Master's Degree Dissertation
Master's Degree in Petroleum and Mining Engineering

Machine Learning Methods in Fault Detection

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Declaration

I hereby declare that the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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2021

I would like to dedicate this thesis to my only love, Nafas

Abstract

As the seismic data obtained during hydrocarbon exploration today are significantly increasing, manual interpretation is getting longer, and study is being increased. For instance, up to one terabyte of data can be produced daily by a single seismic survey, and seismic data sets may exceed many petabytes quickly. In the last decade, interpreters have been using computer applications to accelerate the interpretation process. Research employing machine learning (ML) is being actively conducted in the petroleum industry in recent years. This study reviewed research papers published over the past decade that discuss ML techniques for fault detection and interpretation. The research trends and machine learning models explored in the 79 articles were studied in depth. The results demonstrated that ML studies had been actively conducted in the industry since 2010, primarily for fault interpretation. The convolutional neural network was utilized the most among the ML models, followed by deep learning models.

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Chapter 1

1. Introduction and Background

Oil and gas are two critical energy sources that will continue to satisfy the world's growing power demands for several decades to come. Seismic surveys, both onshore and offshore, are used by resource explorers to create accurate images of different facies, sedimentary rock formations, and their geometrical distribution and structural features within the Earth's crust.

Subsurface mapping by seismic surveys provides accurate images of different rock formations and local geology. In a seismic study, elastic waves from seismic sources such as vibrator trucks (onshore) or air guns (offshore) propagate through the Earth crust and undergo attenuation, diffractions, refractions, and reflections along their paths and at geological layer boundaries. These waves are recorded by sensors, such as geophones or hydrophones, located on the ground surface. Seismic records, called raw seismic data, are manipulated through on purpose processing workflows made of a variety of processing steps (Yilmaz, 2001) such as deconvolution (Griffiths et al., 1977; Margrave et al., 2011), velocity analysis (Alkhalifah & Tsvankin, 1995), stacking (G. Liu et al., 2009) and migration (Gray et al., 2001; Sava & Fomel, 2006), is the result of the processing is a compact volume of data, typically referred to as migrated data or stacked seismic volume, that is then interpreted through a variety of attributes and modeling and inversion processes aim at extracting structural and petrophysical in the formation.

The interpreter works to identify significant geological structures closely related to hydrocarbon traps such as salt domes and faults in seismic volume and further estimate the location and size of hydrocarbons' reservoirs. An effective seismic interpretation requires geological understanding and considerable expertise. As the seismic data obtained during hydrocarbon exploration today are significantly increasing in size, manual interpretation is getting longer and represent the bottleneck of the exploration workflow. For instance, up to one terabyte of data can be produced daily by a single seismic survey, and seismic data sets may exceed many petabytes quickly (Bouzas, n.d.). If manual interpretation is the only option accessible to an interpretation team, interpreters must label and locate all essential structures in such a data collection and the process can last for months.

In the last decade, interpreters have been using computer applications to accelerate the interpretation process. However, it is almost unimaginable for a machine to mimic an expert interpreter with enough geological knowledge because of complicated sub-surface details. While fully automated interpretation is hard to adapt, computer programming can extract the quantitative characteristics of different geological structures and facilitate seismic manual interpretations. Any automation systems have effectively shown their ability to cut down on interpretation tasks, time, and labor costs. Besides, computer interpreting approaches also need to entail interactivity with interpreters to improve the interpretation's accuracy and robustness. In the majority of instances, a user-friendly interactive process may help prevent time spent on tuning parameters. Consequently, computer interpretation with minimal human intervention has gained more room in practice than traditional manual interpretation. New seismic interpreting methods and strategies for researchers have recently advanced into image processing techniques and artificial intelligence (deep learning and machine learning) algorithms.

For years, theories and algorithms in image processing have been used to aid in structural interpretation and make essential contributions. Structural interpretation typically requires two key steps, extraction of features and identification of structures. Attributes collecting main seismic data elements are extracted from the image and using signal processing methods. For instance, instantaneous attributes

(Taner et al., 1979) are derived using the Hilbert transform, and spectral attributes (Neelamani & Converse, 2013; Sinha et al., 2005) are the results of multi-resolution analysis such as continuous wavelet (Rioul & Vetterli, 1991) and curvelet transforms (Starck et al., 2002). In the context of seismic images, geological features, edges, textures, and shape details are to be defined, which are essential for characterizing objects in natural images. Initially developed for natural pictures, edge detectors (Asjad & Mohamed, 2015; SOBEL & I., 1990), texture descriptors (Amin et al., 2017; Haralick et al., 1973), and Hough transform (N M AlBinHassan & Marfurt, 2003; Duda & Hart, 1972; Jacquemin & Mallet, 2005) have shown their strong ability to distinguish geological features in seismic images. In addition, the interpretation depends on the human visual system (HVS) as a complicated and subjective task. Recently, the HVS model algorithms such as color space analysis (Zhen Wang, Temel, et al., 2014) and saliency detection (Shafiq et al., 2018) were suggested to mimic the interpretation process by extracting the most distinctive features of seismic data.

Machine learning has introduced new insights into its seismic interpretation role in recent years, allowing geologists to understand the connection between large quantities of geological information or data. Machine learning algorithms trained on input data promote seismic interpretation by delivering replicative and accurate outcomes and mitigate two primary challenges faced by interpreters, interpreting vast quantities of data simultaneously and recognizing the relationship between different forms of data. Machine learning approaches for interpretation are based on two significant models of perception. In one, multi seismic attributes were derived based on interpreter domain knowledge and then trained on machine learning models, which could be supervised or unsupervised, such as K-means clustering (H. Di & Alregib, 2017), Gaussian mixture model (Berthelot et al., 2013), the multi-layer perceptron (MLP) (H. Di & Alregib, 2017; Z. H. Zheng et al., 2014) and the support vector machine (SVM) (H. Di & Alregib, 2017). The other performs attribute extraction and structure classification of machine learning models, which is efficient in analyzing visual imaging by the input of local patches (H. Di et al., 2018; Haibin Di et al., 2018). Instantly, patch-based learning models can create mapping relationships between post-stack amplitude and structure spaces rather than extract predefined multiple feature attributes and automatically generate a set of features by considering local seismic reflection patterns. The seismic noise (random or coherent) and processing objects involved in local patterns can then efficiently be detected and excluded. Without interference by interpreters, patch-based learning models focus mainly on the presence of geological structures in the dataset and replicate interpreters' actions to a certain level. Computer-assisted seismic volume interpretation often has two strategies. The first is to implement interpretation algorithms on two-dimensional (2D) seismic sections. However, interpreters must eventually tune each section's parameters to achieve high interpretation accuracy, thus increasing interpretation time and interpretation cost and reducing interpretation performance. The other is to expand seismic interpretation algorithms into 3D space and then apply them to seismic volumes. While 3D interpretation methods save time on tuning parameters, they typically have high time and space complexities. Methods with high numerical complexity take a long time to complete. Furthermore, 3D interpretation approaches strive for accurate interpretation from a global perspective, overlooking local regions' details.

Seismic faults have important geologic implications for petroleum and gas explorations in the Earth's subsurface because they form structural traps for oil and gas reservoirs and block hydrocarbon movement due to their sealing characteristics. For prospective field development, it is essential to consider and evaluate the intricate relationships between fault networks, fractures, and stratigraphy. As a result, one of the critical steps in hydrocarbon exploration and production is the detection and delineation of faults.

In this project we mainly focus on the systematic literature review of the fault detection using ML methods, and the goal is to provide solutions to questions that are initially arranged to define the scope and overall objectives of the review. Our two main questions are: RQ 1: What are the current ML research trends in fault detection (yearly, publication sources, application fields in detail)? And RQ 2: Which ML models were frequent in the research papers (data type, large data, model usage frequency, application in the field)? A search method is then developed to efficiently collect research papers on research questions and set criteria to choose appropriate studies from search results. The abstracts and results of the articles are then reviewed to assess their relevance in the field of research. Following that, data is extracted from the paper to differentiate and structure the relevant details.

The main objective of this review is to provide an update on the current state of ML in seismic fault detection. The research questions were determined based on the purpose. The aim of RQ 1 is to describe the current state of ML study in the field. It refers extensively to the present state of the annual publication and its field-related implementations. RQ 2 lists the ML model used in the analysis. It expressly refer to the learning data type, the use of a large volume of data, the frequency of use of the model, and its extensive use in the field. At the end of this project, we expect to identify more effective methods for Machine Learning applied to fault detection.

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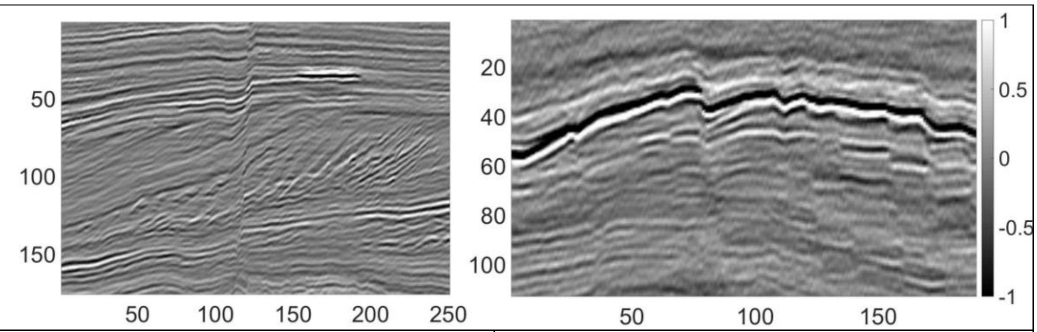
Chapter 2

2. Fault Detection Methods

A geological fault is characterized as a plane surface over which the relative movement of tectonic units take place. According to the filling of the fractured zone, a fault may represent either a preferential path for fluid flow or an impermeable boundary that can contribute to build hydrocarbon structural traps or act as reservoir compartmentation. Therefore, for hydrocarbon exploration, faults have significant geological impacts, and for future field development, understanding and analyzing the complicated connections between fault networks and fractures is necessary. The development process defines two features of the faults. One is the geological feature that is the discontinuity of the horizon. The other is a geometric feature, like linear and curved forms in 2D seismic sections that appear as curved surfaces in 3D seismic volumes. Methods of fault detection are generally built based on these two features. Figures 2.1a and 2.1b contain single and multiple faults, respectively.



