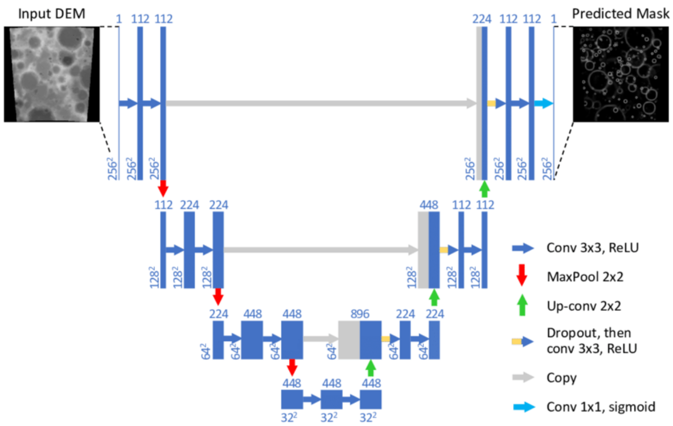

Fig. 8. U-Net Structure. The input DEM image goes through the neural network at all its levels undergoing changes in the size and value of its pixels until it reaches the segmentation.

Convolutional networks are characterized by applying a specific scalar multiplication (convolution) on matrices representing the input images. From this we detect details that are very relevant such as edges, textures, colors and other features. Then, we can give meaning to certain areas in the images. In this case, our areas of interest are those with salt.

A. Hyperparameters

- **Convolution.** For each convolution we have used 8 kernels of 3x3, max pooling 2x2 and four depth levels of the neural network. The stride for the convolution is 1 and for the deconvolution is 2. The transposed convolution kernel has a size of 2x2.
- **Activation.** After the double convolution at each level, the RELU trigger function was used, which is widely recommended for image segmentation by data science experts. Also, in the last deconvolution layer, the SIGMOID trigger function was applied to obtain a binary image for better identification of the salt bodies.
- **Image Size** The input images were recalled at 128x128 pixel dimensions to reduce the likelihood of misinterpretations in the areas near the edges of the original images.
- **Other hyperparameters.** In the learning process, situations arise where the network begins to learn imprecise information about what we want to classify. For this reason the neural network must be supported by external functions that help in its learning process. ADAM is an adaptive learning method that optimizes the learning process of the neural network. In addition, a function called EarlyStopping was created to stop the training process when the loss in validation and the loss in learning no longer have significant improvements.

B. Training

In the training a dataset of 3500 seismic images and their respective masks were used. The number of optimal epochs was determined by the EarlyStopping function resulting in 24 optimal epochs. When the validation and training loss became very small, exactly at epoch 24 the validation loss started to increase its error while the training loss continued its trend to zero. When this happens it means that the network is probably not going to improve its accuracy because it has already reached a very low degree of loss and if it continues to train it will start to increase the loss due to the high redundancy. This is when our braking function kicks in.
After the training, some adjustments were made for the input of further information to the neural network so that it would accept the test images. The test images are seismic images with their respective segmented mask. They are images that have not passed through the network and are used to evaluate the accuracy of the neural network in various ways. For the evaluation of the neural network a dataset of 500 seismic images and 500 masks was used.

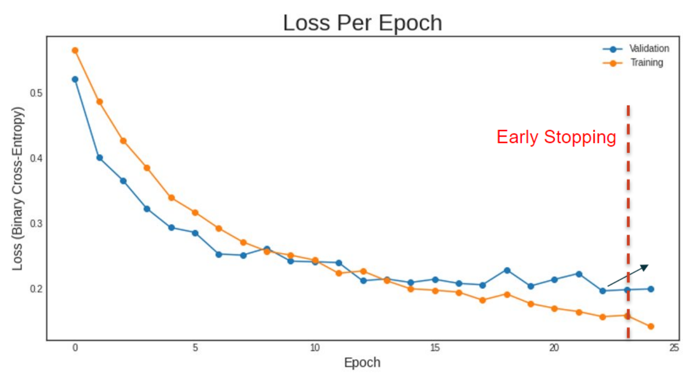

Fig. 9. The loss of both training and validation reached out a very accuracy point and starts to going y opposite directions.

