Journal of Engineering Science and Technology Review 16 (5) (2023) 204 - 208

Research Article

JOURNAL OF
**Engineering Science
and Technology Review**

www.jestr.org

CNN based Automatic Fault Detection in 3D Seismic Images

Sandhya G.[1,*], Jaya Babu B.[2] , Ganesh Babu P.[1] and S. Yallamandaiah[1]

[1]Department of ECE, VNITSW, Guntur,Andhra Pradesh, India.
[2]Department of EEE, VLITS, Guntur,Andhra Pradesh, India.

Received 6 May 2023; Accepted 21 September 2023

Abstract

Fault detection in seismic images is important in interpreting seismic changes because the faults confirm unexpected subsurface topographical changes. In the traditional approach, faults are manually detected from post-stack seismic data and identified as reflection discontinuities, which is a very tedious process. To increase efficiency and reduce time consumption, a number of automatic fault detection techniques have been developed, of which techniques based on deep learning have proven to be efficient. This work proposed a deep learning based method to generate a seismic attribute called fault probability to highlight fault zones in the 3D seismic images. Since the technique detects the faults directly from seismic volumes, pre-computed attributes such as those used in coherence or edge detection methods are not strictly necessary. The proposed technique is instigated in two stages— training and prediction. In the training stage, a CNN model is trained with real data taken from 7 annotated seismic volumes, in which every point is labeled as fault or no-fault. Then in the prediction stage, the trained network is used to calculate the fault probability at every location in the new seismic image volumes. Both synthetic and real data sets are used to validate the proposed method. The obtained results proved that the proposed deep learning-based fault detection method outperforms some existing methods and also achieves effective performance compared to humans on an expert labelled seismic image dataset, much exactly predicting subtle faults which cannot annotate by an expert interpreter.

Keywords: Seismic images, Fault detection, CNN, Fault Probability.

1. Introduction

Detection and characterization of the faults in seismic images are very important in the interpretation of subsurface structures and in the assessment of reservoirs. These faults can act as a seal or conduit for the transport of oil and gas, and these fault zones are favorable regions for depositing hydrocarbons in carbonate rock structures [1,2]. But the process is crucial and time taking. In general, it takes weeks to months for an expert to hand-pick the discontinuities from raw seismic images of a typical seismic volume. In the standard fault detection techniques faults are identified as reflection discontinuities or abruptions by the expert interpreters and recognise the faults on 2D and 3D seismic images. It is extremely operator-intensive, depends heavily on the experience of the interpreter. These manually selected results are different for different experts, hence bias is unavoidable. A group of seismic features which are helpful in seismic fault interpretation are proposed to highlight the seismic discontinuities. Seismic coherence is the eminent feature [1, 3], which can identify the seismic faults by measuring the similarity between seismic traces. Other type of attributes such as variance [4], curvature [5], and gradient [2], highlights the faults by finding dissimilarity between the seismic traces. Subsequently these attributes may be regarded as fault images since seismic reflection has been eliminated and discontinuities have been highlighted.

Various approaches have been developed to detect faults in seismic images, such as B. seismic coherence estimation, edge detection and ant tracking, etc. The extraction of coherence features from the seismic image volume [1,6,3] was a widely used technique. In [7], Admasu et al. detected the fault discontinuities using an automatic tracking algorithm, and Dorn et al. [8] proposed an automatic extraction of the faults. Most of these methods are deterministic and mainly suffer from two limitations. First off, these techniques are difficult to adapt to various discontinuities found in several seismic images. Coherence technology, for instance, is less susceptible to gradually changing faults. Second, these methods are unable to learn systematically from the experience of interpreters**.** Hence the results are greatly affected by the knowledge and experience of the interpreters.

In recent times, the advancements in machine learning algorithms have paved the way for the design of a range of techniques based on the convolutional neural networks(CNN), which enhances the seismic fault interpretation. Technologies of machine learning, particularly deep learning, are efficient at extracting features from the data that makes them ideal to learn from human experience [9-11]. Many effective deep learning techniques are proposed in the literature to handle big-data analysis. CNN is the mostly employed deep learning procedure and is highly effective in the areas of image detection and classification [12,13] . Deep learning techniques can also be used for the seismic images processing and interpretation, seismic phase classification, data interpolation, in addition to geophysical feature extraction [14,16]. Various deep learning technologies are proposed for the automatic extraction of geophysical features for the fault detection in seismic images. In [17,18] deep learning is used with 2D and 3D synthetic tests to extract the geophysical features for the detection of seismic faults from a

