U-NET, RESNET OR NONE, COMPARING AND CONTRASTING CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE IN INTERPRETATION OF A SALT SEISMIC SETTING

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ABSTRACT

One of the most crucial tasks in seismic reflection imaging is the identification of salt bodies and subsequent reservoirs for oil and gas. For the most part salt body identification has been done visually determining the salt/sedimentary sequence boundary, which invites error and requires a non-consequential amount of work. Deep learning techniques have given rise to impressive levels of object identification, enough to supplant the visual analysis currently performed by the industry. Convolutional Neural Networks (CNN) have been invaluable in computer vision applications and are the primary tool we shall apply in this setting. The architecture of a CNN is important as certain architectures lend themselves to certain tasks. We shall explore the differences between architectures of U-Net, ResNet and LeNet in the application of salt boundary identification. CNN adjustments including activation functions (ReLu, Sigmoid, SoftMax) and K-fold cross validation have been applied to increase network prediction accuracy. The preliminary result shows that U-Net has provided the best prediction so far of the data and indicates this as the best architecture in salt body identification.

1. INTRODUCTION

1.1 Purpose and Scope

The main objective of this study is to determine which CNN architecture and activation function perform the best on a set of training data of noisy salt dome features. Specifically varying architecture (U-Net, ResNet and LeNet) and activation functions (ReLu, ELU, Sigmoid, Softmax) will provide useful insights as to the most efficient methodology in performing this work. K-fold validation will be employed to increase the overall accuracy of all models.

1.2 Importance of This Study

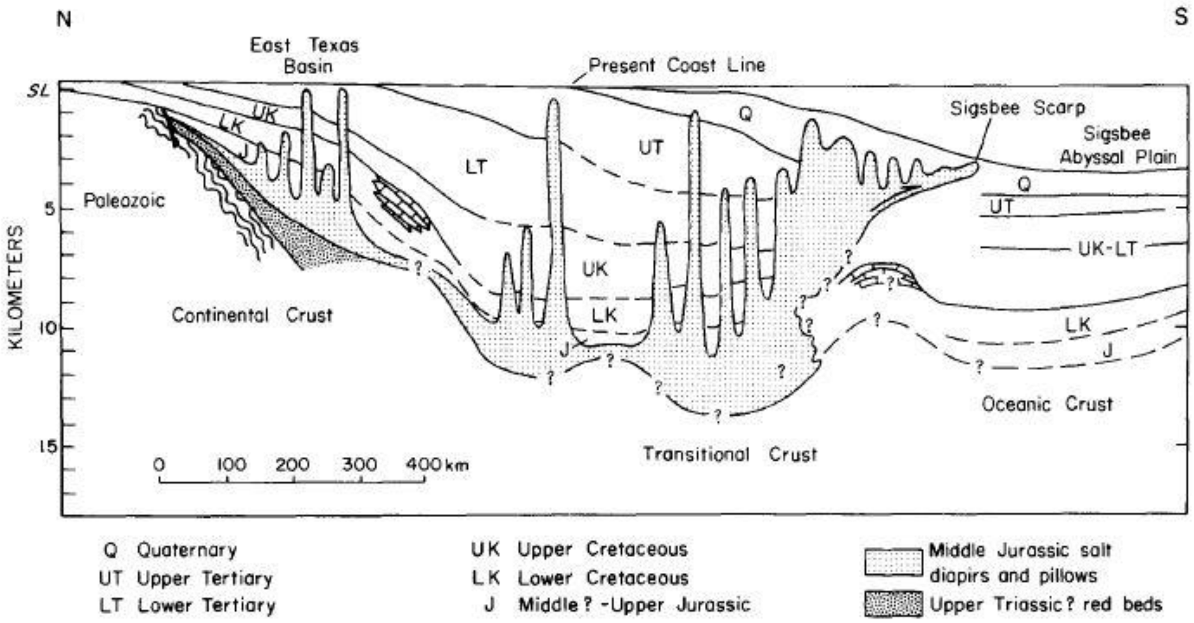
This is an important question; salt bodies interfaces are one of the primary reservoirs for oil and natural gas. In a basin after the oil is generated and starts migrating out of the host rock and through the reservoir rock, certain salt body geometries act as impermeable boundaries and act as cap rock (Posey, 1988), trapping that fluid in its fold. In the Gulf Coast of the United States due to the thick salt sequence and subsequent halokinesis has given rise to one of the world's best developed salt dome provinces (Posey, 1988). In fact, the most famous gushing oil well in history at Spindletop Dome (Halbouty, 1979) is the result of these salt dome geometries.

