2D Seismic Data Classification using Convolutional Neural Network and 2D Synthetic Data

Alice Y. Yang[a], Musa Manzi[b], Michael Westgate[b], Ling Cheng[b]

[a] *Cape Town, South Africa*
[b] *Johannesburg, South Africa*

Abstract

The following paper looks at classifying 2-dimensional seismic data extracted from South African geo-location using a Convolutional Neural Network (CNN) that is trained with synthetic data. The purpose of this paper illustrates the difficulties in working with seismic data and the precision needed for automating feature extraction within the CNN architecture in order to achieve a 90%. The CNN architecture is mainly constructed using 2D convolutional and max-pooling layers.

Keywords: 2D Seismic Data, Convolutional Neural Network, Synthetic Data, Gold mines

1. Introduction

In recent years, Artificial Intelligence (AI) has grown exponentially and has been applied to multiple disciplines. It is no surprise that it has found its way into geology. Given that the geologist work with large sets of geological data to map both surfaces of the earth and faults below the surface, which has an enormous potential for AI. The traditional method of interpreting subsurface data includes manual fault picking and horizons on section, which is then followed by qualitative enhancements [1]. The qualitative enhancement techniques involves structurally-oriented semblance, tensor, duo and etc. for highlighting the fault structure within the subsurface seismic dataset [1]. This paper addresses alternative approaches for classifying seismic data using Artificial Intelligence and more specifically, Convolutional Neural Network (CNN) for classifying 2D seismic image data. The objective of the purposed technique is to detect whether intersecting faults or non-intersecting faults are present within 2D seismic data. The paper is structured such that Section 2 provides a brief background of the techniques used in this paper. Section 4 describes the methodology and the process of achieving the results addressed in Section 5, before concluding in Section 7.

2. Background

2.1. Convolutional Neural Network

The Convolutional Neural Network (CNN) is a subsidiary of supervised23 technique within in the deep learning field. It is commonly employed for24 image classification purposes due to its exceptional ability to purpose image25 analysis using the mathematical convolutional operation and obtaining high26 classification accuracies [2, 3]. Due to the CNN's high classification accuracy, it has been utilized within multiple fields including the geological realm for earthquake detection and location [4], seismic inversions [5], and fault detection [6, 7].

Given that the CNN is a supervised neural network, it learns images features based in order to form an end-to-end model with the trained parameters through the gradient descent method. Therefore, the CNN model makes use of connected weights within the network as a form of sharing "knowledge" and reducing the number of training parameters, and as a result also reducing redundant complexity [3, 8]. In general, the first few layers of the CNN architecture consists of convolution and pooling layers, whilst the layers following there after are fully-connected network [6, 9].

The training of the CNN is conducted mainly using both back- and forward propagation algorithms to adjust the weights of the neurons based on the given training data. The objective of the back-propagation algorithm is to adjust the weights to minimise loss based on the network's overall outcome and the target. The network's overall outcome is obtained using the forward propagation. The back-propagation loss function, $E(W, b)$ is expressed in 1 as the Mean Squared Error (MSE).

$$E(W, b) = \frac{1}{|Y|} \sum_{i=1}^{|Y|} (Y(i) - \bar{Y}(i)^2) \tag{1}$$

where W is the weight value and b is the bias value. Both the weight value, W and bias value, b are updated during the back-propagation training according to 2 and 3, respectively.

$$W_i = W_i - \eta \frac{\partial E(W,b)}{\partial W_i} \tag{2}$$

$$b_i = b_i - \eta \frac{\partial E(W,b)}{\partial b_i} \tag{3}$$

where η is the learning rate.