*E-mail address: Sandhyag406@gmail.com
ISSN: 1791-2377
doi:10.25103/jestr.165.25

pre-migrated data. In [19], A novel training method is proposed by Araya Polo et. al to train the deep neural network that can detect the faults from the natural seismic data. With the appropriate features and by using a synthetic seismic volume, Huang et al. [14] trained CNN to identify the faults. Several authors proposed pixel-wise classification methods to detect the faults with help of various seismic features and CNN [15,16]. In [17], Xiong et al. trained a fault classification CNN network with the training samples extracted from field seismic data. Di et al. proposed a multilayer perceptron procedure to detect the faults in multiple seismic feature zones [18]. In [20], Wu et al. proposed a synthetic seismic patch based trained CNN model which can detect the faults as well as can find the orientation of the faults.

This paper proposed a CNN model to detect geologic faults that exist in 3D seismic images. The network is trained to detect the faults present in the raw seismic images taken from 3D seismic volumes. The training dataset is created using real data acquired from seven annotated seismic volumes, while one volume is utilized for validation or testing. The ability of the proposed trained model to detect the faults is first tested with synthetic seismic images with artificial faults. Then this trained network is operated on another real seismic cube that it has not once seen earlier during training. Compared to the coherence detection the fault probability obtained by the proposed CNN model is better and highlights the seismic discontinuities well.

2. Methodology

This section describes the proposed algorithm to find the faults in seismic Images.

2.1 Problem Formulation

The detection of seismic defaults is formulated as a problem of image classification. Seismic image patch centred on a point O extracted from the seismic image volume is the input for the classification task. The output is a binary classification result as fault or no-fault for the central point. 2D slices with a dimension of 24×24 are extracted along the in-line, cross-line, and time axes with respect to the centre point O in the 3D seismic cube. As depicted in Figure 1, those three slices combine to create the network's input data sample x of size 24×24×3. Similar to the standard RGB-colored image classification problem, the proposed CNN input has three channels. In the interim, point O is associated with a label y denoted as 1: fault or 0:no-fault specifying whether a fault exist or not. Each sample in the training dataset is denoted as (x, y) which represents the input data x associated with a label y. Manually picking results are considered as groundtruths.

By taking the input data sample x the CNN outputs the probability that centre point O contains a fault, is referred to as fault probability. It is the broadly used phrase for the identification of seismic faults and it is an attribute that can highlights seismic image discontinuities [3,21]. In detail, the network assigns a probability of $p(Y = y|x)$ to the centre point O of the sample (x, y). For a group of n number of samples $\{(x_k, y_k), k = 1, \dots, n\}$ of the training dataset, the proposed network is trained to minimize the following objective function designed using cross-entropy

$$L = -\frac{1}{n}\sum_{k=1}^{n} log\,(Y = y_k|x_k) \quad (1)$$

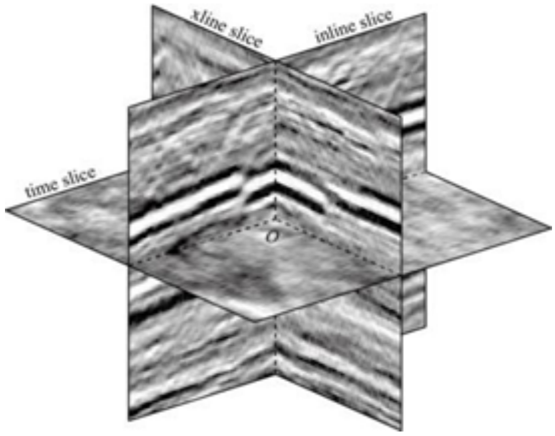
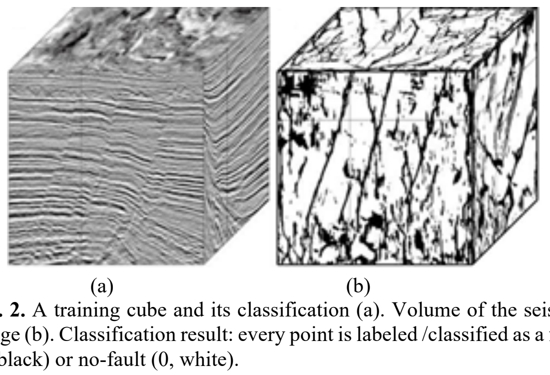