2. LITERATURE REVIEW

2.1 **Halokinesis and Hydrocarbon Migration**

Salt Tectonics and salt movement (Halokinesis) ultimately play a substantial role in oil and natural gas production. Particularly in the United States in which these are the primary cap structures for traditional oil and natural gas reserves. Approximately the Gulf offshore oil production accounts for about 15% of US total crude oil (U.S Energy Information Administration, 2022), with salt structures being the cap rock for these systems. In a traditional petroleum trap, hydrocarbons migrate from the source rock (shale) through a reservoir rock formation (porous/fractured formation) until the fluid either degrades as its positive buoyancy migrates surface bound, or is trapped beneath/alongside an impermeable formation. In the Gulf of Mexico this impermeable formation are typically salt domes. These structures as seen in fig 1, due to overburden pressure move in the subsurface and create pillar/diapir structures.

Fig 1. Cross-section of the northern Gulf Coast region. Modified after Salvador and Buffler (1982).



These provide migration pathways from source rocks to reservoir rocks and due to the irregularity of the salt dome itself, the salt acts as a caprock for hydrocarbon fluids. Figure 2 displays the form of hydrocarbon trap created by salt diapirs.

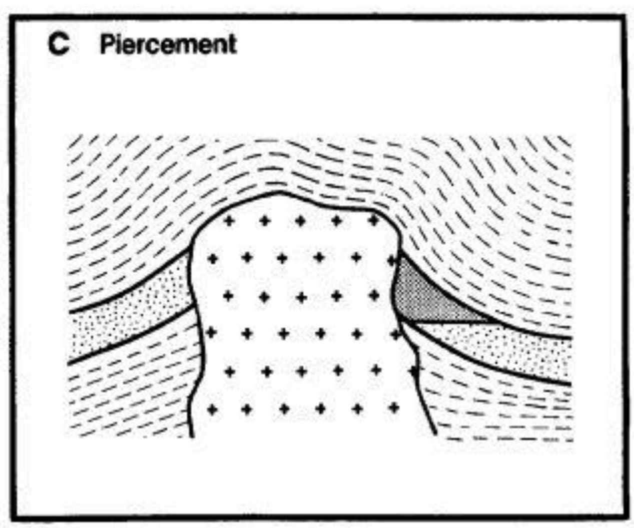


Fig 2. This figure shows how a salt diapir (formation denoted by '+' texture) moves isostatically through other formations and creates a piercement trap. The hydrocarbons in this system (denoted by the shaded section) are located within the porous reservoir rock, and surrounded by cap rock (the formation denoted by '-' texture and the salt diapir). Modified from Biddle and Wielchowsky.

The way the industry determines the size, orientation and location of these structures is to interpret seismic reflection surveys performed over the area. These surveys are the result of pressure waves (P and S form waves) reflecting off of density boundaries within the subsurface. This data undergoes a series of processing functions to stack data from seismometers, and reduce the signal to noise ratio. Presented in figure 3 is an example from the dataset used in this study of a seismic reflection image.