(a) Single fault	(a) Multiple faults

Figure 2.1: Examples of seismic sections containing single and multiple faults

Faults in seismic images (Figure 2.2) are frequently identified as laterally high discontinuity or low continuity of reflections. Based on this fact, various approaches for highlighting faults by computing attributes that measure reflection continuity have been proposed. Several seismic attributes including curvature, (Roberts, 2001), similarity (Tingdahl & de Rooij, 2005), variance (van Bemmel & Pepper, 2000), coherence (Bahorich & Farmer, 1995), flexure (Haibin Di & Gao, 2017), and entropy (Cohen et al., 2006) could characterize the discontinuity of faults. Amongst these, coherence is most common to highlight faults. On the other hand, by comparing the dissimilarity of local regions on both sides of a fault, Marfurt et al. (Marfurt et al., 1998) calculated semblance.

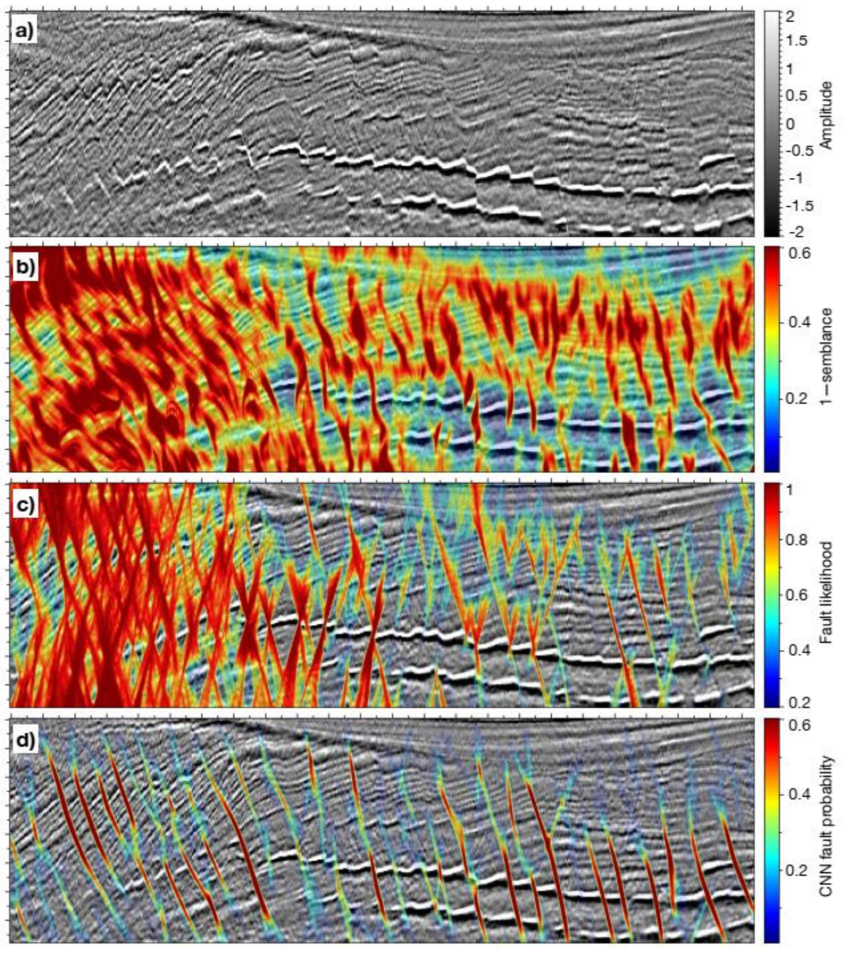


Figure 2.2: A 2D seismic image (a) displayed with 1-semblance (b), fault likelihood (c), and CNN fault probability (d) (X. Wu, Shi, Fomel, & Liang, 2019)

Later, Gersztenkorn and Marfurt (Gersztenkorn & Marfurt, 1999) presented eigenstructure-based coherence (known as C3 coherence), which analyses the eigenstructure of windowed seismic traces' covariance matrices. Instead of computing eigenvalues of the covariance matrix, Yang et al. (T. Yang et al., 2015) proposed a computationally efficient coherence technique based on a normalized information divergence criterion. To map discontinuities at different scales, Li and Lu (F. Li & Lu, 2014) have employed a combination of spectral decomposition and complex coherence computation. Sui et al. (Sui et al., 2015) suggested a coherence method for steeply dipping structures that evaluates the eigenstructure of seismic spectral amplitudes to prevent inaccurate low-coherence values. The generalized-tensor-based coherence (GTC) characteristic was suggested by Alaudah and AlRegib (Y. K. Alaudah & Alregib, 2016), and it develops covariance matrices from the unfolding matrices of a seismic analysis tensor along multiple modes corresponding to time, inline, and crossline directions. GTC enhances the details of discontinuity in seismic data, in contrast to C3 coherence. Using a directional Gaussian preprocessing kernel and applying a 3D rotational matrix to the associated covariance matrix, Alaudah and AlRegib (Y. Alaudah & AlRegib, 2017) employed GTC to develop directional selectivity. While likely fault regions can be highlighted in attribute maps, labeling faults cannot achieve acceptable accuracy due to noise. Enhancement methods such as non-linear mapping (Zhen Wang & Alregib, 2014) and structure-oriented filtering (Fehmers & Höcker, 2003; Hale, 2013) have therefore been employed to strengthen the contrast between faults and surrounding structures. Furthermore, since 2000, researchers have suggested a few interactive fault identification algorithms based on seismic attributes to identify fault surfaces in seismic volumes or faults in 2D sections, intending to improve accuracy and reliability. By assuming that a fault is continuous and slightly curved, Peterson et al. (Pedersen et al., 2002) suggested using an ant-tracking or ant-colony optimization approach to identify fault surfaces. Similarly, Silva et al. (Silva et al., 2005) used the antitracking algorithm to detect fault surfaces on seismic attributes of chaos and variance (Randen et al., 2000). AlBinHassan et al. (Nasher M.

AlBinHassan et al., 2006) used a smoothing operator on coherence cubes to reduce noise and improve fault detection. With the suggested directional filters, Cohen et al. (Cohen et al., 2006) work improved the contrast of normalized differential entropy and used the skeletonization method (Pavlidis, 1980) to extract one-pixel width fault surfaces from probable fault zones. The cascade Hough was proposed to identify fault surfaces in seismic volumes by Jacquemin and Mallet (Jacquemin & Mallet, 2005). In contrast to the global detection of fault surfaces mentioned above, Gibson et al. (Gibson et al., 2005) created a multi-stage method that highlights fault points in modified semblance cubes, generates local planar patches from clustered fault points, and then merges small patches into large fault surfaces. Wang and AlRegib (Zhen Wang & AlRegib, 2014) employ the 3D Hough transform to identify small patches from clouds of probable fault locations, which are subsequently combined to outline the entire fault surface. To construct complete fault surfaces, Wu and Hale (X. Wu & Hale, 2016) have proposed using a simple linked data structure that includes fault likelihood, dip, and strike Figure 2.3 and Figure 2.4. Due to the use of 3D information, seismic fault surfaces show global fault structures that are more accurate than those identified by 2D sections. However, the methods used for interpreting faults on the entire seismic volume are often highly time-spatially complex and need strong computer resources.

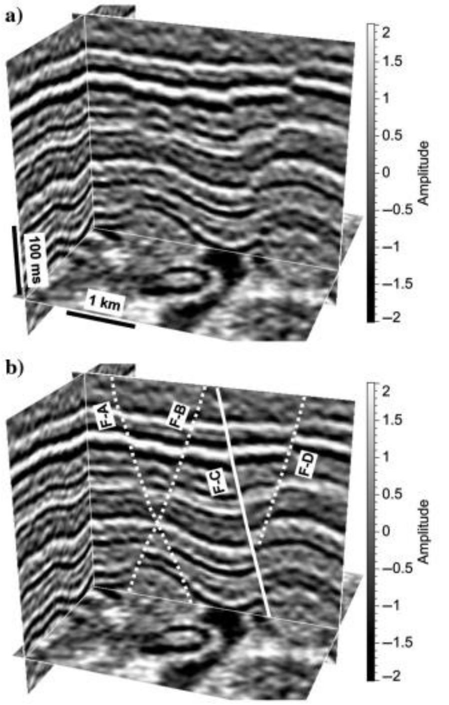


Figure 2.3: A 3D synthetic seismic image (a) with four faults manually interpreted in panel (b). The dashed lines in panel (b) represent normal faults, whereas the solid line represents a reverse fault (X. Wu & Hale, 2016)

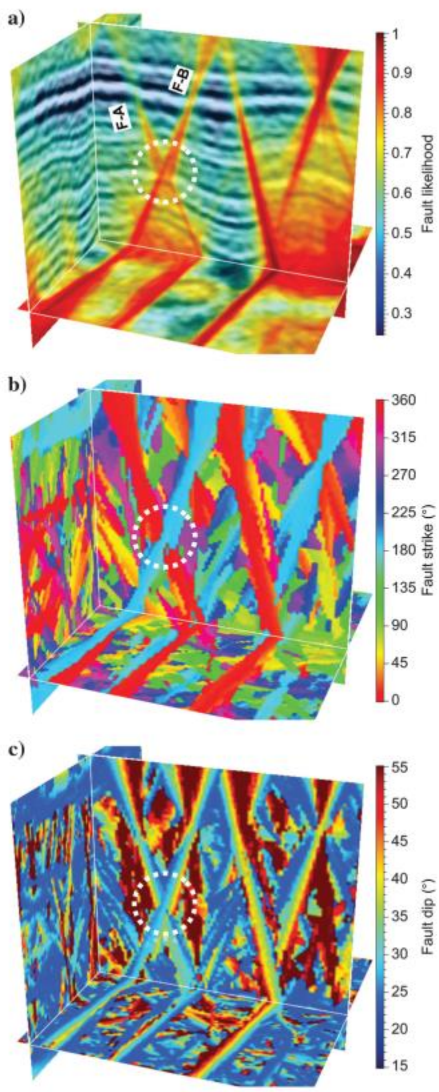


Figure 2.4: A 3D seismic image with (a) fault likelihoods, (b) strikes, and (c) dips displayed in color. The dashed white circle in each image indicates one location at which fault F-A intersects fault F-B (X. Wu & Hale, 2016)

Researchers have used image processing and computer vision techniques to detect faults from seismic or time sections to overcome computational power constraints and simplify detection. To detect faults in meshed temporal sections, Hale and Emanuel (Hale & Emanuel, 2003) recommended employing conventional image segmentation methods such as normalized cuts (J. Shi & Malik, 2000) and stochastic clusters (Gdalyahu et al., 2001). Hale (Hale, 2013) improved semblance maps with directional Gaussian filters, then chose fault points with the greatest semblance values and linked them to label faults in another study. False features in identified faults reduce labeling accuracy, even though this method is reliable and automated. Zhang et al. (B. Zhang et al., 2014) have employed a biometric approach to detect faults in temporal sections, based on the idea that faults are remarkably similar to human capillary veins. Wang et al. (Zhen Wang, Temel, et al., 2014) created RGB color images by combining the semblance maps of every three adjacent time parts. By investigating the human visual system's influence on seismic interpretation, the proposed technique transforms RGB color images to other color spaces, extracts likely faults from corresponding luminance components, and integrates likely faults under geological and connectivity constraints. AlBinHassan and Marfurt (N M AlBinHassan & Marfurt, 2003) employed the Hough transform to detect all lines in coherence maps derived from seismic amplitude maps because of the line shapes of faults in 2D seismic sections. However, this approach only identifies the raw forms of faults without noise rejection. Wang and AlRegib (Zhen Wang & Alregib, 2014) have therefore suggested a fault detection approach to address this limitation, which extracts the line characteristics of faults with the Hough transformation and eliminates noisy features with geological constraints.