Fig. 1. Diagrammatic representation of the CNN input data

The training data set is formed with the faults detected by humans or by the auto-picking algorithms. This work classified real data of eight distinct 3D seismic images using a skeletonized-coherence-based auto-picking technique [22]. Classification results in the labeling of all the points in the training cube as fault or no-fault. The threshold technique is used to label the points. The point with skeletonized-coherence value greater than a predefined threshold is labelled as a fault, while the point with coherence value smaller than the predefined threshold is labelled as a no-fault. Figure.2 presents one of the training cubes and its annotation. The cube is taken from the GeoFrame^{TM} reservoir characterization software [23]. The other real 3D seismic data cubes are obtained from the Saudi Aramco. For all the cubes the interval value for the vertical time sample is either 0.002sec or 0.004 sec, and all of the cubes have identical inline and cross-line axes spatial grid size of 25 meters. To demonstrate the proposed CNN's adaptability and robustness, the same time sampling interval is maintained for real data. A network that has been successfully trained should be able to identify samples exactly provided that the trained dataset includes an adequate distribution of the samples. The network may fail to identify exactly the faults in seismic cubes if the sampling time interval is far away from the values in the trained datasets.

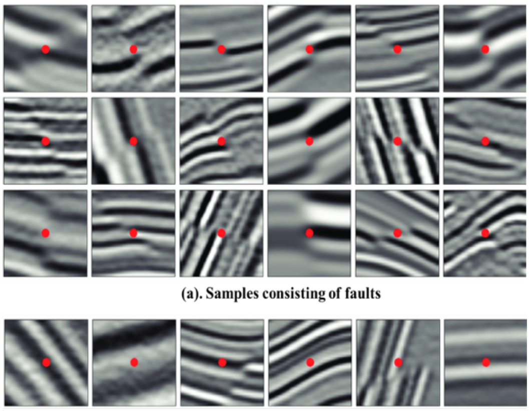


(a) (b)

Fig. 2. A training cube and its classification (a). Volume of the seismic image (b). Classification result: every point is labeled /classified as a fault (1, black) or no-fault (0, white).

Among the 8 distinct seismic volumes considered one is randomly chosen for the validation purpose and it is not included in the training phase. The remaining seven are utilised to construct the training dataset. To create the training dataset, from each cube 100000 points which are labeled as faults or around 0.4% of all the existing fault points in the seismic cube and one more 100000 points from every cube that have been labeled as no-fault are randomly chosen. Owing to the characteristics of the seismic image, in general the no-fault points are substantially higher in number than the fault points. For training equal number of the fault and no-fault training samples are considered to make the possibility of examining both classes equally. The training dataset totally have 0.7 million samples. Data augmentation is also employed while training to switch the inline and cross-line axes for each sample because any space axis can be designated as inline or cross-line.

It is very difficult for the human eye to discriminate every fault and no-fault sample, but can observe a systematic difference between the two classes. Figure 3 displays a few examples of the fault and no-fault samples drawn from the training dataset in random. More continuous seismic events are visible in no-fault samples but the fault samples consist of irregular structures. The same techniques are used to construct the test dataset, that is used to test the proposed trained model and decide when to terminate the training.



(a). Samples consisting of faults

(b). Samples consisting of no-faults

Fig.3. Example samples of (a) fault, (b) no fault.

2.2. CNN Model and Training

The proposed seismic fault detection as an image classification is modeled using Convolutional Neural Network. Figure.4 presents the Fault detection workflow using the proposed CNN model.

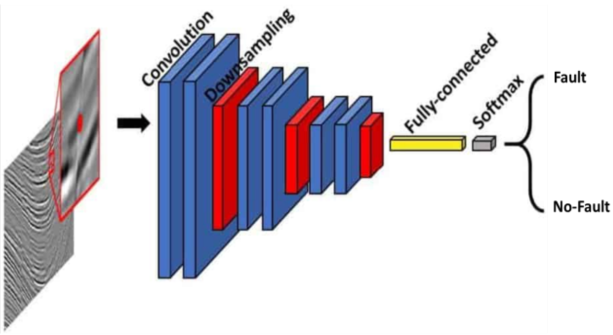


Fig. 4. Seismic Fault detection workflow using CNN model.