3. Literature Review

Wu, X. et al.performed image-to-image binary fault detection using a fully-supervised CNN [6]. The authors made use of 3D seismic images which where labelled with ones for fault and zeros elsewhere. The CNN model was trained with 200 3D synthetic seismic images with a $128 \times 128 \times 128$ dimension for each fault and non-fault category. The training of the neural network was performed on a TITAN Xp GPU which took the authors approximately 2 hours to train. The authors validated the network with 20 pairs of unseen synthetic image data, in which the network achieved a 95% classification accuracy. The generated synthetic data consists of faults at varying angles, specially at 90°, 180°, and 270°. Additionally, the authors applied the trained CNN to detect faults on surveyed 3D data from four different locations, namely the Netherlands off-shore data, Clyde Petroleum Plc., Costa Rica margin North West of Osa Peninsula, and Campos Basin which is off-shore of Brazil.

Zheng, Y. et al. presents two separate case studies involving supervised deep learning as an alternative for the conventional techniques in seismic data interpretation and inversion [10]. In the first case study, the authors apply the CNN for seismic image classification as a way of interpretation. The CNN is trained with 3D seismic volumes, such that images are classified into two categories, namely, fault and non-fault. The fault data consists of certain dips as well as azimuth, which are distinguishing features in the data considered as faults. In the second case study, the authors present an elastic model building, in which a CNN is trained to perform predictions of 1D velocity and density profiles within the given seismic data. In both case studies, the authors have trained the CNN models using synthetic data and tested the models on survey field data. The authors have found that both CNN models obtained effective and efficient predictions when testing on field data, therefore showing high-quality fault picks. However, challenges are presented when the authors worked with pre-stacked seismic inversions, where subsurface geological variations and preconditioning of the input seismic data plays an important factor in the ability of the CNN models to perform accurate predictions.

The author, Zhao, T. presents an encoder-decoder CNN model for seismic facies classification [11]. The architecture of the encoder-decoder CNN model consists of an encoding component, in which the input data given to the model is reduced and a decoding component, whereby the reduced data is then expanded once again. The purpose of the encoding component is to reduce the input data such that only the significant portions of the input data is kept, whilst the decoding component further highlights and expands on the significant data such that contributing noise within the input data is removed. This allows for enhanced fault predictions in seismic faces. Additionally, the author has compared the presented CNN model to the architecture of the more traditional patch-base CNN model, in which the author found that the patch-base CNN model requires less training effort compared to the encoder-decoder CNN model, however the patch-based CNN produced suboptimal predictions compared to the encoder-decoder CNN.

Di, H et al. introduces a CNN model for the application of salt-body delineation from 3D seismic data [12]. The authors have found the implementation of the CNN model is far more superior when compared to the traditional schemes of sample-based multi-attribute classification. The implemented CNN model takes the local seismic patterns which are distinguishing features within the target salt-body. Furthermore the CNN allows for optimal mapping relationship between the seismic signals and the salt-bodies, and as a result it does not require laborious manual attribute selection as performed in the traditional classification schemes. The CNN model was trained using synthetic data from the SEG-SEAM dataset.

Xiong, W. et al. developed a method which employs the CNN to automate and map fault detection in 3D seismic images to mimic the traditional approach by interpretors. The CNN is trained with image cubes obtained from field data which are labelled as either fault or non-fault. The trained CNN is then applied to unseen field data to predict the fault probabilities at every location with given cube images. The authors have been able to obtain a 99% classification accuracy using the trained CNN.

4. Methodology

The technique consists of two distinct processes. The first is training the and the second is applying the trained CNN to unseen 2D seismic data. The seismic data is extracted from South African geological sub-surfaces. The two processes are illustrated in Figure 1, in which the training process is depicted on the left and the test process on the right.

