The classification and interpretation of the polyphase fault network on the North Slope, Alaska using deep learning
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Summary
Accurate detection of faults is critical to subsurface interpretation, stress history analysis, and resource recovery. Over the years, manual seismic interpretation and seismic attributes have been used for identifying the faults. However, this process is time-intensive and subject to various interpretations by geoscientists. In this study, we use the convolutional neural network (CNN) to classify and predict the complex normal fault network system on the North Slope, Alaska. In essence, this is a binary image classification problem for a focused geologic study. The subsurface on the North Slope is controlled by polyphase fault development history due to several episodes of tectonic events, affecting a few formations multiple times and in multiple directions. In this study, we use two 3D seismic surveys for fault classification over a total area of ~400 sq. miles (1036 sq. km). The results show that a few original seismic sections with labeled faults can be directly used in the CNN model for automated fault classification through the 3D volumes with high accuracy and in limited time, thereby, bypassing the manual and seismic attribute-assisted fault detection. The classification accuracy of faults is ~88.5%. The fault distribution pattern reveals a complicated structural history of the study area, which underwent several episodes of deformation.

Introduction
The North Slope of Alaska has been producing hydrocarbons over several decades. Our study area is near the Prudhoe Bay field. The Prudhoe Bay is the largest oil field in North America, discovered in 1968. The subsurface of the North Slope is significantly complicated due to several episodes of tectonic events (extension, compression, and flexure), leading to numerous faults in different orientations, the end result of which is compartmentalized reservoirs and variability in hydrocarbon production.

Nixon et al. (2014) studied the fault distribution in the Milne Point area (west of our study area) and found two generations of faults, Cenozoic aged NNE-oriented faults, and Jurassic aged WNW-oriented faults. Tatarin (2019) identified four different fault sets and analyzed the stress history in the Storms 3D survey area, just south of the Prudhoe Bay field. Bhattacharya and Verma (2019) and Verna and Bhattacharya (2019) used long-wavelength and short-wavelength curvature and aberrancy (or flexure) attributes to illuminate the fault distributions in the area. Some of the formations, such as the Shublik Shale has been affected by several episodes of faults along multiple orientations. However, the computation of curvature and aberrancy attributes, and generation of fault models is expensive, in terms of time and cost (Di and Gao, 2014; Verma and Bhattacharya, 2019). In this study, we use deep learning (e.g., CNN) to classify and predict faults with high accuracy and interpret the results.

Deep learning is one of the frontier areas of research in machine learning and geophysics now. Recently, there has been a major uptick in deep learning-assisted seismic interpretation. Huang et al. (2017), Di et al. (2018), and Wu et al. (2019) used deep learning algorithms for automated fault classification. Several of these published studies used synthetic seismic datasets and publicly available datasets from the North Sea and New Zealand. Apart from fault interpretations, deep learning is being used in stratigraphic interpretations (Alaudah et al., 2019; Alfarraj and AlRegib, 2018; Di et al., 2019; Jesper and Luthje, 2018; Zhao, 2018). In this study, we apply CNN on two 3D seismic datasets (North Shore 3D and Storms 3D). The results from the CNN algorithm is used to interpret the faults. To date, there have been few published studies on machine learning in subsurface geosciences in Alaska.

Geology of the study area
Our study area is on the North Slope, Alaska (Figure 1a). The subsurface geology on the North Slope is complex. The main tectonic episodes on the North Slope can be summarized by four major tectono-stratigraphic sequences, such as the Franklinian, Ellesmerian, Beaufortian, and Brookian sequence (Figure 1b). Northern Alaska has undergone several tectonic events, including the Caledonian orogeny (Lane, 2007; McKerrow et al., 2000), Ellesmerian orogeny (Grantz et al., 1994), Beaufortian rifting (Hubbard et al., 1987), Brooks Range orogeny (Blythe et al., 1997; Nixon et al., 2014), and Eocene resurgence (Houseknecht and Bird, 2011), etc. All these events have resulted in reactivation of older faults and subsequent propagation of younger faults. This has complicated the subsurface structure significantly, with several fault-controlled petroleum systems. The Triassic Shublik Shale is perhaps the most important source rock on the North Slope (Figure 1b). It is a prominent marker on the seismic data, and we focus our study on this formation.

3D seismic data
In this study, we use two post-stack 3D seismic surveys. North Shore 3D area: 124.71 sq. miles, ~323 sq. cm) and Storms 3D area: 280.17 sq. miles, ~726 sq. km), which were acquired in 2007 and 2005, respectively. These surveys are ~10 miles (~16 km) apart. Storms 3D dataset is not as good quality as the North Shore 3D. We use a few deep wells near the survey areas for the well-seismic tie. Please see Bhattacharya and Verma (2019) for details on geology. Figure 2 shows the seismic sections.
Deep-learning-based Fault Classification

Convolutional Neural Network

CNN is one of the deep learning algorithms. It is a powerful algorithm, which can represent high-dimensional data, learn feature complexities, deal with non-linearity, generalize models, and optimize model parameters (Huang et al., 2017; LeCun et al., 2015; Liu et al., 2019). In general, there are two types of CNN models, including patch-based classification and encoder-decoder segmentation (Zhao, 2018). In this study, a patch-based classification CNN model is used, which is composed of convolutional layers, pooling layers, and fully-connected layers. In a patch-based model, the CNN model receives the input training data as a 2D or 3D grid of pixels, which are fed into the convolutional and pooling layers. These layers consist of a number of filters, which learn different features of the input data. Then, the fully-connected layer classifies the data pattern. The output is a single value representing the labels, fault or no-fault, at the center of the input patch. Figure 3 shows the network architecture used in this study.