The proposed network comprises of two convolution layers, two fully-connected layers, and one softmax classifier, that can predict the label probability as either fault or no-fault. Three orthogonal 2D seismic images of 24×24 size are given as input to the proposed network, and the network outturns a label prediction for the centre point O. Before being fed into the network the input is normalized by subtracting the mean and dividing it by the standard deviation. The network considered is identical to the network in classical CIFAR-10 classification problem [24,25]. Each of the convolution layers has 64 filters of size 5×5. The two FC layers include 384 and 192 feature maps, respectively. ReLU is applied after each Conv layer and Fully-Connected layer. After the two Conv layers, max-pooling with a size and step of 2×2 and the local response normalization (LRN) are applied. At the end softmax classifier generates a probability that indicates the possibility of a fault at the center point O of the input. Label prediction of the output can be done by applying a threshold of 0.5 for the values of output probability, such that the values above the threshold are regarded as a fault location, and the values below it are no-fault.

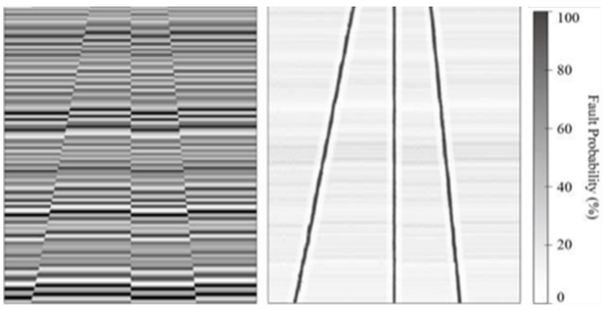
The network is trained by initializing the weights of each layer according to the CIFAR-10 tutorial [25,26]. Gradient descent optimization technique with initial learning rate of 0.2 and default parameters is used. To achieve good network performance, for each epoch the training samples are shuffled randomly prior to giving them to the network. When the error function in eq (1) plateaus during the optimization phase, the model is saved, and is then validated using the validation dataset. For both the training and validation datasets the proposed model achieves classification accuracy of about 83%.

3. Results and Discussion

This section presents the results of the proposed seismic fault detection and their description. The obtained results are also compared with the outcomes of the Coherence method.

A properly trained CNN Model is first operated on a basic 3D synthetic seismic volume to detect the faults. Figure.5 presents the results of the proposed model on simple synthetic seismic data. A single trace of a training cube is extended horizontally along the length of inline axis to create the synthetic cube. Three exact fault lines with distinct slopes are used as artificial discontinuities, and the 2D section is additionally extended along the cross-line axis with a 5-degree rotation along the time axis as displayed in Figure 5 (a). The Figure 5(b) displays the result of fault probability by the proposed network for an inline section. The synthetic cube is then used to extract the CNN testing data.

Experiment results classification accuracy of 96% for the considered synthetic cube. Even though the network is not aware of these artificial faults, it is obvious that the three faults are exactly detected by it. The fault probability map shows some horizon traces footprints for values below 0.4. Close observation reveals that the footprints are feeble whereas the seismic trials are strong and hence clearly visible. The tests demonstrate that these type of artifacts can be eliminated by using learning samples taken from the synthetic cube to train the network. Such footprints or imperfections are in fact helpful to differentiate between true fault probabilities from the false fault probabilities. The effectual detection of the exact faults signifies that CNN has learned to differentiate faults from no-fault zones.



(a) (b)

Fig.5. Results of the proposed CNN model for synthetic seismic data. (a). Inline section consisting of 3 artificial seismic faults, (b). Probability of the seismic faults acquired by the proposed method.

For testing the network, a 3D seismic test image cube of actual data, is next applied to the trained network, as illustrated in Figure 6. The dimensions of the cube are 1000×655×1083. The top, front, and side panels are displaying time section T=310, in-line section Y=420, and cross-line section X=415 respectively. The black lines present in the figure indicate the locations of the sections. The classification accuracy achieved by the CNN for this real data cube is around 83%, which is comparable to the results for the training and validation datasets.

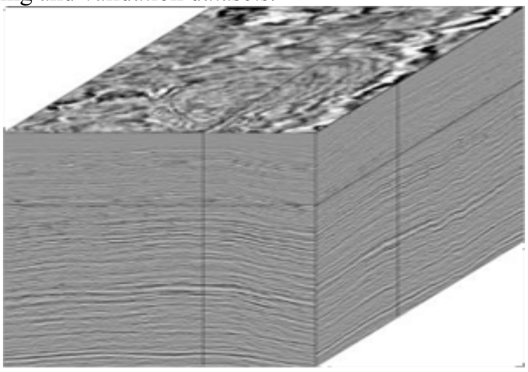
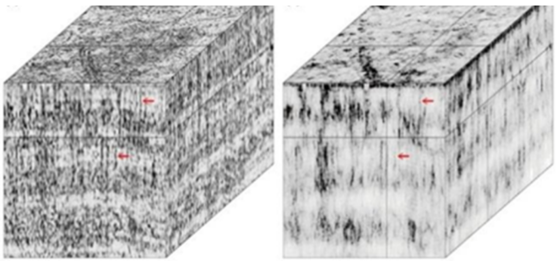