C. Results

The results obtained are shown in 10 In the first row we have the seismic images, in the second row the segmented image, in the third row the neural network prediction and in the fourth row a contrast from the mask and the prediction. Based on the experience gained from the work done with seismic images, at first glance it can be seen that the pedrictions are close to the presented mask. Figure 10 shows 5 images randomly chosen from the dataset of 500 test images.
As we can see in the image, the predictions in column c) vary very little from the segmented images in the images in row b). The model took 54.6 milliseconds to analyze all the validation images. Some additional appreciations

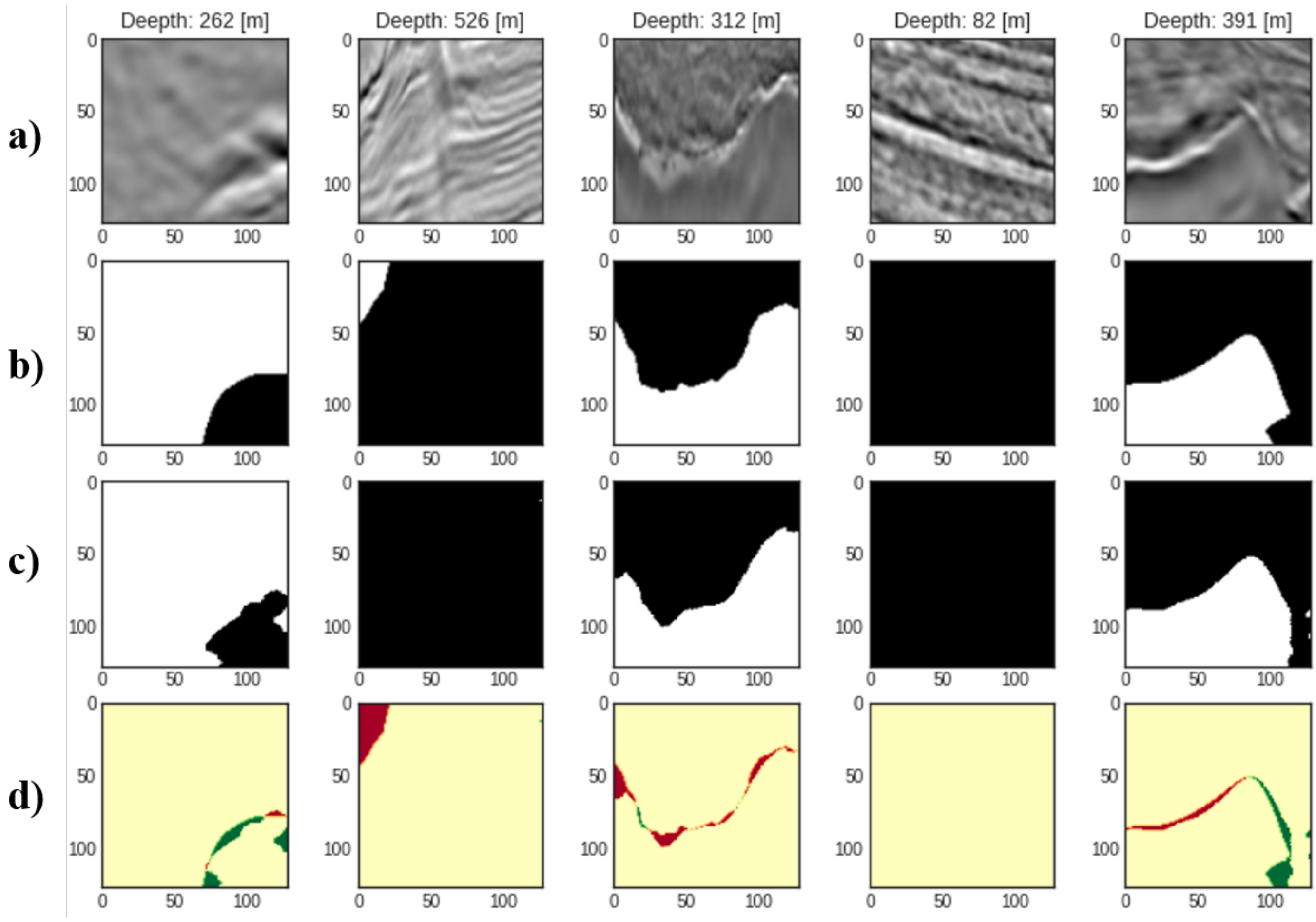

Fig. 10. a) Seismic image. b) Ground truth. c) Prediction. d) Contrast [Red means parts where the model skip salt bodies, and green parts where model over added salt.]

that can be made to the obtained result is that the edges of the salt bodies obtained by the model are not very uniform in relation to the real mask. On the other hand, column 2 shows a seismic image with little presence of salt. It seems easy to identify the salt segment, however the model does not show any salt presence despite its existence in a small area in the upper left corner. On the other hand, we have been able to determine from these images that the images that have an intermediate depth are the ones with the highest salt indices. The shallower and deeper images have almost no salt index. We could state on this basis that the salt bodies are not found at shallow depth from the ground. In this case we would find salt bodies from about 200 meters. Evidently, the appreciations exposed above are from the visual-analytical point of view. We will now make an analysis of the accuracy of the neural network according to 2 comparison metrics.

