Convolutional Neural Networks for Salt Bodies Mapping using Machine Learning: A Case Study of the F3 Block, North Sea

Olawale Ibrahim[1], Ayomide Daramola[1] and Sekinat Kemisola Oyero[1]
[1] Federal University of Technology, Akure.

ABSTRACT

Particular to companies in the oil and gas industry, salt mapping which is an important structure when interpreting seismic data is an important process in the exploration for hydrocarbon accumulation. Identifying salt bodies is pivotal to seismic reflection interpretation in the oil and gas industry. Manual interpretation and mapping are done by the geologist which takes a long period of time to complete which is also subjective to human biases. Convolutional neural networks can be used for the mapping of salt bodies from seismic data using machine learning. The U-net model architecture was used in this study for the semantic segmentation of salt regions from seismic amplitude data. Different convolutional neural network architectures were tested. The deep CNN models were trained on 4000 different labelled seismic patches and corresponding masks using a supervised machine learning approach. Pixel accuracy of > 94% was recorded and the models were evaluated using other metrics as well. The trained models were used to predict regions of salt from the F3 block 3D survey in the North Sea. Seismic image patches from selected 2D inlines were passed through the pre-trained model for predictions. Machine learning salt mapping results serve as a first and second-order interpretation guide to the human interpreter, while also speeding up interpretation workflows more than before.

Keywords: Machine Learning, Convolutional Neural Network, Artificial Intelligence, Prediction, U-Net architecture.

INTRODUCTION

Identifying salt bodies is pivotal to seismic reflection interpretation in the oil and gas industry. Manual interpretation and mapping are done by the geologist which takes a long period of time to complete which is also subjective to human biases. One of the major challenges of seismic imaging is the localization and delineation of subsurface salt bodies (Babakhin *et. al.,* 2019). The precise location of salt deposits helps to identify reservoirs of hydrocarbons, such as crude oil or natural gas, which are trapped by overlying rocks (Babakhin *et. al.,* 2019). Successful seismic interpreters are experts at pattern recognition: identifying features such as channels, mass transport complexes, and collapse features (Zhao *et. al.,* 2015). The challenge as interpreters is that the data volumes to be analyzed keep growing in size and dimensionality, whereas the number of experienced interpreters has remained relatively constant. One solution to this dilemma is for these experienced interpreters to teach their skills to the next generation of geologists and geophysicists, either through traditional or on-the-job training (Zhao *et. al.,* 2015). An alternative and complementary solution is for these experienced interpreters to teach their skills to a machine (Zhao *et. al.,* 2015). Manual interpretation and mapping are done by the geologist which takes a long period of time to complete which is also subjective to human biases. Convolutional neural networks can be used for the mapping of salt bodies from seismic data using machine learning. Convolutional Neural Networks (CNN) have been used on image classification for more than two decades (LeCun *et al.,* 1998). There was a resurgence of these techniques after the breakthrough work of one of the first works using CNN for semantic segmentation applied a modified version of a classification network to generate per pixel classification (Long, 2016; Long *et al.,* 2014).

Literature Review

The study area is located in the North Sea, Netherlands (offshore) as shown in Figure 1. The F3 block is a block in the Dutch sector of the North Sea. The block is covered by 3D seismic that was acquired to explore for oil and gas in the Upper-Jurassic - Lower Cretaceous strata. "The upper 1200ms of the demo set consists of reflectors belonging to the Miocene, Pliocene, and Pleistocene. The deltaic package consists of sand and shale, with an overall high porosity (20-33%). Some carbonate-cemented streaks are

We acknowledge TGS for the competition data and the open source Kaggle community for starter code notebooks.

present. The most striking feature is the large-scale sigmoidal bedding, with textbook quality downlap, toplap, onlap, and truncation structures. Bright spots are also clearly visible and are caused by biogenic gas pockets. Several seismic facies can be distinguished: transparent, chaotic, linear, shingles." - (dGB Earth Sciences). Experiments have shown the transparent facies to consist of a rather uniform lithology, which can be either sand or shale. The chaotic facies likely represent slumped deposits.

The shingles at the base of the clinoforms have been shown to consist of sandy turbidites. The salt dome from the survey belongs to the Zechstein group.