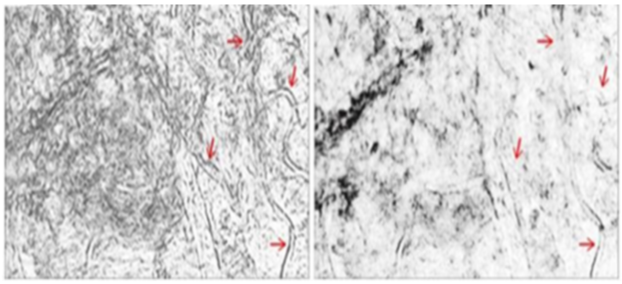
Fig.6. A real seismic test image cube

The fault probability results of the proposed model are justified by comparing with the results of seismic coherence. The fault probability cube resulted by the CNN is displayed in Figure.7(a), and 7(b) displays the results by the seismic coherence. Seismic coherence is a popular and commonly used characteristic to highlight the seismic image discontinuities [1]. From Figure.7 and 8, it can be concluded that the CNN results exhibit seismic faults with greater resolution as compared to coherence volume. The CNN results also exhibit clearer channels compared to coherence. The computation of the fault probability is carried out for individual points. The contours of the discontinuities in the images of the fault probability are fair and continuous which ensures that the proposed CNN model performs effectively even in the existence of noise.



(a) **(b)**

Fig. 7. Results for a real data cube (a). Fault probability cube predicted by the proposed CNN model and (b). Fault probability cube predicted by the seismic coherence.



(a) (b)

Fig. 8. Fault probability time slices (a).CNN (b). Coherence

The proposed method requires high computational time since the model has to estimate the fault probability at every point in the 3D seismic image cube. Every computation involves, feeding the trained network with an input sample at a specific location and finding the fault probability as output. One such computation requires 10msec of time with one core processor. Since each location's calculations are independent of one another, they can be carried out simultaneously. Employing a computer cluster having 20 nodes of 40 core processors at each node, it has taken around 2 and half hours to find the fault probability for a considered 3D image. Hence the proposed method can be more effective by reducing the redundant calculations.

4. Conclusion

This work proposed a CNN-based technique for the detection of seismic faults in 3D seismic images. The fault probability results of the proposed method on real seismic data surpassed the results of the seismic coherence. The network is trained with 100000 training samples which is nearly 0.4% of the available fault samples in the training cubes hence it can detect synthetic and real faults exactly. In this work the training samples are generated using auto-picking hence the network training may be biased due to this strategy. It is very effective if the faults are picked up by the best interpreters and the network will learn from several experienced interpreters which can decrease human bias. Deep learning technologies have demonstrated their ability to perform as humans and sometimes surpass human judgment in various applications related to image detection and image classification. The ability of the CNN in detecting seismic faults makes it very appealing to deploy in upcoming automatic seismic interpretation systems.

References

[1] M. Bahorich and S. Farmer, "3-D seismic discontinuity for faults and stratigraphic features: The coherence cube," *The Lead. Edg.*, vol. 14, no. 10, pp. 1053–1058, Oct. 1995, doi: 10.1190/1.1437077.

[2] A. A. Aqrawi and T. H. Boe, "Improved fault segmentation using a dip guided and modified 3D Sobel filter," in *SEG Technical Program Expanded Abstracts 2011*, Society of Exploration Geophysicists, Jan. 2011, pp. 999–1003. doi: 10.1190/1.3628241.

[3] X. Wu, "Directional structure-tensor-based coherence to detect seismic faults and channels," *Geophys.*, vol. 82, no. 2, p. A 13-A 17, Mar. 2017, doi: 10.1190/geo2016-0473.1.

[4]P. Van Bemmel and R. Pepper, "Seismic signal processing method and apparatus for generating a cube of variance values," 6.151.555

[5] H. Di and D. Gao, "Efficient volumetric extraction of most positive/negative curvature and flexure for fracture characterization from 3D seismic data," *Geophys. Prospect.*, vol. 64, no. 6, pp. 1454–1468, Nov. 2016, doi: 10.1111/1365-2478.12350.