All of the problem mentioned above detection methods are based on conventional image processing techniques, which generally contain a set of parameters. The performance of interpretation is determined by parameter selection. These algorithms struggle to attain high recall and precision while extracting faults concurrently given the presence of parameters.

An aggressive scenario with high recall (most/all true faults retrieved) but poor precision (many artifacts introduced) or a conservative scenario with high precision (few artifacts introduced) but low recall (few true faults extracted) is the most common conclusion (Haibin Di, Limited, et al., 2017).

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Chapter 3

3. Literature of Machine Learning in Fault Detection

Introduction

Fault Detection and Fault Interpretation

Fault detection is performed by manually interpreting seismic data and picking horizons. This technique primarily relies on the interpreter's expertise and regional geological knowledge, which is inefficient and has shown to be inaccurate. With the fast growth of seismic attributes, a variety of fault detection approaches, such as semblance and coherency, have developed. These approaches detect faults as lateral reflection discontinuities in a 3D seismic map. These seismic attributes, however, are sensitive to noise and stratigraphic features, which correspond to reflector discontinuities in a seismic profile. This means that simply measuring the continuity or discontinuity of seismic reflection is insufficient for detecting faults. In recent years, an increasing number of academics have tried to use Machine Learning in seismic interpretation and fault detection that we explain in the following sections (J. Wu et al., 2021).

Fault Mapping

Manual picking on horizontal and vertical portions of seismic amplitude has traditionally been used to interpret faults, and the accuracy of manual interpretation is highly dependent on the interpreter's knowledge and expertise. Fault enhancement attributes are now assimilated into fault interpretation by co-rendering them with the original amplitude, which helps to pick faults that are not easily noticeable from amplitude due to weak waveform and/or amplitude variations, thanks to recent developments in seismic attribute analysis and multi-attribute visualization, see figure 3.1, (Haibin Di, Limited, et al., 2017).

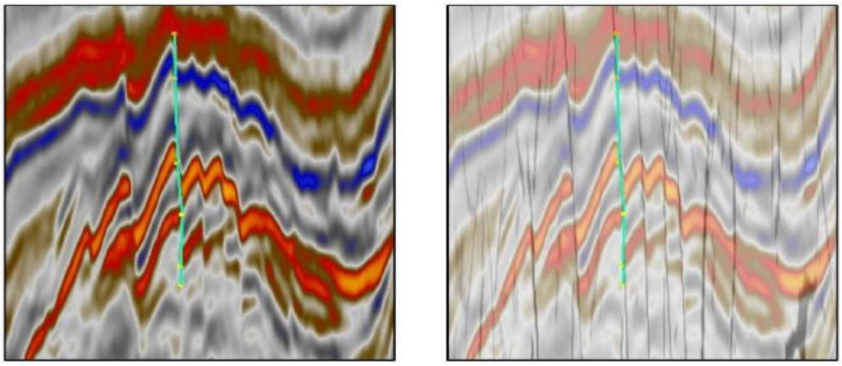

Figure 3.1: Manual fault interpretation (light blue) from post-stack amplitude (Haibin Di, et al., 2017)

Various forms of seismic features, such as faults, have been successfully detected using semi-automatic object detection. Three stages are frequently used in semi-automated fault identification. To highlight faults and suppress non-fault objects, the seismic data is first scanned, and a set of seismic attributes is computed. Then, on a few sections of seismic amplitude and/or characteristics, faults are manually selected. Finally, a computer program learns the hand picking and applies it to the entire cube, creating 3D patches throughout the entire volume, see figure 3.2, (Haibin Di, Limited, et al., 2017).

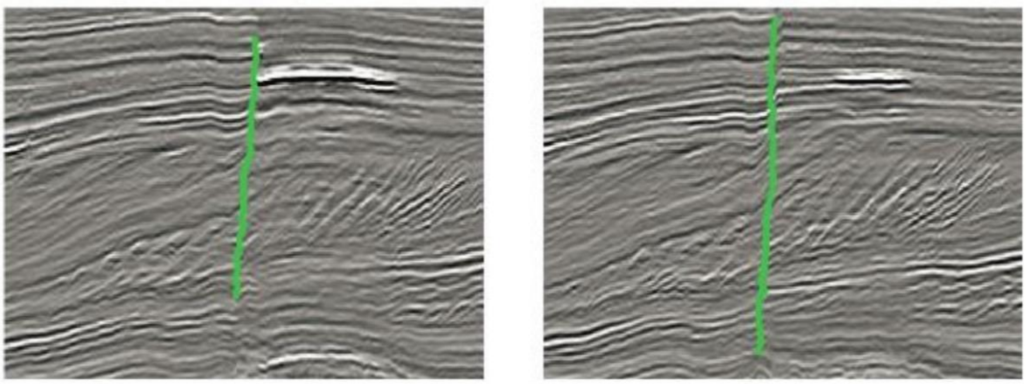

Figure 3.2: Semi-automatic fault extraction as shown in two seismic sections (Zhen Wang, Long, et al., 2014)

In comparison to manual picking and semi-automatic extraction, automatic seismic object recognition eliminates manual picking, which is time-consuming and susceptible to interpretational bias, and is thus superior in both efficiency and accuracy. The automated fault detection process is likewise divided into three phases. First, the seismic dataset is preconditioned by filtering and/or smoothing as needed, and discontinuity characteristics are generated from the amplitude volume, which might be the above-mentioned or alternative derivations. The discontinuities are then reduced to one pixel thick using fault-enhancement techniques, and the thinned lineaments allow computers to uniquely characterize basic features about a fault, such as its location, geometry, and size. Finally, fault patches are recovered from the thinned lineaments, with each patch representing a subsurface fault (Haibin Di, Limited, et al., 2017).

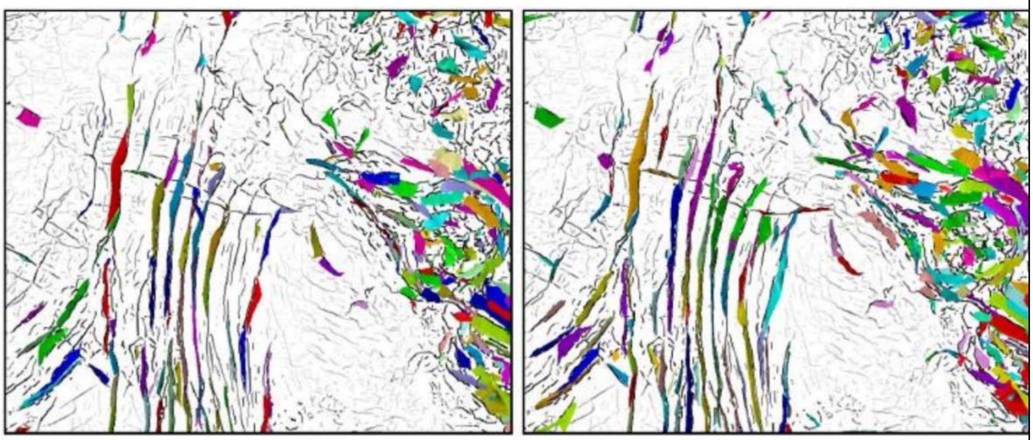

Figure 3.3: Manual fault interpretation (light blue) from post-stack amplitude (Haibin Di, Limited, et al., 2017)

New Fault Detection Methods

In general, the exploration process is divided into two components: technological tools and labor. The advancement of tools, as well as the inclusion of high-performance computation, has aided in the reduction of turnaround times for seismic imaging (Rastogi, 2011; Rubio et al., 2009). Even in the most extreme situation, when processing tools execute in near-zero time, the issue of manpower persists; there is no logical method for domain experts to interpret and analyze all incoming data. The optimal solution must exchange domain-expert time for computing time. As a result, part of that domain knowledge must be codified and integrated into existing and future capabilities. One possible approach is to use algorithms that learn, for example, from old data that has been well verified. We can use machine learning to take advantage of new algorithms, software ecosystems, and specialized hardware (Araya-Polo et al., 2017).

Machine Learning in Fault Detection

Although a comprehensive understanding of geophysics and field training have long been seen as prerequisites for developing efficient interpretation procedures, recent advancements in machine learning have shed new light on its role in this domain-specific issue. Machine-learning models trained on input data can produce consistent, reliable seismic interpretation results, relieving two key challenges that interpreters may face: understanding huge amounts of data and grasping the relationship of several types of data at the same time. For machine-learning-based interpretation techniques, there are two primary approaches. Numerous seismic characteristics are extracted from interpreters' domain expertise and experience and trained using standard supervised or unsupervised machine-learning models like as the self-organizing map, multilayer perceptron, and K-means clustering. The other employs deep-learning models, specifically the convolutional neural network (CNN). With the massive growth in computing power and data accessible in recent years. The CNN motivated by the visual cortex in the brain is one form of deep-learning model that consists of one or more convolutional layers. Because 2D kernels in convolutional layers are trained to gather spatial and structural features from input images, the CNN is better suited for visual tasks. The CNN's first convolutional layer collects low-level visual features including edges, lines, and corners. In contrast, higher convolutional layers extract more abstract high-level features like as shapes and patterns. Unlike standard machine-learning models, which rely on predetermined features, the CNN takes 2D amplitude images as input, builds mapping connections between poststack amplitude and structure spaces, and automatically extracts features during the training process. The CNN-based process is entirely dependent on the availability of geologic structures in the data set and, to some extent, simulates interpretation behavior without the assistance of interpreters (Zhen Wang et al., 2018).