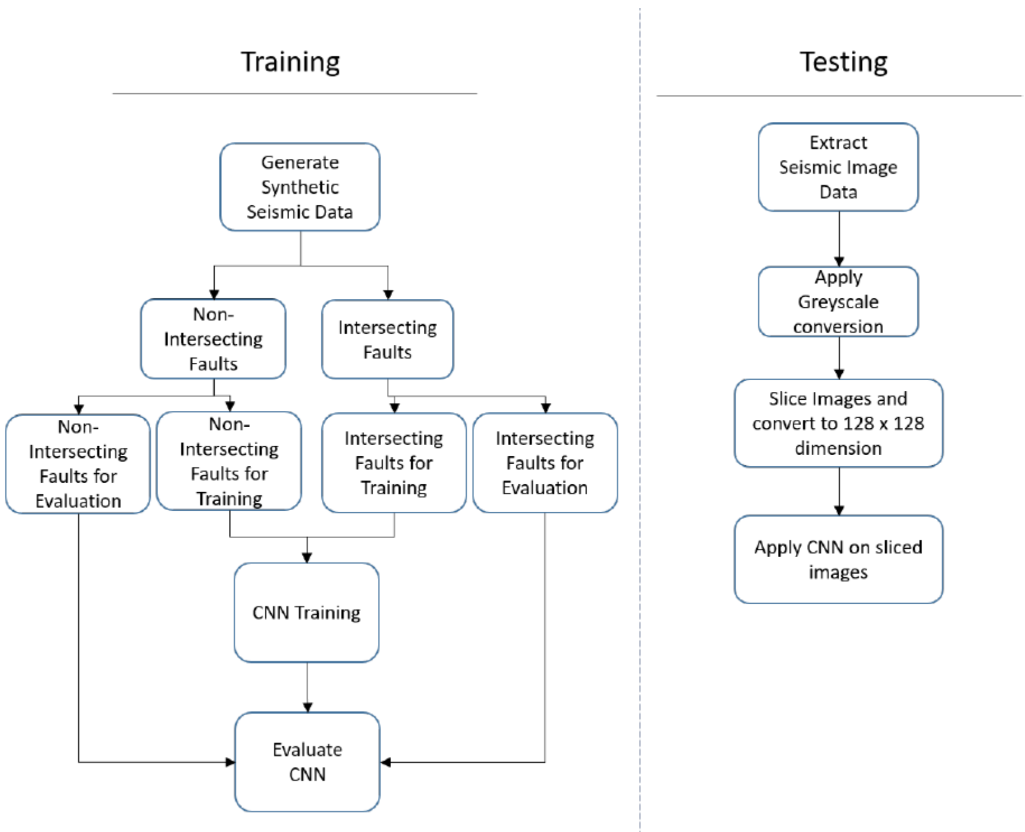
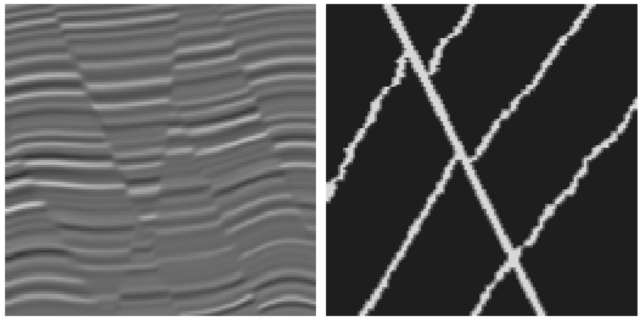


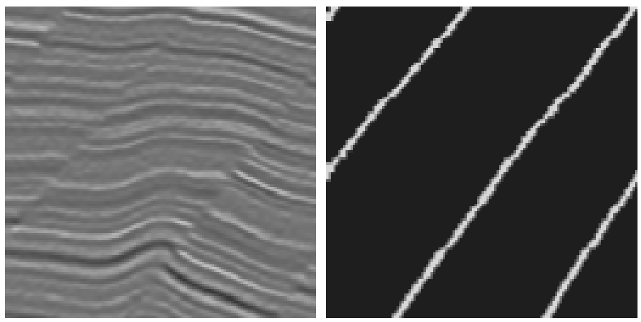
Figure 1: Diagrams illustrating the training and testing processes involving the Convolutional Neural Network.