3D seismic interpretation

First, we interpret the Shublik surface in both surveys based on the well-seismic tie and regional geologic knowledge (Figure 4). The structure maps (time-domain) show a segmented appearance of the surface along several directions, which is indicative of faults. Based on the map pattern, there is a structural high present between the North Shore 3D and Storms 3D surveys.
Deep-learning-based Fault Classification

Application of Convolutional Neural Network

1. **Fault labeling:** First, we label a few seismic sections (26 lines in the North Shore 3D and 31 lines in the Storms 3D out of 1,000s of inlines and crosslines) with faults based on the visible reflector offset and curvature patterns (Figure 2). Then, we use the annotated 2D seismic sections (pixel size 31x31) as the input to the CNN model (Figure 3).

2. **Model training:** Next, we train the CNN model using two convolutional layers, followed by two fully-connected layers. The convolution masks have a size of 2x2. The convolutional layers generate 32 and 64 features, respectively. We use the 2x2 maximum pooling to reduce the dimensions of output features after convolution. We use the dropout technique to avoid overfitting by preventing complex co-adaptations on training data (Hinton et al., 2012). The fully-connected layers have 1,024 and 256 neurons, respectively, and we compute the cross-entropy for measuring the probability of error between the classification and the true labels. The activation functions at all neurons are initialized as noises in a normal distribution with the standard deviation of 0.1 and are updated while the training continues.

3. **Model testing:** After model training, we use three test seismic sections (labeled with faults) to evaluate the performance of CNN. The overall accuracy (for the test data set) is ~99.2% and ~88.5% for faults only (Table 1). In the end, the fully connected layers generate the 3D fault volume (Figure 5). Then, we extract the fault patterns on the Shublik surface (Figure 6).

![Figure 3. The architecture of CNN used in this study for fault classification and prediction.](image)

![Figure 4. Shublik time-structure maps in the North Shore 3D (a) and Storms 3D (b) surveys areas.](image)

![Figure 5. Schematic workflow used in this study (after Di et al., 2018).](image)

<table>
<thead>
<tr>
<th>Overall Accuracy: 0.992</th>
<th>False positive rate: 0.005</th>
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<tbody>
<tr>
<td><strong>Prediction</strong></td>
<td></td>
</tr>
<tr>
<td>No fault</td>
<td>1664999</td>
</tr>
<tr>
<td>Fault</td>
<td>8932</td>
</tr>
</tbody>
</table>

Table 1. A confusion matrix showing the CNN model performance on test data.
Deep-learning-based Fault Classification

Fault interpretation

The Shublik surface shows the presence of several intersecting faults (in yellow) along multiple directions in the North Shore 3D and Storms 3D surveys (Figure 6a and b). There are three dominant directions, along which the faults are present, such as WNW-ESE, NE-SW/E-W, and N-S.

Based on geologic knowledge in the study area, it is known that an underlying structural grain is present in the basement trending WNW-ESE, which was reactivated several times and controlled the propagation of younger faults (Bhattacharya and Verma, 2019). Houseknecht and Connors (2016) suggest that this deep basement extensional structure present along the Beaufort Margin was initiated during the Mid-Late Devonian or Mississippian, and reactivated later. This structure is related to the WNW-ESE faults (oldest). The E-W/NE-SW faults crosscut the WNW-ESE faults. These faults are younger than WNW-ESE faults. Based on layer-by-layer fault mapping, Tatarin (2019) showed that these E-W/NE-SW faults could be generated during the Permian to Cretaceous, with a decreasing intensity both above and below the Shublik. The overall length of these younger faults is small. The last set of dominant faults, which crosscut both WNW-ESE and E-W/NE-SW, are along the N-S. It appears that these faults used the underlying structural fabric of the old faults systems for its propagation.

These are the youngest faults present in the study area identified by CNN. This is also indicative of the change in stress directions over time. Figure 6c shows the fault patches extracted from CNN on one seismic section in the Storms 3D dataset, which can be used in further geologic modeling. In the North Shore 3D, a few significantly big faults are present with large throws across, as we come across the Prudhoe Bay high into the rift zone to the north.

Conclusions

The results show that the CNN algorithm can be used successfully to classify and predict faults with high accuracy. This will aid in interpreting complex fault systems in the subsurface. In our study area, CNN helped to illuminate faults along three different directions (WNW-ESE, NE-SW/E-W, and N-S), related to polyphase tectonic deformation in northern Alaska. We can use such results in analyzing the seal integrity of the petroleum systems and 3D fault model development for reservoir modeling.

Acknowledgments

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Figure 6. Plan view of the results from CNN-based faults on the Shublik Shale in the North Shore 3D (a) and Storms 3D (b) surveys. The arrows show the predominant directions of the faults and their cross-cutting nature. (c) A 3D view of fault patches extracted from CNN in the Storms 3D showing the vertical distribution of faults. The seismic section is marked in light yellow color in Figure 1a.
REFERENCES