We analyzed all the studies for the classification of work and grouped them in four categories, and a map of ML methods in fault detection was created figure 3.4.

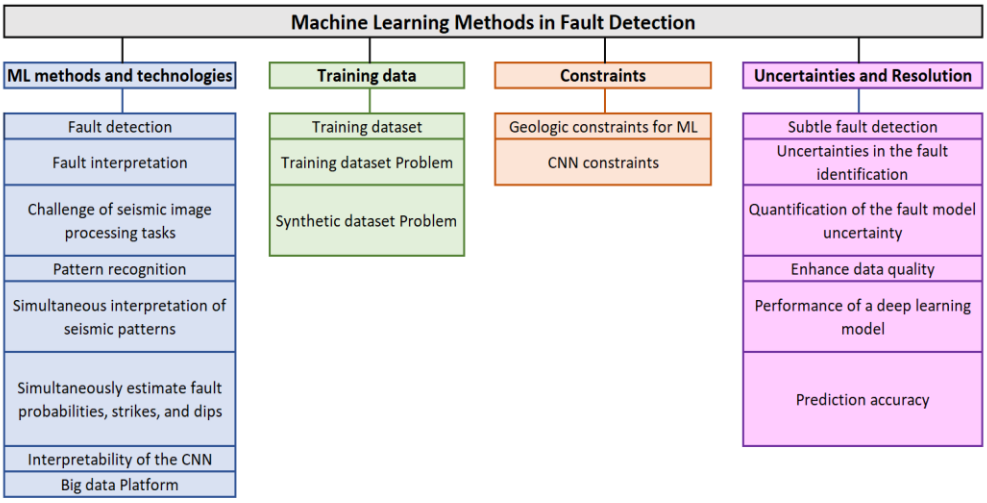

Figure 3.4: Research application

The first category included eight topics of fault detection, fault interpretation, challenge of seismic image processing tasks, pattern recognition, simultaneous interpretation of seismic patterns, simultaneously estimate fault probabilities, strikes, and dips, interpretability of the CNN, and big data Platform. Each item was explained in detail. The second category consisted of training dataset, training dataset problem, and Synthetic dataset Problem. The constraints category was classified as geologic constraints for ML and CNN constraints. The uncertainties and resolution category was divided into subtle fault detection, uncertainties in the fault identification, quantification of the fault model uncertainty, enhance data quality, performance of a deep learning model, and Prediction accuracy.

3.1. . ML methods and technologies

3.1.1. Fault detection

In (Gao et al., 2021), design a new machine-based fault-detection technique using a U-shaped multi-scale connection-fusion neural network (MCFU). The most key part of this MCFU approach is that it connects feature maps of different spatial resolutions using skip connections and generates the final fault map using a fusion operation.

Authors in (J. Wu et al., 2021) develop a FCN-based method to automatically detect faults in sandstone reservoirs. The architecture of FCN is a modified version of the VGGNet. The FCN model is trained by using only 300 pairs of 3D synthetic seismic and fault volumes, which were all automatically generated.

(Zhu et al., 2021) propose a workflow to use instance segmentation algorithm to detect different fault lines. A modified CNN is trained using automatically generated synthetic seismic images and corresponding labels. Then the trained CNN, tested using both synthetic and field collected seismic data.

A Foundation Network was developed to identify faults in a seismic cube, in (J. Lowell & Szafian, 2021). In this network the Artificial Intelligence is closely aligned with the interpreters' way of working, allowing tightly coupled interaction as appropriate for the dataset and the individual interpreter's workflow.

To differentiate adjacent faults and remove the jamming of seismic noise, (D. Yang et al., 2020) propose a method based on 3D U-net++ to detect faults. To extract faults from 3D seismic images, they design a 3D U-net++ structure with dense connection and focal loss. The obtained results indicate high accuracy, clean background, and clear fault edges on synthetic seismic data and seismic survey data.

Faults are usually detected in seismic data by seismic attributes, which require a complex mathematical calculation such as a dip-steered cube. In (Noori et al., 2020), the Gaussian process regression model (GPR), a nonparametric probabilistic model based on Bayesian statistics, is used in this analysis to detect faults as global anomalies on 3D seismic data. In order to detect fault locations a Gaussian process (GP) model was trained on 3D seismic data to characterize seismic amplitude data as a multivariate Gaussian model. GP regression, on the other hand, fails to explain seismic data at fault locations adequately. As a result, the GP's failure in the regression phase was investigated to identify possible fault points, which were highlighted by measuring the variance of the GPR results. Finally, a consistent reconstruction morphological algorithm was used to improve the detected probable fault points and extract them from the context data.

Considering the fault interpretation as an image segmentation problem, (N. Liu et al., 2020) add residual units to U-Net (Res U-Net). Using the Res U-Net model, they develop a fault-versus-azimuth analysis based on offset vector tile data, which, as common-azimuth seismic data, provide more detailed and helpful information for interpreting seismic faults. To avoid manual picking, they use synthetic seismic data with a random number of faults with different locations and throws as the training and validation data sets. Res U-Net is finally trained using only synthetic data and tested on field data.

(Qi et al., 2020) have introduced a U-Net architecture to fault detection and compared it to a more conventional attribute-based image processing fault enhancement workflow. The CNN model was trained using synthetic seismic amplitude and fault labels computed for normal faults. Based on the results, the U-Net architecture CNN performed well on automatic fault detection.

(C. Yuan et al., 2021) propose a novel network (GCS-Net) which includes a global context block (GC) and channel attention module together with spatial attention module (CS) between the encoder and decoder, instead of the U-Net-based convolutional neural network. The GC block captures the long-range dependencies, and the CS block is utilized to integrate local features with their global dependencies further adaptively. The proposed approach was trained on synthetic seismic data and tested by the real data.

(B. Wang & Ma, 2020) have suggested a framework for seismic fault recognition that combines an improved VGG convolutional neural network with a multi-scale fusion attention mechanism. The useful features from the seismic attributes are extracted using the improved VGG network. Furthermore, by utilizing the attention mechanism, local features can be better learned, resulting in a smoother and more continuous predicted fault curve.

In (Y. Zheng et al., 2019), a CNN model is trained for 3D automated fault classification. The model predicts the fault probability, dip, and azimuth simultaneously. Applications on real data show that the CNN model can produce reliable fault picks in various seismic images.

(D. Li et al., 2019) proposed an automatic interpretation method of coalfield structures based on machine learning. This paper focuses on the backpropagation (BP) neural network, radial basis function (RBF) neural network, SVM, decision tree, and random forest, and it applies them for the identification of collapsed columns and fault structures. The seismic attributes were sensitive to the structure used as the input layer data in the prediction network model to predict the geologic structure.

(Philit et al., 2019) present an optimized processing method for automatic fault detection. Our workflow is based on the Fault Plane attribute obtained from the variance, the creation of a Thinning volume, and, finally, the extraction and creation of 3D fault patches. The method allows intercepting most of the seismic faults, with coherent positions and fairly capturing the structural complexities of fault interactions.

(Q. Zhang et al., 2020) developed a deep CNN model trained on synthetic data for 3D automatic fault picking. The model outputs the fault probability, dip, and azimuth simultaneously.

(Lapteva et al., 2019) test different CNN models for fault detection and derive the critical neural network parameters that influence the faults' localization. The goal is to derive the CNN parameters from detecting thin areas of the fault and balanced detection of the unmarked faults.

Coherence-detected faults can be contaminated by other discontinuities, necessitating the use of processing methods to increase coherence's accuracy and performance. By incorporating adaptive spectral decomposition and SR deep learning into fault detection, (Z. Yuan et al., 2019) suggested a framework for improved fault detection. To obtain a dominant-frequency-optimized amplitude spectrum, adaptive spectral decomposition is first applied to seismic data. To delineate fault discontinuities, eigenstructure-based coherence with dip correction is determined. A convolutional neural network (CNN) model is built to obtain improved performance and then given fault-detection images as input.

The residual neural network (ResNet) is used to build the U-net model for seismic fault detection in (D. Chang et al., 2019), and multi-scale and multi-level features are extracted from seismic data. The field dataset is used to train the U-net model in the training stage.

(Xiong et al., 2018) introduce the CNN for detecting faults from 3D seismic images in this paper. In a supervised learning approach, raw seismic images sampled on 3D grids or voxels are used to train a CNN model. The training data set is made up of real data from seven annotated seismic cubes, with one seismic cube serving as validation.

Using the CNN, (H. Di et al., 2018) propose a new approach for attribute-free fault detection. Instead of using attributes as input, the CNN-based approach uses local seismic reflection patches, which have been classified as fault or non-faulting areas depending on where the central point is located. The mapping relationship between seismic signals and fault structures is established by training the predefined CNN on local patches.

(Maniar et al., 2019) pose the fault interpretation task as a supervised pixel classification problem and use a deep neural network to solve it. They explain various neural network architectures to address this fault detection problem.

(Dekuan Chang et al., 2018) propose a new seismic fault detection method based on depth learning (SFDU-net), which employs the CNN to extract multi-scale and multi-level fault features from seismic data. The network training efficiency can be improved by using the pre-training model to initialize the SFDU-net parameters and dynamic learning rate.

(Haibin Di, Shafiq, & AlRegib, 2019) proposes a method for seismic fault detection based on semi-supervised classification of multiple attribute patches through the multi-layer perceptron (MLP) technique. Such a method consists of five components: (a) attribute selection, (b) training sample labeling, (c) attribute patch retrieval, (d) MLP model training, and (e) volumetric processing.

(Ma et al., 2018) and (Ma et al., 2019) developed a convolutional neural network (CNN) method to generate a fault-probability attribute for highlighting fault zones in seismic amplitude images. The proposed method detects faults directly from seismic amplitude cubes, so that precomputed attributes are not required. In the training step, a CNN model is trained with annotated real seismic image cubes, where each point is labeled as fault or non-fault. In the prediction step, the trained network is applied to compute the fault probability at each location in the new image cubes.

(B. Guo et al., 2019) and (B. Guo et al., 2018) build a CNN-based method for detecting faults automatically from 3D seismic amplitude images. Human-labeled 2D images sliced from 3D cubes are used to train the network, with each pixel labeled as fault or non-fault. The CNN predicts fault probabilities at any location in the image after training. The experiments' findings on synthetic and field data images indicate that the CNN correctly predicts fault locations.