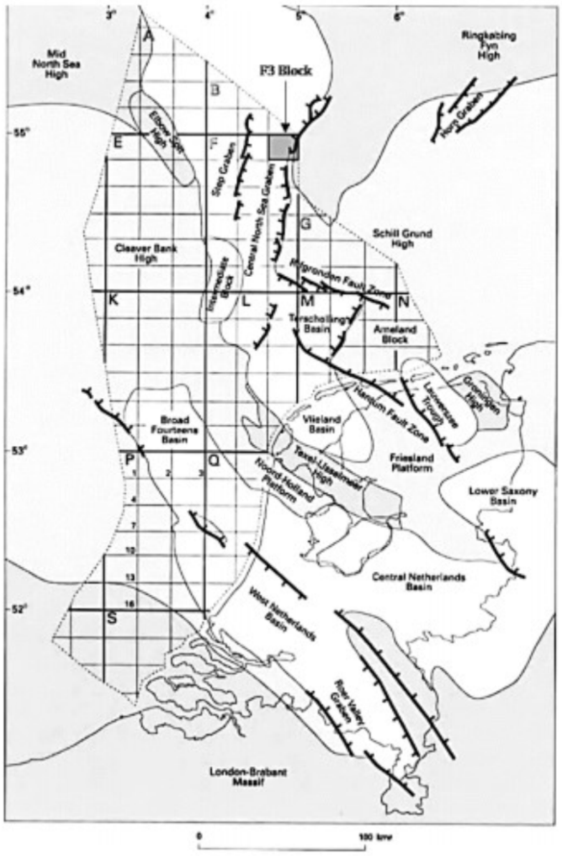


Figure 1: The F3 block located in the North Sea.

MATERIALS AND METHODS

Training and Validation Dataset: TGS Salt Identification Challenge

TGS Salt Identification Challenge is a Machine Learning competition on a Kaggle platform (Kaggle: TGS Salt Identification Challenge). The data for this competition represents 2D image slices of a 3D view of the earth's interior. For this reason, input data is a set of single-channel grayscale images showing the boundaries between different rock types at various locations chosen at random in the subsurface (Babakhin et. al., 2019). For the competition purpose, large-size images were transformed into 101 × 101 pixel crops by the organizers. Further, each pixel is classified as either salt or sediment and binary masks are provided. Visualization of this is displayed in figure The goal of the competition is to segment regions that contain salt. Note that if the 101x101 image contains all the salt pixels, it is treated as an empty mask in the data (Babakhin et. al., 2019). Such peculiarity is explained by the organizers as they are more interested in segmenting salt deposit boundaries instead of full-body salt (Babakhin et. al., 2019). The whole dataset has been split into three parts: train, public test, and private test. The train set consists of 4000 images together with binary masks and is used for model development (Babakhin et. al., 2019). The developed trained salt model is used for predicting salt regions from the F3 survey.

Machine Learning

Machine learning (ML) is a branch of Artificial Intelligence (AI) whereby computers are designed to perform intelligent tasks without being explicitly programmed to do so. With the aid of algorithms, computers are trained to learn from data, identify existing patterns and use these patterns in making future predictions. This branch of AI is heavily dependent on data as it is required by the machines to learn from data and make inferences on new and unseen data.
Machine learning is largely divided into two types of learning; supervised learning and the unsupervised learning.

Supervised Learning

In supervised learning, the computers are trained with labels. This refers to a system of learning where the algorithm is provided with both input(s) and output to establish and identify patterns in the data. It is a ML technique whereby the ML algorithms are fed with labelled data.
The chosen algorithm is trained on a labelled dataset that uses the provided labels(target) to control and evaluate the training process. Examples of algorithms used for supervised learning tasks are linear regression, random forest, support vector machines, KNN, gradient boosting algorithms, Artificial and Convolutional Neural Networks (ANNs, CNNs) as well as Generative Adversarial Networks amongst others, e.t.c.

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) is a popular type of neural network primarily used for image recognition problems. They are used for image classification and object detection. They are designed around the idea of convolutions which are used to extract patterns - referred to as feature maps - from an image object. The networks are generally made up of an input layer, convolutional layers, pooling layers, and fully connected layers. Figure 2 shows a typical convolutional operation on an input image using a convolutional mask or filter. Figure 3 shows a typical CNN architecture.