[6] Y. Luo, W. G. Higgs, and W. S. Kowalik, "Edge detection and stratigraphic analysis using 3D seismic data," in *SEG Technical Program Expanded Abstracts 1996*, Society of Exploration Geophysicists, Jan. 1996, pp. 324–327. doi: 10.1190/1.1826632.

[7] F. Admasu, S. Back, and K. Toennies, "Autotracking of faults on 3D seismic data," *Geophys*, vol. 71, no. 6, pp. A49–A53, Nov. 2006, doi: 10.1190/1.2358399.

[8] G. Dorn, H. James, D. Dopkin, and B. Payne, "Automatic Fault Extraction in 3D Seismic Interpretation," in *67th EAGE Conference & Exhibition*, Madrid, Spain,: European Association of Geoscientists & Engineers, 2005. doi: 10.3997/2214-4609-pdb.1.F035.

[9] B. Fulkerson, "Machine Learning, Neural and Statistical Classification," *Technometrics*, vol. 37, no. 4, pp. 459–459, Nov. 1995, doi: 10.1080/00401706.1995.10484383.

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.

[11] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural Netw.*, vol. 61, pp. 85–117, Jan. 2015, doi: 10.1016/j.neunet.2014.09.003.

[12] Y. LeCun and Y. Bengio, "Convolutional networks for images, speech, and time series," in *Handbook of Brain Theory and Neural Networks*, M. A. Arbib, Ed., MIT Press, 1995, p. 3361.

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *Advances in Neural Information Processing Systems*, F. Pereira, C. J. Burges, L. Bottou, and K. Q. Weinberger, Eds., Curran Associates, Inc., 2012. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2012/file/c399862d3b9d6b76c8436e924a68c45b-Paper.pdf

[14] L. Huang, X. Dong, and T. E. Clee, "A scalable deep learning platform for identifying geologic features from seismic attributes," *Geophys*, vol. 36, no. 3, pp. 249–256, Mar. 2017, doi: 10.1190/tle36030249.1.

[15] D. Rocha, P. Sava, and A. Guitton, "3D acoustic least-squares reverse time migration using the energy norm," *Geophys.*, vol. 83, no. 3, pp. S261–S270, May 2018, doi: 10.1190/geo2017-0466.1.

[16] B. Guo, L. Li, and Y. Luo, "A new method for automatic seismic fault detection using convolutional neural network," in *SEG Technical Program Expanded Abstracts 2018*, Anaheim, California: Society of Exploration Geophysicists, Aug. 2018, pp. 1951–1955. doi: 10.1190/segam2018-2995894.1.

[17] W. Xiong *et al.*, "Seismic fault detection with convolutional neural network," *Geophys.*, vol. 83, no. 5, pp. O97–O103, Sep. 2018, doi: 10.1190/geo2017-0666.1.

[18]H. Di, M. Shafiq, and G. AlRegib, "Patch-level MLP classification for improved fault detection," in *SEG Technical Program Expanded Abstracts 2018*, Anaheim, California: Society of Exploration Geophysicists, Aug. 2018, pp. 2211–2215. doi: 10.1190/segam2018-2996921.1.

[19] M. Araya-Polo, T. Dahlke, C. Frogner, C. Zhang, T. Poggio, and D. Hohl, "Automated fault detection without seismic processing," *The Lead. Edg* vol. 36, no. 3, pp. 208–214, Mar. 2017, doi: 10.1190/tle36030208.1.

[20] X. Wu, Y. Shi, S. Fomel, and L. Liang, "Convolutional neural networks for fault interpretation in seismic images," in *SEG Technical Program Expanded Abstracts 2018*, Anaheim, California: Society of Exploration Geophysicists, Aug. 2018, pp. 1946–1950. doi: 10.1190/segam2018-2995341.1.

[21] D. Neff, J. Grismore, and A. Lucas, "Automated seismic fault detection and picking," WO 00/14575

[22]J. Qi, G. Machado, and K. Marfurt, "A workflow to skeletonize faults and stratigraphic features," *Geophys*, vol. 82, no. 4, pp. O57–O70, Jul. 2017, doi: 10.1190/geo2016-0641.1.

[23]"Geophysics Software." SLB, 2017. [Online]. Available: https://www.software.slb.com/products/disciplines/geophysics

[24] A. Krizhevsky, *Learning Multiple Layers of Features from Tiny Images*. University of Toronto, 2009. [Online]. Available: https://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf

[25] Google, Tensorflow tutorials: convolutional neural networks, . [Online]. Available https://www.tensorflow.org/Tutorials /deep_cnn, 2017.