(Araya-Polo et al., 2017) propose a solution to the multistep seismic model building problem. It uses raw seismic recordings as input to train a deep learning algorithm to map out a fault network in the subsurface. The use of the Wasserstein loss function, which is well-suited to problems with outputs that are spatially layout oriented, is a defining feature of the solution. On synthetic data sets with simple fault networks, they demonstrate the system's performance.

For fault detection, (Haibin Di, Shafiq, et al., 2017) presents a workflow based on a multi-attribute support vector machine (SVM) analysis of a seismic volume consisting of four steps. First, three groups of seismic attributes are selected and computed from the volume of seismic amplitude, including edge-detection, geometric, and texture, all of which clearly highlight the seismic faults in the attribute images. Second, two sets of training samples are prepared by manually picking on the faults and the non-faulting zones, respectively. Third, the SVM analysis is performed on the training datasets that build an optimal classification model for volumetric processing. Finally, applying the SVM model to the whole seismic survey leads to a binary volume, in which the presence of a fault is labeled as ones.

In the study (Guitton et al., 2017), a supervised machine learning algorithm highlights faults in 3D seismic volumes. An automatic fault-picking system is used to label the faults. Two object recognition algorithms, Histograms of Oriented Gradients (HOG) and Scale Invariant Feature Transforms (SIFT), are used to create feature vectors for the training and classification steps. A Support Vector Machine classifier with Gaussian kernels was used to train and classify seismic data. When both SIFT and HOG are used together, the false positive rate is reduced, resulting in better fault images.

When no seismic data has been migrated, (C. Zhang et al., 2014) implemented a method to assist interpreters during the initial stages of velocity model building

(VMB). The approach uses machine learning methods to automatically classify and locate faults in seismic data that has not been migrated.

In (Z. H. Zheng et al., 2014), by using a neural network-based fault detection system, attributes that have the capacity to highlight faults and fractures are grouped into a single fault likelihood attribute. When compared to individual attributes, this attribute predicts improved results. The distinction between faults and their environments is improved, and noise has less of an effect on interpretation.

(Tingdahl & de Rooij, 2005) demonstrate that an artificial neural network can effectively combine many different attributes, including similarity, frequency, and curvature, all of which can theoretically improve the visibility of faults. As compared to single-attribute cubes, this results in a fault 'probability' cube with more continuous faults and less noise.

3.1.2. Fault interpretation

Accurate mapping of structural faults and stratigraphic sequences is essential to the success of subsurface interpretation, geologic modeling, reservoir characterization, stress history analysis, and resource recovery estimation. In the past decades, manual interpretation assisted by computational tools — i.e., seismic attribute analysis — has been commonly used to deliver the most reliable seismic interpretation. Because of the dramatic increase in seismic data size, the efficiency of this process is challenged. The process has also become overly time-intensive and subject to bias from seismic interpreters.

(Haibin Di, Truelove, et al., 2020) implement deep convolutional neural networks (CNNs) for automatic interpretation of faults and stratigraphies. In general, both the fault and stratigraphy interpretation are formulated as image segmentation problems, and each workflow integrates two deep CNNs. Their specific implementation varies in the following three aspects. First, the fault detection is binary, whereas the stratigraphy interpretation targets multiple classes depending on the sequences of interest to seismic interpreters. Second, while the fault CNN utilizes only the seismic amplitude for its learning, the stratigraphy CNN additionally utilizes the fault probability to serve as a structural constraint on the near-fault zones. Third and more innovatively, for enhancing the lateral consistency and reducing machine prediction artifacts, the fault workflow incorporates a component of horizontal fault grouping, while the stratigraphy workflow incorporates a component of feature self-learning of a seismic data set.

In (Oke et al., 2020) demonstrate how Machine Learning (ML) can aid with fault perception in complex fault systems with subtle throws. Input data was standard amplitude volume with minimal user-end conditioning. PSTM time and PSDM depth seismic volumes were used in separate runs to confirm that applied ML technology is domain agnostic. The ML-Assisted workflow included: Generating a fault prediction cube based on user-supplied fault interpretation labels made on six training lines; Creation of fault planarity and azimuth cubes; Parameterization of automated extraction function; Extraction of segmented 3D fault pointsets; Creation of fault framework and fault sticks that can be integrated into traditional methods in seismic and geological modeling domains.

In this study (Bhattacharya & Di, 2020), the convolutional neural network (CNN) is used to classify and predict the complex normal fault network system on the North Slope, Alaska. This is a binary image classification problem for a focused geologic study. In this study, the authors use two 3D seismic surveys for fault classification. The results show that a few original seismic sections with labeled faults can be directly used in the CNN model for automated fault classification throughout the 3D volumes with high accuracy and in limited time.

(X. Wu, Liang, Shi, & Fomel, 2019) have discussed using an end-to-end CNN to effectively detect faults from 3D seismic images, where fault detection is considered as a binary segmentation problem. To save GPU memory and computational time, this neural network is a simplified U-Net. We use a balanced loss function to optimize the CNN model parameters since the distribution between fault and non-fault samples is heavily biased. We use 3D synthetic seismic and fault volumes to train the neural network, which are all created automatically by randomly adding folding, faulting, and noise to the volumes.

(Egorov, 2019) presented application of convolutional neural networks for fault interpretation from seismic data.

(Lin et al., 2017) consider using a machine-learning detection approach to extract subsurface geologic features automatically. To increase computing performance and memory use, a data reduction technique was used in combination with the conventional kernel ridge regression method. They use a randomized numerical linear algebra technique to minimize the dimensionality of the feature space while preserving the information content needed for effective detection.

3.1.3. Challenge of seismic image processing tasks

The identification of faults in a seismic image is an essential aspect of structural interpretation. Structure-oriented smoothing with edge-preserving removes noise in a seismic image while optimizing seismic structures and sharpening structural edges, making seismic structural interpretation easier and faster. Many other seismic data processing tasks include the calculation of seismic normal vectors or reflection slopes. Since they both include the study of seismic structural elements, the three seismic image processing tasks are related. However, in traditional seismic image processing systems, these three tasks are often done separately by various algorithms, and challenges remain in each of them (X. Wu, Liang, Shi, Geng, et al., 2019).

Using a single convolutional neural network (CNN), (X. Wu, Liang, Shi, Geng, et al., 2019) proposes to execute all three tasks simultaneously. Thousands of 3-D noisy synthetic seismic images and corresponding ground truth of fault images, clean seismic images, and seismic normal vectors are generated automatically to train the network. The network learns to correctly perform all three image processing tasks in a general seismic image while only being trained with synthetic data sets.

3.1.4. Pattern recognition

In this paper (Xu et al., 2021), a fault and fracture network characterization method based on 3D convolutional autoencoder is proposed. First, in the autoencoder training frame, 3D prestack data are used as input, and the 3D convolution operation is used to mine the spatial structure information to the maximum and gradually reduce the spatial dimension of the input. Then, the residual network is used to recover the input's details and the corresponding spatial dimension. Lastly, the hidden features extracted by the encoders are recognized via k-means, SOM, and two-step clustering analysis.

3.1.5. Simultaneous interpretation of seismic patterns

(Y. Guo et al., 2020) developed a CNN model training method focused on structural geological modeling, which allowed for the rapid and accurate identification of fault and horizon labels. The findings revealed that CNNs are capable of correctly forecasting both faults and horizons at the same time.

(Alfarhan, Maalej, et al., 2020) introduce a framework for delineating salt boundaries and faults simultaneously using a Res-Net with U-Net DL architecture in this paper. Despite the limited number of labeled data available for testing, the proposed segmentation-based DL model should distinguish all events with reasonable accuracy when validated on real-world seismic images.

Using an improved U-Net with Res-Net DL architecture, (Alfarhan, Deriche, et al., 2020) proposed a novel approach for concurrent detection of multiple seismic events. The proposed system has two advantages: first, it uses the well-known U-Net architecture combined with Res-Net to address seismic interpretation as a general segmentation-based problem, allowing accurate separation of salt domes and faults from other seismic structures. Second, domain adaptation was used to make using a pre-trained Res-Net model for transferring learning from natural images to seismic images easier. Despite using a limited volume of labeled data to train the model, it achieves a detection accuracy of more than 96 percent.

(Haibin Di, Gao, et al., 2019) provided a seismic texture database (StData-12) with 12 common seismic patterns to aid in applying and testing machine learning in the seismic domain and a seismic texture interpretation network (StNet) to aid in the discrimination and classification of 3D seismic features. The StNet's main benefit is its ability to quickly screen and recognizes several typical seismic patterns in a seismic volume. Aside from its computational efficiency, the StNet provides the base architecture for modern seismic interpretation networks that are more task-oriented and cover various seismic textural patterns.

(Y. Shi et al., 2021) design a deep learning workflow to track seismic geobodies interactively. The algorithm is based on a flood-filling network, which performs iterative segmentation and moves the view (FoV). The proposed network takes the previous mask output and the seismic image in a new (FoV) as a combined input to predict the mask at this FoV. The flood filling algorithm guides the movement of the FoV in order to visit and segment the full extent of a geobody. Unlike conventional seismic image segmentation methods, the proposed workflow can detect geobodies and track individual geobody instances.

(Hami-Eddine et al., 2017) propose a fast-track machine learning method applied to probabilistic fault detection, AVO analysis, and geobody detection.

(Meldahl et al., 2001) develop a seismic-object detection method that produces more accurate results and does not require expert knowledge. The method recombines multiple attributes into a new attribute that gives the optimal view of the targeted object. Including specific spatial knowledge about the targeted object allows us to separate objects of different geologic origins with similar attribute characteristics. The method comprises an iterative processing workflow using directive seismic attributes, a neural network, and image processing techniques.

3.1.6. Simultaneously estimate fault probabilities, strikes, and dips

Instead of predicting only fault probabilities as in the previous CNN-based fault classification methods, (X. Wu, Shi, Fomel, Liang, et al., 2019) have proposed to use a single CNN to simultaneously estimate fault probabilities, strikes, and dips from an input seismic image, which is formulated as a classification problem.

(X. Wu, Shi, Fomel, & Liang, 2019) proposed an automatic fault interpretation method by using convolutional neural networks (CNN). In this method, a 7-layer CNN is built for estimation of fault orientations (dips and strikes) within small image patches that are extracted from a full seismic image. They then construct anisotropic Gaussian functions with the estimated fault orientations that mainly extend along with the estimated fault dips and strikes. Finally, all the locally fault-oriented Gaussian functions are stacked to generate a fault probability image. Although trained using only synthetic seismic images, the CNN model can accurately estimate fault orientations within real seismic images. The fault probability image, computed from the estimated fault orientations, displays cleaner, more accurate, and more continuous fault features than those in the conventional fault attribute images.