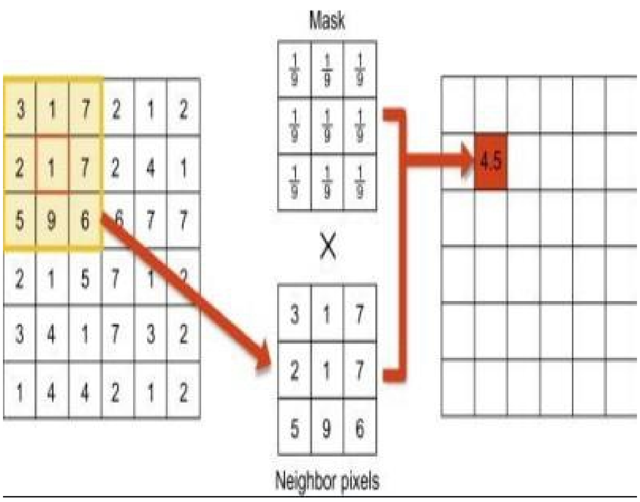


Figure 2: A 3 by 3 3 convolution operation.

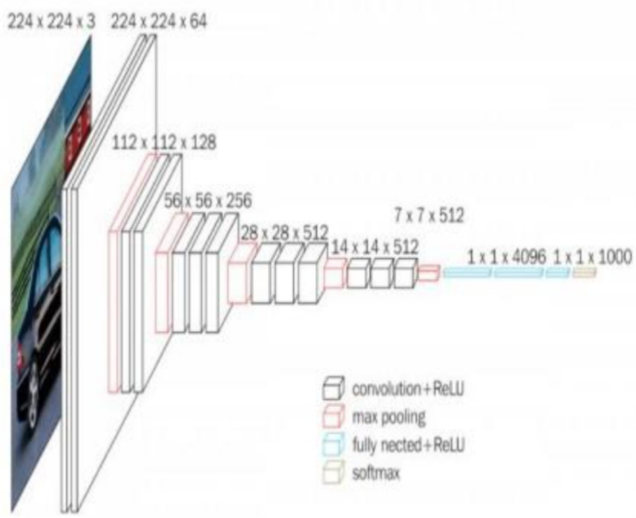


Figure 3: A typical CNN model architecture.

Model Architecture and Training

A 2D U-net model architecture was used to train the model. A 5 block encoding-decoding architecture was employed. As a binary classification challenge, the binary cross-entropy loss was used in optimizing the model performance while the pixel accuracy was used for model evaluation. The RELU activation function was used all through the network's hidden layers and the adam optimizer for gradient and weights optimization. The sigmoid activation function was used in the last layer to output the classification probabilities.

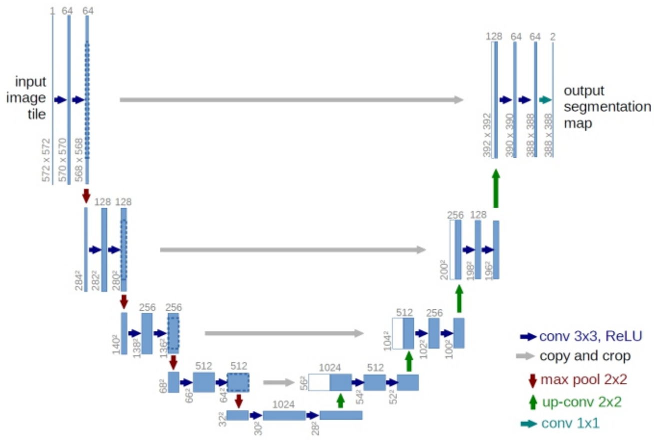


Figure 4: A typical Unet model architecture.

Data Preparation

The model was trained on 4000 training input (seismic amplitude patches and their corresponding salt masks) provided by TGS. Upsampling of the input images and masks was done from 101 by 101 to 128 by 128 as a form of data resizing and preprocessing. The original F3 dataset used as a case study to apply the trained model is rather noisy. To remove the noise, a dip-steered median filter with a radius of two traces was applied to the data (dGB Earth Sciences). 64 by 64 non-overlapping image patches were extracted from the entire F3 processed survey cube to give a total of 63798 from the survey. The images were labelled according to their survey indices (inline, crossline and depth ranges) and passed through the trained model for salt region detection.

RESULTS

Training and Validation with Competition Data

The CNN model recorded a pixel accuracy of >93% on the validation and train set indicating a very good performance with just little training epochs as shown in Figure 5b. This shows the model's performance to generalize well without overfitting. The training and validation loss also decreased progressively while converging with increasing epochs as shown in Figure 5a. This indicates that further training will further increase model performance. Figure 6(a-f) shows examples of the predicted test masks and actual masks indicating close similarities and good model prediction performance. The white regions from the image masks represent regions of