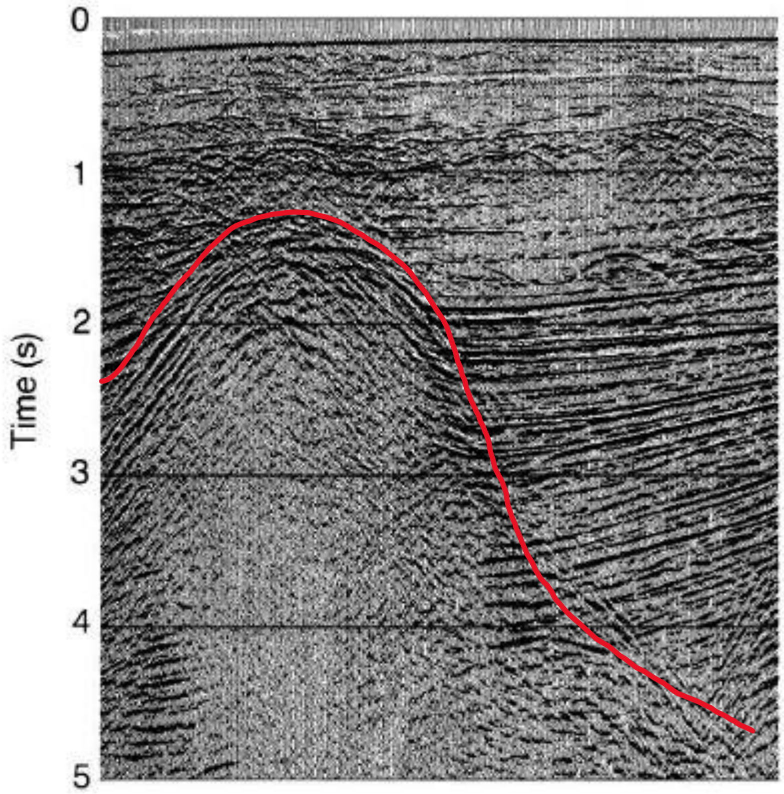


Figure 3. This figure shows the seismic reflection image of a salt diapir and surrounding formations. The diapir presents as the large structure with the red marked boundary.

Images such as Figure 3 are typically interpreted visually by hand. Automation has increased in gathering much of this data and parsing out structures that are not salt diapirs, however ultimately the reports and locations are interpreted by humans at the end of the day, which is a production bottleneck for the oil/gas industry. Deep learning thus has a far-reaching potential in this field in interpreting these structures quickly and accurately.

2.2 **U-Net Architecture**

The U-Net (Ronneberger et al., 2015) structure, combines a down-sampling path to extract context information and an up-sampling path to extract location information. A schematic view of a U-Net is provided in figure 4.

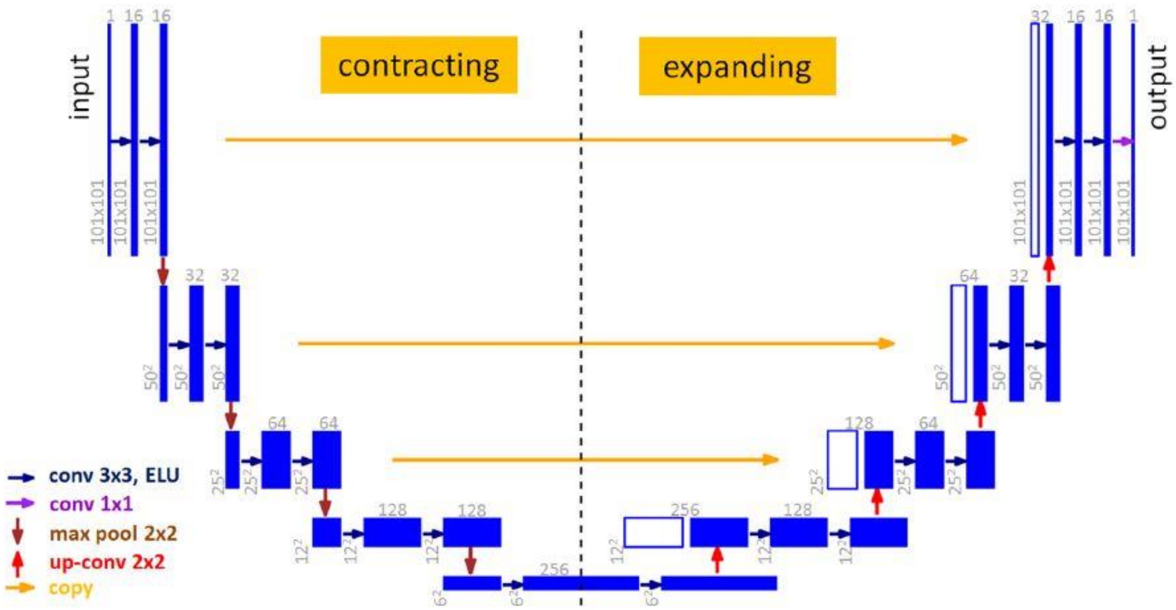


Figure 4. A schematic view of a U-Net architecture. The blue boxes denote a multi-channel feature map, where the number of channels increase by stage. The right half of the schematic denotes the opposite in which the number of channels then decrease stage by stage. The horizontal arrows denote the overall movement of the information through each stage of the system, starting in a contracting phase and ending in an expanding phase. Modifed from Zeng et al.,2019.