4.1. Training Images

The data used for training the CNN is taken from FaultSeg3D: using synthetic datasets to train an end-to-end convolutional neural network for 3D seismic fault segmentation whereby the data is given as three-dimensional $128 \times 128 \times 128$ seismic data, which is generated by Wu, X. et al [6]. The data



(a) Seismic image with intersecting faults (b) Highlighted image with intersecting faults



(a) Seismic image with non-intersecting faults (b) Highlighted image with non-intersecting faults

is transformed from 3D to 2D, by taking slices of the 3D block to generate 2D 128×128 seismic data. From the synthetic data, only the seismic data which has intersecting and none-intersecting fault are selected. Figures in 2a and 2b illustrates the training data. Both images 3a and b are not used as part of the training data, however are used to assist in the labelling of intersecting and non-intersecting fault data. A total of 350 seismic images are used in each category for the training of the CNN.

4.2. Convolutional Neural Network

The CNN is comprised of three distinct layers excluding the input and output layer, namely 2D convolutional, max pooling and fully connected layers. There are a total of four hidden layers in the neural network architecture. The 2D convolutional layer makes use of the Rectified Linear Unit (Relu) function. Figure 4 shows the detailed architecture of CNN. The CNN is trained with 25 epochs. Figure 5 shows the accuracy and validation accuracy of the CNN at each epoch.

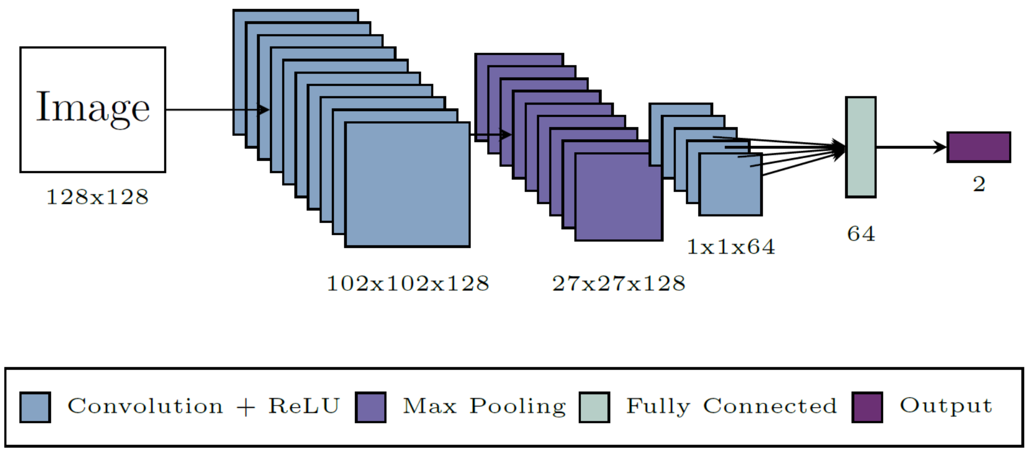


Figure 4: Figure illustrating the architecture of the Convolutional Neural Network