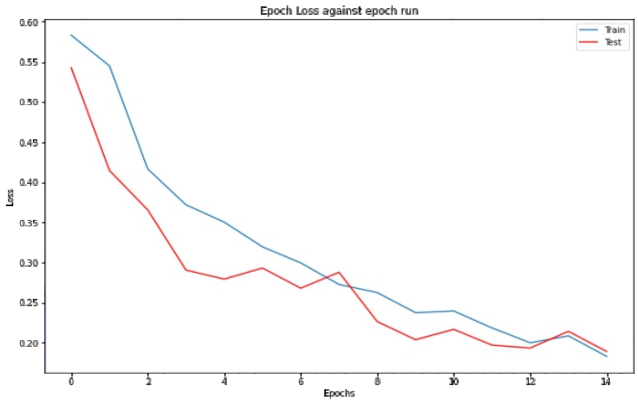


Figure 5a: Training and validation accuracy across increasing epochs.

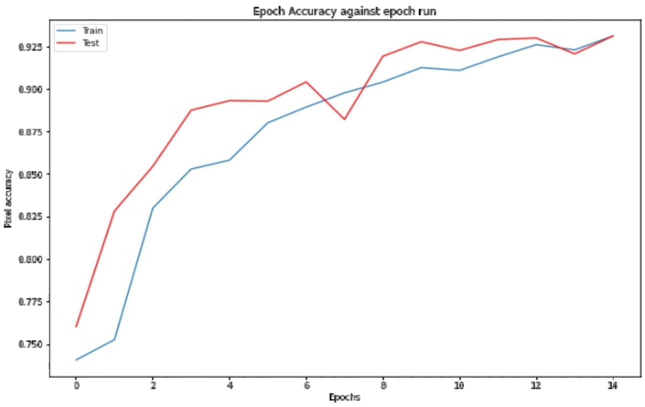
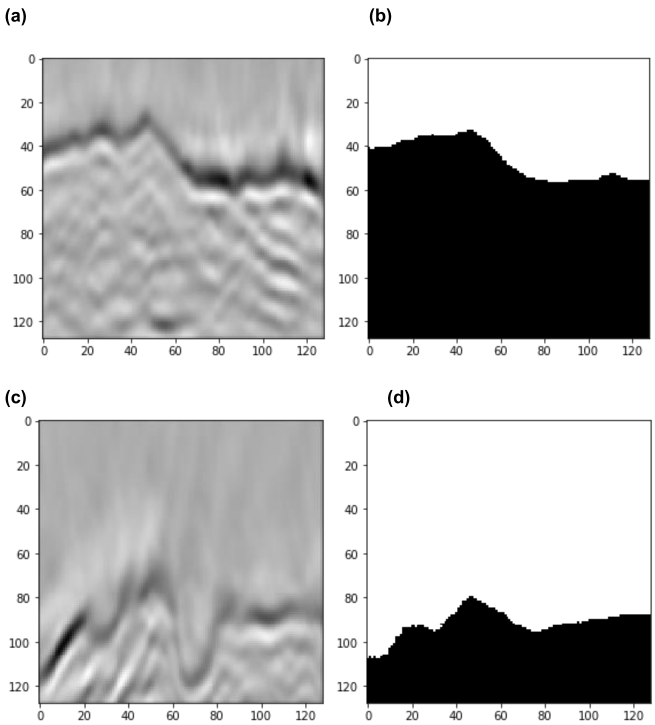


Figure 5b: Training and validation loss across increasing epochs.



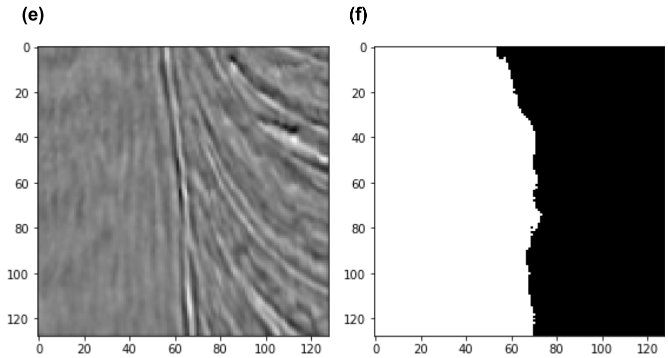


Figure 6(a-f): Input image patches and corresponding predicted salt masks by the model.

salt while the dark patches represent regions of no salt.