2.3 **ResNet Architecture**

ResNet is a variant of U-Net architecture to overcome the degradation problem (He et al., 2015). A ResNet is constructed by creating and adding an identity mapping shortcut on top of every few stacked layers. This results in the model having greater precision due to learning the perturbations of the mapping layer, instead of the full input (Zeng et al., 2019).

2.4 **LeNet Architecture and History**

LeNet was the first CNN architecture and was used to recognize handwritten numerals (MNIST dataset). Originally developed by LeCun et al, this network created CNN's with a seven layered, including four convolutional and pooling layers which were followed by three fully-connected layers of an artificial neural network which was called LeNet-5 (Sakib et al., 2019). Figure 5 shows the generalized schematic for a LeNet CNN.

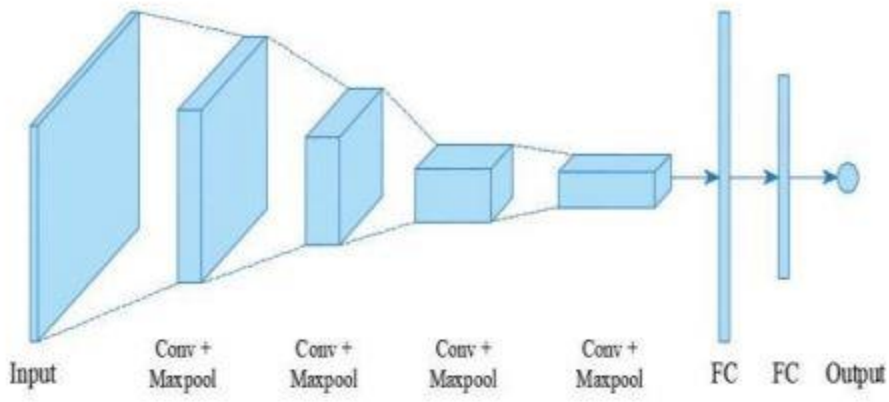


Figure 5. A simplified schematic of a CNN architecture. Modified from Sakib et al., 2019.

3. DATA AND PREPROCESSING

3.1 Data Source

Data for this study comes from the Kaggle competition "TGS Salt Identification Challenge" as this provides a large dataset with noisy images which reflect the reality of the images this network would work with. Data consists of .png images within a zipped file along with corresponding depths and training files (csv file format). Images are 101x101 pixels and each pixel is classified as either salt or sediment. Figure 6 shows some of the images with corresponding masks.

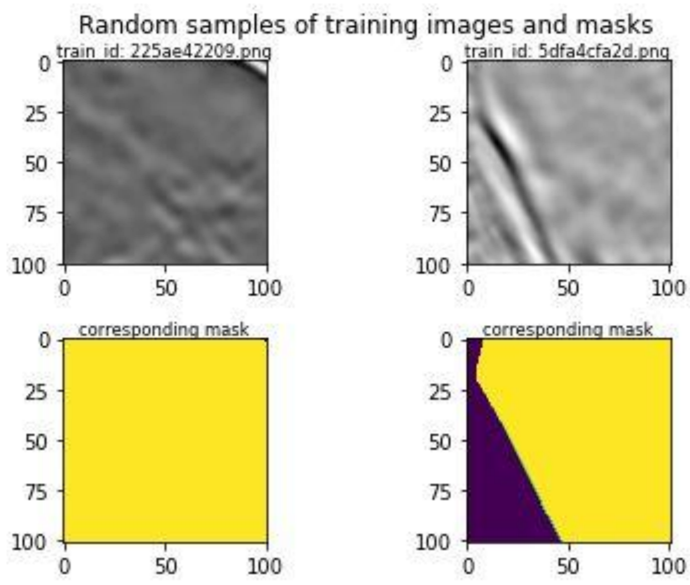


Figure 6. Displays some of the images in (128x128 pixel) image size with corresponding mask. Mask refers to the classified material as either salt (purple) or sediment (yellow).