SSIM Metric The Structural Similarity Index (SSIM) metric helps to determinate how similar is an image from

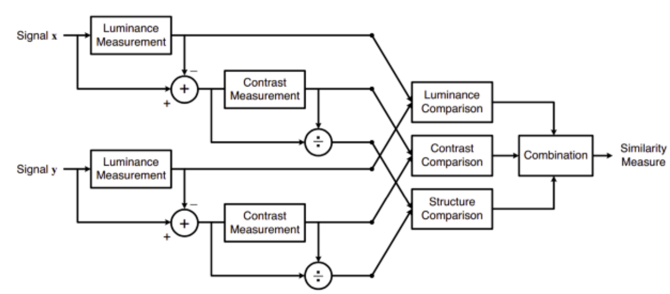

Fig. 11. SSIM Illustrative explanation.

other one by extracting 3 key features: luminace, contrast and structure. The value goes from 0 to 1.

Pixel Accuracy Metric This is another way to measure the similarity of an image with another one. The method includes identifying pixels by value and counting the number of each group for the two images. Then, we can compare the the images with the amount of pixels of the same kind. For binary images it is easier because there is only two kinds of pixels with values 0 or 1. If we know the size of the image in pixels, then we can count the amount of white pixels of each image and that is enough to compare them. If both have the same number of white pixels they are the same according with this method. However if you think a little bit more about it, you realized that also matters how they are arranged. Because this method does not take importance by the order, this is not much accurate. However, it works fine of binary images.

U-Net networks are accurate in image segmentation according to various opinions of the data science community. We wanted to cross-check this claim by modifying by removing the concatenations of our neural network to obtain a network similar to an autoencoder. Having done this the results between the U-Net and Autoencoder predictions varied significantly. Table I presents the results of both networks and their similarity values according to each metric.

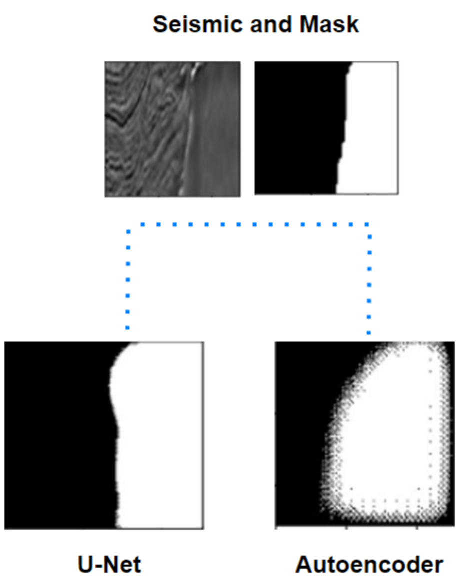

Fig. 12. Comparation between neural networks

As can be seen in Figure 12 the U-Net network shows a better accuracy in the prediction of the seismic image. The autoencoder network also identifies a good part of the salt body, however the edges are not very well defined.

TABLE I
SIMMILARITY METRICS

	SSIM	Accuracy Pixel
Autoencoder	0.460	0.85
U-Unet	0.862	0.92

These are the results obtained by evaluating both convolutional networks. Certainly the qualitative results stated above could be evidenced by the quantitative results in the table. An important detail is that the pixel accuracy metric shows a great similarity of part of the prediction of the autoencoder network even though this image is not very accurate. Thus we can be sure that the U-Net network has better accuracy for this case and that the Accuracy Pixel metric is inferior in reliability with respect to the SSIM.

CONCLUSIONS

Through the analysis of results, it was possible to show how the U-net architecture provides better results in the segmentation of seismic images compared to the Autoencoder network.

This U-net neural network model can be adopted by other sectors that require image analysis, due to its structure it allows modifications depending on the interests that are required, therefore it has great potential in the future.

The segmentation of salt in seismic images contributes positively to help improve the interpretation of the experts, likewise it contributes to accelerating the process of reading and interpretation of seismic images, therefore it becomes a more efficient and effective process.

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