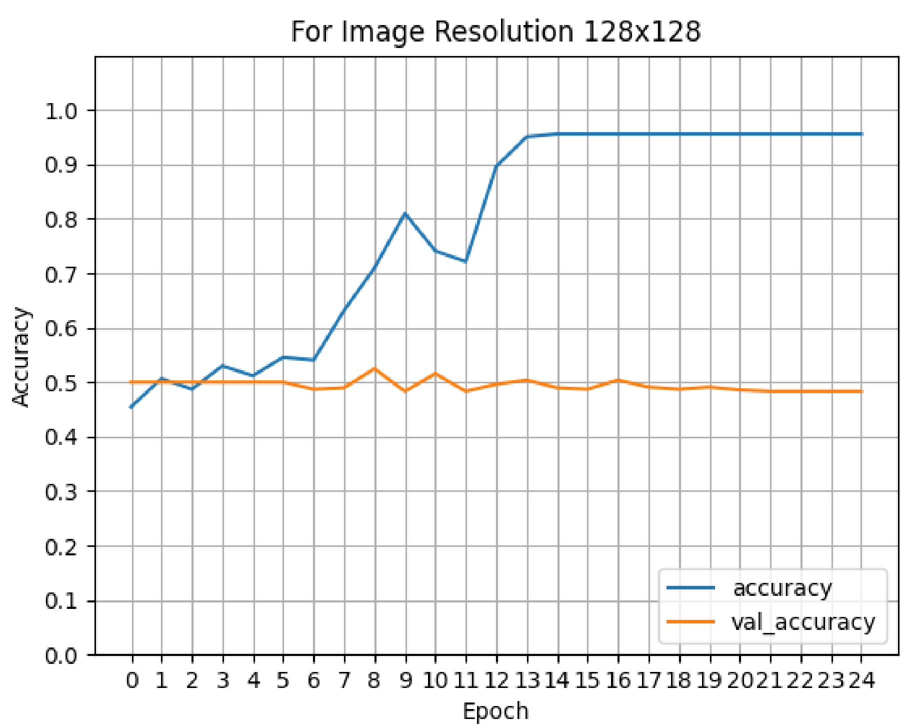


Figure 5: Figure illustrating accuracy of the CNN at each epoch

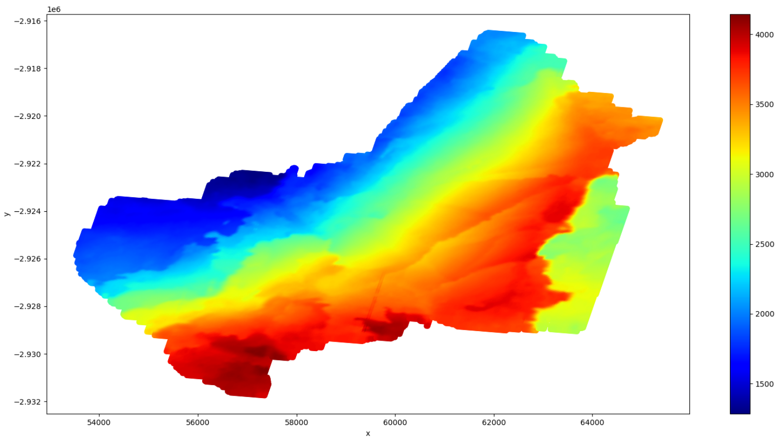


Figure 6: Figure illustrating the orebody surface extracted from a gold mine

4.3. Seismic Data Testing

The seismic testing data consists of surface and edge detected images of the orebody. The two image considered are shown in Figure 6 and 7, in which both images are taken from South African gold mines.

5. Results

6. Application

7. Conclusion

References

[1] P. S. J. Lowell, N.Tessen, Artificial intelligence and seismic interpretation, 2019. URL: `http://www.geoexpr.com/articles/2019/05/artificial-intelligence-and-seismic-interpretation`.

[2] A. Krizhevsky, I. Sutskever, G. E. Hinton, Imagenet classification with deep convolutional neural networks, Advances in neural information processing systems 25 (2012).

[3] W. Zhiqiang, L. Jun, A review of object detection based on convolutional neural network, in: 2017 36th Chinese Control Conference (CCC), IEEE, 2017, pp. 11104–11109.