3.2 Data Preprocessing

Data preprocessing took form of image loading and resizing, loading into a NumPy array and resizing into 128x128 pixel format. Normalization occurred by dividing resulting values by 255 to have a range from 0-1 in which the model could handle.

3.3 K-Fold Validation

K-Fold cross-validation means splitting the dataset into K-number folds, then train on K-1 folds to make predictions and evaluate against the 1 remaining fold. This methodology is greater than typical train_test_split methods as K-folds contains a representative sample of the dataset within each fold.

4. METHODOLOGY

4.1 U-Net Methodology

This methodology is the original U-Net with 9-layers, ReLu activation with an output activation function of sigmoid. Loss function of binary_crossentropy and model metrics being the meanIoU (Intersection over Union) and val_loss (value loss). The intersection over union metric is standard for CNN metrics relating to images.

4.2 ResNet Methodology

This methodology is similar to the U-Net however with ResNet block architecture. This will have 9 layers as well with 4 contracting layers, 1 middle hidden layer and 4 expanding layers. Table 1 describes layers and input block size.

Layer	Input Block Size	Activation Function	Loss Function
1	101	ReLu	Lovasz Hinge
2	50	ReLu	Lovasz Hinge
3	25	ReLu	Lovasz Hinge
4	12	ReLu	Lovasz Hinge
5	6	ReLu	Lovasz Hinge
6	12	ReLu	Lovasz Hinge
7	25	ReLu	Lovasz Hinge
8	50	ReLu	Lovasz Hinge
9	101	ReLu	Lovasz Hinge

Table 1. This table shows the input block size, activation function and loss function for each layer within the ResNet CNN.

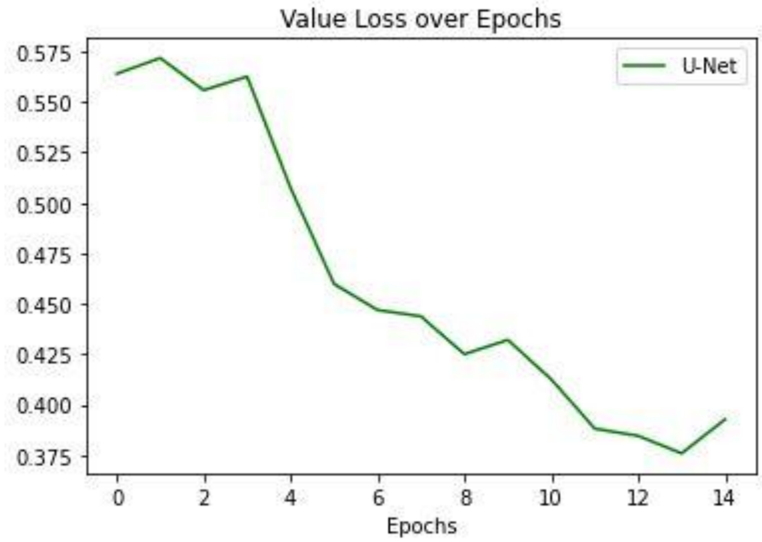
4.3 LeNet Methodology

This methodology will have 5 layers with ReLu activation function, loss function of binary-crossentropy and accuracy as its validation metric.

5. RESULTS

Preliminary Results:

Primarily the U-Net original has met with the most success, in figure 7 value_loss from the most effective run has been promising. Overall mean_IoU scores have been somewhat low and will be improved before the final product. Problems have arisen with ResNet implementation, due to broken file pathways.



5.1 **U-Net Results**
5.2 **ResNet Results**
5.3 **LeNet Results**

6. ANALYSIS AND INTERPRETATION

6.1 Comparison and Analysis
6.2 Discussion

7. CONCLUSIONS

8. FUTURE WORK