3.1.7. Interpretability of the CNN

Determining the location of the seismic fault is a crucial step in seismic interpretation. Convolutional neural networks (CNNs) have proved to be more efficient for automatically learning effective representations as compared to traditional approaches that construct a variety of hand-crafted features based on the observed characteristics of the seismic fault. However, in the training and inference process, the CNN is often used as a black box, which may contribute to confidence problems. Humans' inability to comprehend the CNN will be more troublesome, particularly in sensitive areas such as seismic exploration (Z. Liu et al., 2020).

(Z. Liu et al., 2020) suggest a way to convey domain information using CAMs to match the CNN's interpretation with geological understanding from human experts.

The CNN's generalization potential and interpretability have vastly improved by jointly improving prediction accuracy and consistency between the interpretability of the CNN and domain knowledge.

The visual interpretation of deep neural networks is the research's focus by (W. Yang et al., 2021). For visual interpretation, a qualified seismic fault detection network was chosen as an example. The fault detection process is visualized using visual intermediate activation, visual convolution kernels, and a visual class activation map. They then attempt to interpret these three visual effects to explain that the network can detect faults.

(James Lowell & Erdogan, 2019) explain an innovative AI environment that can be used in conjunction with conventional seismic interpretation methods. The framework provides a more accurate risk assessment, allowing for better exploration, appraisal, and development decision-making. The utterly flexible workflow, which puts the interpreter at the center of the process, guarantees that the interpreter can choose the most suitable resources to produce the most successful result when addressing the question at hand.

(Z. Liu et al., 2019) introduce a technique, *Smooth-Grad*, to provide visual explanations from a convolutional neural network (CNN) that is trained for fault detection. This technique highlights the regions of an input that are particularly influential to the final classification, which is often called the sensitivity map. By analyzing the sensitivity map generated by the CNN trained for fault detection, they find that the CNN does learn some useful features for fault detection, but the way a CNN gives its interpretation is still far from human interpretation.

3.1.8. Big data Platform

(Huang et al., 2017) have implemented a cloud-based seismic data analytics platform that can manage seismic volumes, calculate seismic attributes, conduct feature extraction and selection, and apply machine learning, including deep learning models, to infer geologic features to facilitate the seismic interpretation process. The platform provides a seismic data analytics SDK with deep learning package, a web-based data management tool and workflow interface for interacting with the computing platform, and a remote visualization capability for viewing massive seismic volume data sets using a web browser. The seismic analytics platform is introduced in three parts: seismic software development kit (SDK), workflow, and visualization. In a Spark environment with Hadoop distributed file system, these are coupled with other data analytics and infrastructure technologies.

3.2. Training data

3.2.1. Training dataset

In this paper (An et al., 2021), authors open-source a multi-gigabyte expert-labelled field dataset in response to the challenge of accessing large-scale expert-labelled field datasets. They show that 2D fault recognition within this dataset is an image segmentation or edge detection problem in the computer vision field, that can be expressed as a pixel-level fault/non-fault binary classification. Both types of DCNNs are compared, and authors propose a novel fault recognition workflow, which involves processing and screening of seismic images and labels, training DCNNs and automatic numerical evaluation.

With the introduction of deep learning techniques, the complex task of automated seismic fault detection has recently increased efficiency. Those approaches effectively make use of a large amount of seismic data and have much promise for fault interpretation assistance. They are, however, computationally costly and necessitate a substantial amount of time and effort to create the dataset and tuning the models (Cunha et al., 2020).

(Cunha et al., 2020) propose to use Transfer Learning (TL) on a pre-trained model so that we can work with small datasets, tune a few hyper-parameters, and adapt to various types of data. TL techniques apply the information gained from a trained model to a similar learning mission. On the Dutch offshore F3 block, we test various TL strategies using a CNN trained on synthetic seismic data as the base model.

(X. Wu et al., 2020) simulate structural features in a 3D model using a series of parameters in this workflow, based on certain assumptions about typical folding and faulting patterns. It is possible to create various structure models with practical and varied structural features by arbitrarily selecting parameters from predefined ranges. They produce various synthetic seismic images and the corresponding ground truth of structural labels to train CNNs for structural interpretation in field seismic images based on these structure models with known structural information.

(Hu et al., 2020) suggest a workflow that uses a limited training set to interpret faults using a CNN-based semantic segmentation. To be qualified to predict faults in the whole region, all that is needed is to collect some 2D seismic sections from seismic volume data for interpretation and labeling. The VGG16 model has been simplified and improved to minimize training time and increase performance. To implement end-to-end classification of seismic images, convolution layers were used instead of fully connected layers at the network's end, and dilation convolution was used to improve the receptive field and hybrid dilation convolution to prevent issues. To further improve segmentation results, the authors used the atrous spatial pyramid pooling (ASPP) module. After that, the data was refined using postprocessing. On a set of real seismic results, the proposed method's promising output was verified.

Unlike traditional deep learning methods that use very large datasets to train neural networks, (S. Li et al., 2019) propose a seismic fault detection method based on encoder-decoder CNN that needs only a small training set.

With basic fault geometries, (Pochet et al., 2019) developed a synthetic data set. The network's only input is seismic amplitude; the process would not necessitate calculating any seismic attributes. A patch classification technique was applied to the images, requiring only simple postprocessing to obtain the precise fault position.

3.2.2. Training dataset Problem

Convolutional neural networks (CNNs) have received great success in detecting faults in seismic data. However, to achieve good fault detection results, a neural network model needs high-quality and quantity training data, usually from legacy interpretation.

(Zhao, 2020) present a 3D CNN-based workflow for detecting faults and estimating fault properties from seismic data that does not require human interpretation in training.

3.2.3. Synthetic dataset Problem

For network training, convolutional neural network (CNN)-based methods necessitate a significant number of labeled data. Generating synthetic seismic images with corresponding fault labeling is one way to produce labeled data. However, it is difficult to guarantee that the synthetic data and field data have the identical fault feature distributions, which may lead to inconsistent and unreliable prediction results. Another choice is to manually label the faults, which takes time and is subjective (Zirui Wang et al., 2020).

In order to reduce the in influence caused by the difference between synthetic seismic data and real seismic data on fault detection, authors in (Zhou et al., n.d.) combine the adversarial idea in transfer learning and the deep learning model U-net to propose U-net based on DANN: they extract common knowledge between synthetic seismic data and real seismic data, which makes deep transfer learning model more suitable for real data.

Authors in (Zirui Wang et al., 2020) use knowledge distillation (KD) in this letter to enhance fault detection efficiency by incorporating features from a large number of synthetic samples and a limited number of field samples. The authors use distill knowledge from an ensemble of two teacher CNNs to train a student CNN for seismic fault detection (which is then applied to the final target). One CNN segmentation teacher is trained on synthetic samples with defined ground truth fault labels, while another CNN classification teacher is trained on field samples with manually selected labels. Then, using samples created by voting the results of two teacher models, a classification student network is trained. The student CNN learns the general fault characteristics in the synthetic data and the relevant fault characteristics in the target field data. According to field results, the student CNNs highlight seismic faults more accurately and with higher resolution than the teacher CNNs.

3.3. Constraints

3.3.1. Geologic constraints for ML

Emerging machine learning approaches, such as convolutional neural networks (CNNs), have been extensively applied to the field of seismic structural and stratigraphic interpretation to replicate the intelligence of experienced seismic interpreters to annotate subsurface geology reliably and effectively. However, most CNN architectures used in these applications are relatively basic, relying solely on the original seismic amplitude, and therefore fail to account for the critical geologic constraints that an interpreter would (Haibin Di, Li, et al., 2020).

With fault and stratigraphy interpretation, this thesis proposes constraining machine learning-assisted seismic interpretation (MLSI) by adding commonly known geologic fundamentals and/or the interpretation objective (Haibin Di, Li, et al., 2020).

Authors (Haibin Di et al., 2021) have developed a generally applicable framework for integrating a seismic interpretation CNN with such commonly used knowledge and rules as constraints.

3.3.2. CNN constraints

The CNN has proven its efficiency in utilizing such local seismic patterns to assist seismic fault interpretation, but it is quite computationally intensive and often demands higher hardware configuration (e.g., graphics processing unit).

(Haibin Di, Shafiq, Wang, et al., 2019) have devised a novel method for improving seismic fault detection by combining computationally efficient SVM/MLP classification algorithms with local seismic attribute patterns, called super-attribute-based classification.

3.4. Uncertainties and Resolution

3.4.1. Subtle fault detection

Since faults may shape baffles or conduits that regulate how a petroleum reservoir is swept, subtle fault identification is critical in reservoir development analysis. Seismic amplitude data can ignore small throw faults. Seismic attributes help in the mapping of small faults, but dozens of seismic attributes have been created over the years to provide interpreters with additional enticing but daunting features (M. Hussein et al., 2021).

Using the 3D seismic data, (Marwa Hussein et al., 2020) have generated seismic attributes for fault detection. They find that multi-attribute analysis provides greater geologic information than individual attribute volumes. They extract the geologic content of multiple attributes in two ways: interactive co-rendering of different seismic attributes and the unsupervised machine learning algorithm self-organizing maps (SOM). They suggest eight combinations of 16 various attributes for fault and fracture detection. They use principal component analysis and SOM techniques to integrate the geologic information contained within many attributes efficiently.

(M. Hussein et al., 2021) discovered that analyzing multiple attribute volumes produced more geological evidence than analyzing individual attribute volumes. Principal component analysis (PCA) and an unsupervised machine learning algorithm, Self-Organizing Maps (SOM), are used to derive the geological content of multiple simultaneous attributes. Integrating the geological context, four seismic attributes combined in one classification volume were helped by adding relevant seismic attributes that show anomalous features at the same seismic voxel with PCA and SOM analyses.

3.4.2. Improving the continuity of fault detection

(Zhou et al., 2020) proposes an iterative deep learning architecture to improve the continuity of fault detection: after building a neural network and training the network to learn the basic fault features, the continuity of fault prediction results is improved by automatic image processing with geological expert experience, the features extracted by depth learning are iteratively corrected through seismic data examples and image processing results.

3.4.3. Uncertainties in the fault identification

The interpretation of faults within a geological basin or reservoir from seismic data is a time-consuming and often manual task associated with high uncertainties. Recently, numerous approaches using machine learning, especially various types of convolutional neural networks, have been presented to automate the process of identifying fault planes within seismic images, which have been shown to outperform traditional fault detection techniques. While these proposed methods show good performance, many of these approaches do not investigate the associated uncertainties that arise in the fault identification process (Mosser et al., 2020).