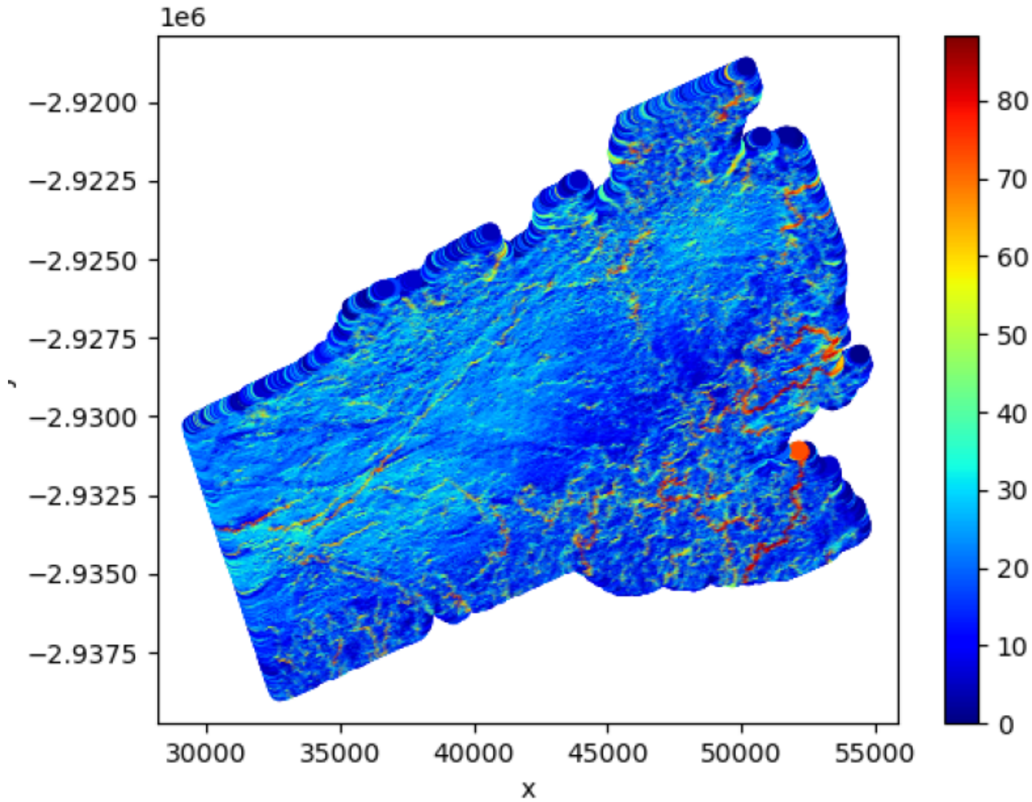


Figure 7: Figure illustrating the orebody surface with highlighted edges extracted from the gold mine

[4] T. Perol, M. Gharbi, M. Denolle, Convolutional neural network for earthquake detection and location, Science Advances 4 (2018) e1700578.

[5] V. Das, A. Pollack, U. Wollner, T. Mukerji, Convolutional neural network for seismic impedance inversioncnn for seismic impedance inversion, Geophysics 84 (2019) R869–R880.

[6] X. Wu, L. Liang, Y. Shi, S. Fomel, Faultseg3d: Using synthetic data sets to train an end-to-end convolutional neural network for 3d seismic fault segmentation, Geophysics 84 (2019) IM35–IM45.

[7] W. Xiong, X. Ji, Y. Ma, Y. Wang, N. M. AlBinHassan, M. N. Ali, Y. Luo, Seismic fault detection with convolutional neural network, Geophysics 83 (2018) O97–O103.

[8] N. Chumerin, Convolutional neural network, Technical Report, Tech. Rep, 2017.

[9] Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, Proceedings of the IEEE 86 (1998) 2278–2324.

[10] Y. Zheng, Q. Zhang, A. Yusifov, Y. Shi, Applications of supervised deep learning for seismic interpretation and inversion, The Leading Edge 38 (2019) 526–533.

[11] T. Zhao, Seismic facies classification using different deep convolutional neural networks, in: SEG Technical Program Expanded Abstracts 2018, Society of Exploration Geophysicists, 2018, pp. 2046–2050.

[12] H. Di, Z. Wang, G. AlRegib, Deep convolutional neural networks for seismic salt-body delineation (2018).