Salt Prediction on the F3 Block

The saved model is used on inline 425 from the F3 survey as shown in Figure 7 and prediction outcomes are shown in Figure 8(a-h). The model demonstrated efficiency in

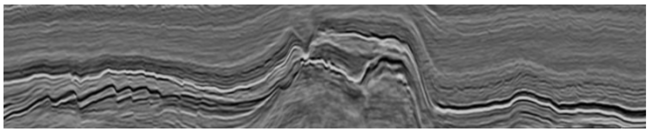
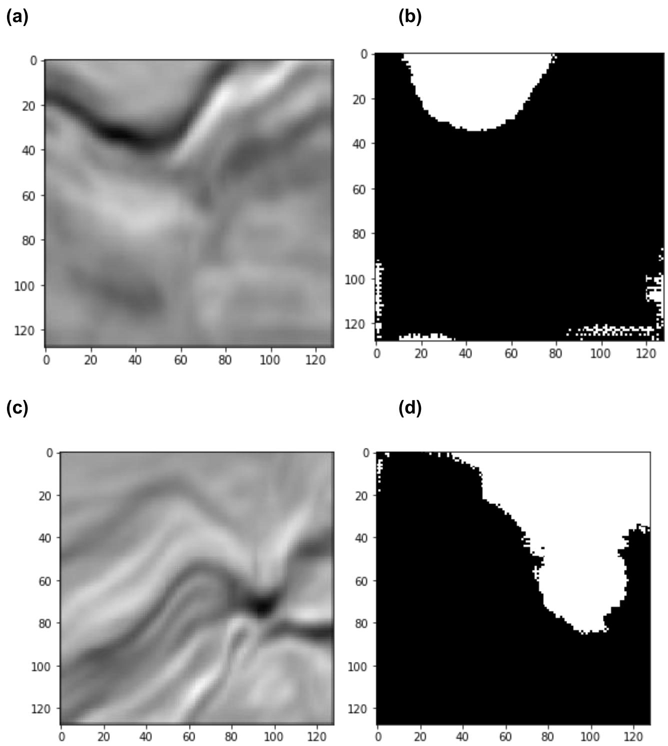


Figure 7: Salt dome region of the F3 survey (inline 425).



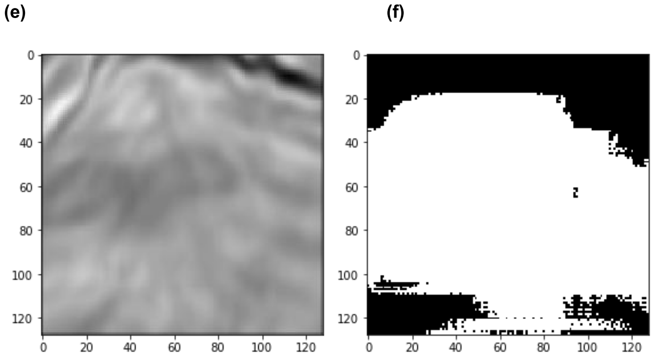


Figure 8(a-f): Input image patches and corresponding predicted salt masks from the F3 block by the model.

identifying salt regions from the survey from the figures, salt regions especially as shown in Figures 8b and 8f.

CONCLUSIONS

Convolutional neural networks have been applied in a supervised learning method for the prediction of salt regions from the F3 survey. Prepared train and validation sets have been used to train and validate model performance. Pixel accuracy of > 94% was recorded and the models were evaluated using other metrics as well. The trained models were used to predict regions of salt from the F3 block 3D survey (inline 425) in the North Sea. Seismic image patches from selected 2D inlines were passed through the pre-trained model for predictions. Machine learning salt interpretation results serve as a first and second-order interpretation guide to the human interpreter, while also speeding up interpretation workflows more than before.

REFERENCES CITED

Kaggle: TGS salt identification challenge. https://www.kaggle.com/c/tgs-salt-identification-challenge (2018), accessed: 2018-10-20

Long, J., E. Shelhamer, and T. Darrell, 2014, Fully convolutional networks for semantic segmentation: CoRR, bs/1411.4038.

Long, J., 2016, Understanding and designing convolutional networks for local recognition problems: PhD thesis, Berkeley.

Tao Zhao, Vikram Jayaram, Atish Roy, , Kurt J. Marfurt. "A comparison of classification techniques for seismic facies recognition". In Interpretation 3(4) (November, 2015).

Yann LecCun, Patrick Haffner, Leon Bottou, Yoshua Bengio (1998). Object Recognition with Gradient Based Learning.

Yauhen Babakhin, Artsiom Sanakoyeu,Hirotoshi Kitamura. Semi-Supervised Segmentation of Salt Bodies in Seismic Images using an Ensemble of Convolutional Neural Networks. https://arxiv.org/pdf/1904.04445.pdf