(Mosser et al., 2020) present a method for detecting faults in seismic datasets using Bayesian deep convolutional neural networks. A Bayesian deep neural network was trained on a large dataset of synthetic faulted seismic images using an approximate Bayesian inference method. The model is then used to detect fault planes and investigate the resulting uncertainty in the predictive distribution using a benchmark dataset and a particular data case.

3.4.4. Quantification of the fault model uncertainty

The goal of this paper (Feng et al., 2021) is to quantify the fault model uncertainty that is generally not captured by deep-learning tools. We have used the dropout approach, a regularization technique to prevent overfitting and coadaptation in hidden units, to approximate the Bayesian inference and estimate the principled uncertainty over functions. Particularly, the variance of the learned model has been decomposed into aleatoric and epistemic parts.

3.4.5. Enhance data quality

It is quite difficult to image geological features in highly deformed and complicated sedimentary basins. Poor data quality is one of the most serious issues. Unwanted noise is usually linked with seismic data, masking geological features. As a result, to increase data quality, undesired noise must be reduced. Data conditioning is a crucial step in reducing noise and emphasizing geological structures. In (Ramu et al., 2021) study, the detection of geological features by using multi-seismic attribute calculations and artificial neural networks has effectively improved the detection of faults and chimneys.

3.4.6. Performance of a deep learning model

Faults and horizons are thin geologic boundaries (1 pixel thick on the image) for which a small prediction error could lead to inappropriately large variations in common metrics (precision, recall, and intersection over union).

(Guillon et al., 2020) suggest new metrics for evaluating a deep learning model's performance in seismic interpretation tasks like fault and horizon extraction. They change their metrics by introducing a tolerance feature, showing their ability to handle seismic interpretation uncertainties.

(Sarajaervi et al., 2020) recommend using a robust Jaccard metric for fault segmentation in seismic data because it allows for minor lateral fault positioning inaccuracies. In fact, this is accomplished by using metrics to compare machine learning results to manual interpretations and applying new variants of the convolutional neural network to field data.

3.4.7. Prediction accuracy

Fault identification in seismic data is a vital but time-consuming step in the seismic interpretation workflow. Recent studies demonstrate how deep-learning techniques, such as convolutional neural networks (CNN), can be used to identify these faults with high accuracy automatically. However, different levels of signal-to-noise ratios in seismic data can degrade prediction accuracy. A low resolution of predicted faults can cause multiple issues, such as failing to identify potential drilling hazards.

A multichannel U-Net architecture was used by (Jiang & Norlund, 2021) to boost the prediction accuracy of fault probability maps for this abstract. The most important attributes were identified as additional channels to feed into the network using a decision-tree-based analysis of feature importance. The approach successfully improved prediction results by identifying more continuous fault segments and predicting missing fault segments that are not estimated using a seismic-only trained model by training with seismic and multiple attributes simultaneously. Implementing a GANs-based reconstruction method clarifies fault locations and aids in eliminating low probability blurred zones, resulting in a higher-quality fault probability map.

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Chapter 4

4. Result of the Literature of Machine Learning in Fault Detection

4.1. Introduction

Machine learning is a branch of computer science dealing with developing algorithms that depend on a series of observations of a phenomenon to be helpful. These examples can be found in nature, created by humans, or generated by another algorithm. ML simulates human learning by allowing computers to recognize and gain information from the real world, allowing them to do well on those tasks depending on the newly learned knowledge. Precisely, ML is defined as follows: "A computer program is said to learn from experience E concerning some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." (Anderson, 1990). ML was deemed an independent discipline in the 1990s, despite its origins in the 1950s (Anderson, 1990). ML methods are used in different fields of computer (Handelman et al., 2019; Malhotra, 2015), environment (Bellinger et al., 2017), health (Spasic & Nenadic, 2020), medicine (Senders et al., 2018), and energy (Mosavi et al., 2019).

In (Alregib et al., 2018; Dramsch, 2020; Zhen Wang et al., 2018), ML applications have been reviewed for Data-driven Geophysics and soft computing technology in Subsurface Structure Analysis. However, there is no systemic review of the research of machine learning applications in fault detection and interpretation. As a result, the approaches used by ML research projects and their applications of fault interpretation are reviewed in detail in this article. The ML research trends, and ML models used in research projects are mainly examined.

4.2. Methods for Systematic Review

A systematic literature review (also known as a systematic review) allows identifying, analyzing, and interpreting all of the existing research on a specific research question, topic, or phenomenon (Budgen et al., 2007). The review's aim is to provide solutions to research-related questions. The research questions in this study were initially arranged to define the scope and overall objectives of the review. A search method was then developed to efficiently collect research papers on research questions and set criteria to choose appropriate studies from search results. The abstracts and results of the articles were then reviewed to assess their relevance in the field of research. Following that, data was extracted from the paper in order to differentiate and structure the relevant details as follows:

RQ 1: What are the current ML research trends in fault detection (yearly, publication sources, application fields in detail)?

RQ 2: Which ML models were frequent in the research papers (data type, large data, model usage frequency, application in the field)?

The main objective of this review is to provide an update on the current state of ML in seismic interpretation. The research questions were determined based on the purpose. The aim of RQ 1 was to describe the current state of ML study in the field. It refers extensively to the present state of the annual publication and its field-related implementations. RQ 2 listed the ML model used in the analysis. It expressly referred to the learning data type, the use of a large volume of data, the frequency of use of the model, and its extensive use in the field.

4.3. Search Method

We used Google, Scopus, and the web of science to find the most related articles. We extracted search keywords relevant to the review's subject: fault, seismic interpretation, machine learning, deep learning. The "machine learning" and "deep learning" were considered as keywords to identify papers that use ML and deep learning techniques among available research methods. Only research projects undertaken between January 2010 and March 2021 were considered to analyze research patterns over the last decade. Using the mentioned process, we were able to secure several candidate papers.

4.4. Selection Criteria

Originality, high impact, and high standards may all be considered qualifications for published articles. This is because such manuscripts are evaluated by experts and then revised before being published. Consequently, we have selected papers that have already been published. The following were the selection criteria: (1) research papers; (2) full text; (3) stratigraphic interpretation exclusion. These factors were chosen for the following reasons: only research papers were used to assess the current state of ML, and full text allowed for a thorough examination of the paper's content. The stratigraphic interpretation was excluded because a few recent studies had reviewed and reported ML applications' topic.

4.5. Results/Exploratory analysis

An SLR is a systematic and coordinated method for investigating research on a subject or functional field and understanding the research's benefits (Ressing et al., 2009). The result also aids in the long-term advancement of approaches and models. This provides an overall perspective of the research and helps to pave the way for further research on a particular subject. An SLR goes through several steps to ensure that all information is gathered and presented efficiently. Exploratory analysis is a step in the process that relies on information about research articles such as publication growth, influential publications, most productive countries, and most frequently used keywords (Ahmed et al., 2020).

4.6. RQ 1: Machine Learning Research Trends in the fault detection

4.6.1. Publication Growth

The figure 1 shows the distribution of research from January 2010 to March 2021. It has been steadily increasing over the last four years. It could be said that only two of the 79 articles were reviewed before 2018. The number of studies published in 2018, 2019, 2020, and March 2021 was 14, 19, 25, and 11, respectively. The number of articles published in 2018 was 2 times higher than the previous year. Research conducted in the last four years accounted for approximately 97 percent of the total research conducted in the last twelve years.

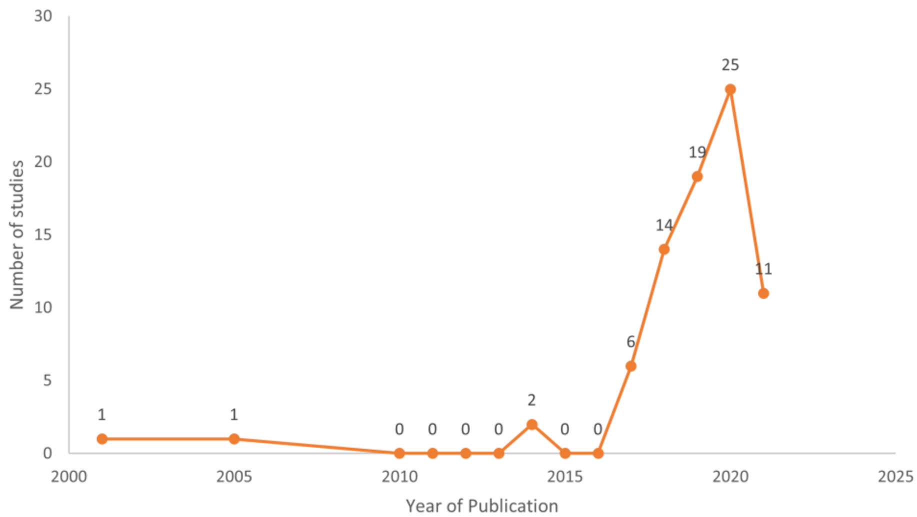

Figure 1: Publications per year

4.6.2. Publication Source

Several academic papers have appeared in peer-reviewed journals. The table 1 summarizes the publication details of top journals and the total number of published papers. Most papers were found in The Leading Edge, Geophysics, SEG Technical Program Expanded Abstracts 2018, Interpretation, followed by others.

Table 1: Summary of top publications

Publication Name	# Research Papers
The Leading Edge	7
Geophysics	6
SEG Technical Program Expanded Abstracts 2018	6
Interpretation	5
SEG Technical Program Expanded Abstracts 2019	5
SEG Technical Program Expanded Abstracts 2020	3
82nd EAGE Annual Conference & Exhibition	3
81st EAGE Conference and Exhibition 2019	3
SEG Technical Program Expanded Abstracts 2017	3
Computers & Geosciences	2
Geophysical Prospecting	2
First EAGE Digitalization Conference and Exhibition	2
IEEE Geoscience and Remote Sensing Letters	2
Journal of Geophysics and Engineering	2
Geophysical Journal International	2
International Geophysical Conference	2

4.6.3. Paper type

In the figure 2, the research papers were categorized on the basis of types of the article as original, methodological, case study, review, and conference papers. Conference papers were found to have the largest share of documents (40.49%), followed by original papers (20.24%).

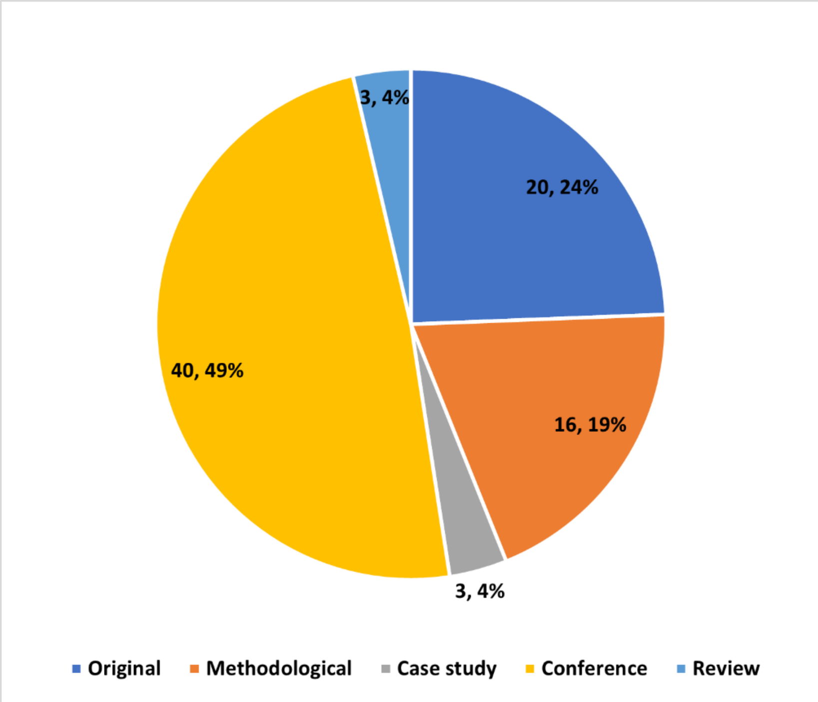

Figure 2: Type of publication

4.6.4. Influential authors and publications

In this section, we explore the influential authors and published journals. The top authors published from 2010 to 2021 are shown in the table 2. The top-three most-cited articles were written by (Meldahl et al., 2001), (Huang et al., 2017), (Araya-Polo et al., 2017), table 3. The Co-citation network analysis is shown by figure 3.

Table 2: Influential authors

First Author	# Research Paper
Haibin Di	9
Xinming Wu	5
James Lowell	2
Ruoshui Zhou	2
Zhining Liu	2
Marwa Hussein	2
Mustafa Alfarhan	2
Yue Ma	2
Bowen Guo	2

Table 3: Influential publications

Title of Paper	# Citation
(Meldahl et al., 2001)	189
(Huang et al., 2017)	157
(Araya-Polo et al., 2017)	157
(Wu, Liang, et al., 2019)	139
(Tingdahl & de Rooij, 2005)	116
(Xiong et al., 2018)	86
(Wu, Shi, et al., 2019)	60
(Zhang et al., 2014)	57
(Alregib et al., 2018)	41

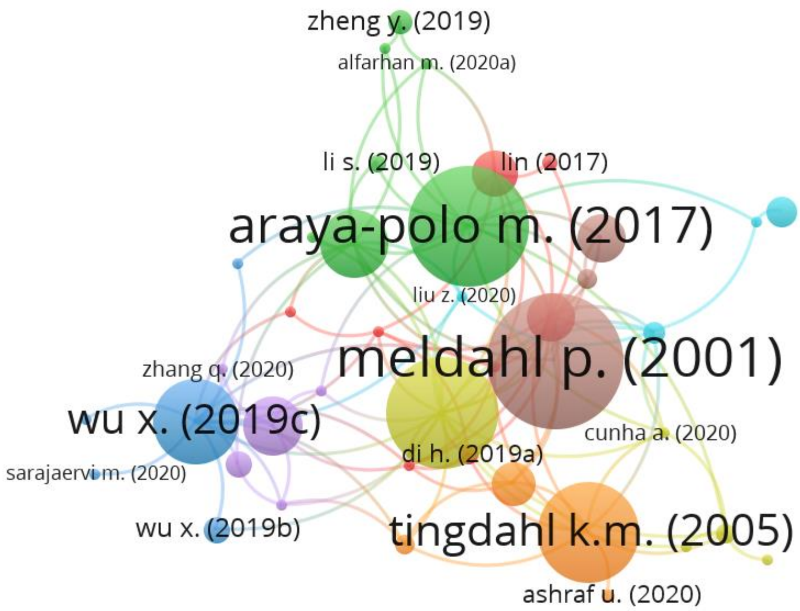

Figure 3: Co-citation network analysis

4.6.5. Productive countries

The table 4 shows the research work performed and the frequency of the publication by country. In terms of the number of publications (NP), China, the USA, and Norway have published 28, 28, and 3, respectively. China's NP and USA's NP are the same, whereas the difference between the second-and third-ranked countries is about 9.3.

Table 4: Productive countries

Top Countries	Count
China	28
USA	28
UK	3
Norway	2
Russia	2
Saudi Arabia	2
Brazil	2
Denmark	2

4.6.6. Most frequently used keywords

The keywords used in a research field are an indication of the concentrated nature of the field. Accordingly, 415 keywords were recorded in this study. The figure 4 shows the co-occurrence network of the most frequently used keywords. The distinct color represents the density of the clusters, whereas the relative font size indicates their frequencies of occurrences. The relative font size could be an indication of their significance and relative advancement.

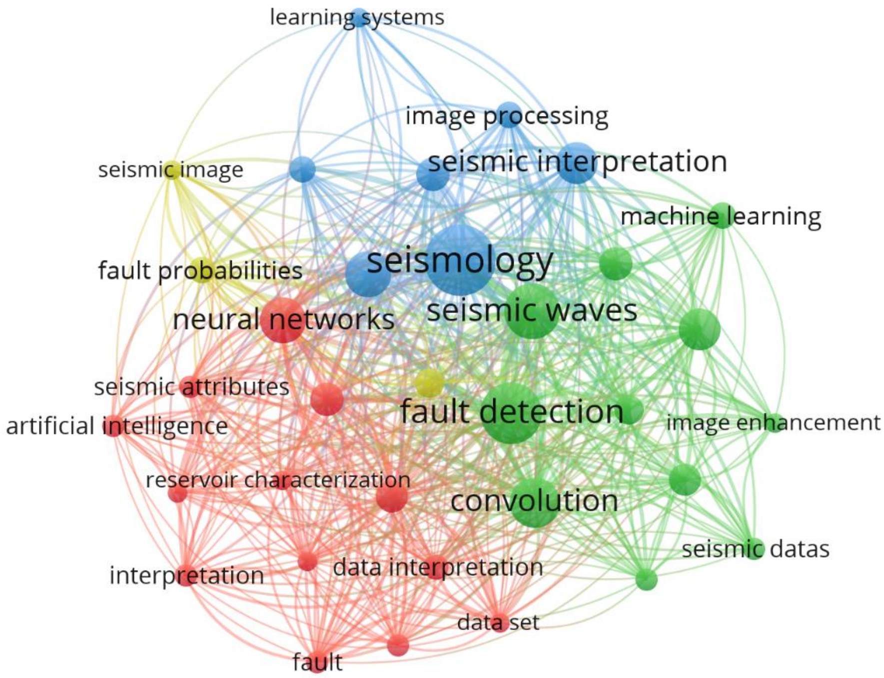

Figure 4: Frequently used author's keywords

4.6.7. Detailed Fields of Application/ content analysis

The breakdown of the research objective is shown in the table 5. Based on the research objectives, 53.2% of the research papers fall into the fault detection and fault interpretation category, which shows that it is indeed a favorable topic in seismic interpretation. The remaining 56.8% of the papers are distributed among the simultaneous pattern interpretation, training dataset problems, etc. The detailed table of the papers and their purposes can be found in the appendix.

Table 5: Summary of research objective

Problem Type	# Research Papers
Fault detection	32
Simultaneous interpretation of seismic patterns	7
Fault interpretation	6
Training dataset	6
Interpretability of the CNN	4
Review	3
Performance of a deep learning model	2
Subtle fault detection	2
Simultaneously estimate fault probabilities, strikes, and dips	2
Synthetic dataset Problem	2
Geologic constraints for ML	2
Training dataset problem	1
Prediction accuracy	1
Uncertainties in the fault identification	1
CNN constraints	1
Improve the continuity of fault detection	1
Challenge of seismic image processing tasks	1
Big data platform	1
Quantification of the fault model uncertainty	1
Enhance data quality	1
Pattern recognition	1

4.7. RQ 2: Machine Learning Models

4.7.1. Dataset types

In ML research, a variety of data sets were used. The dataset was acquired either from publicly available open sources, individually in the case of private data, and synthetic datasets. Therefore, figure 5, the papers were classified based on the synthetic dataset and real dataset that was used for the training of the models.

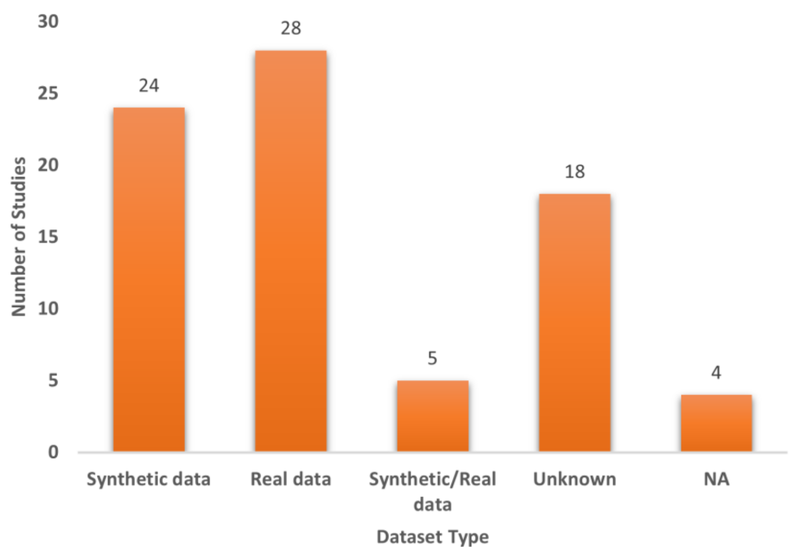

Figure 5: Dataset type

4.7.2. seismic dataset

Due to the vast number of ML and deep neural networks parameters, these methods usually require a large amount of data for training. The figure 6 shows the distribution of studies based on the type of seismic dataset. The figure indicates that the seismic amplitudes were the most common inputs for the training and evaluation steps.

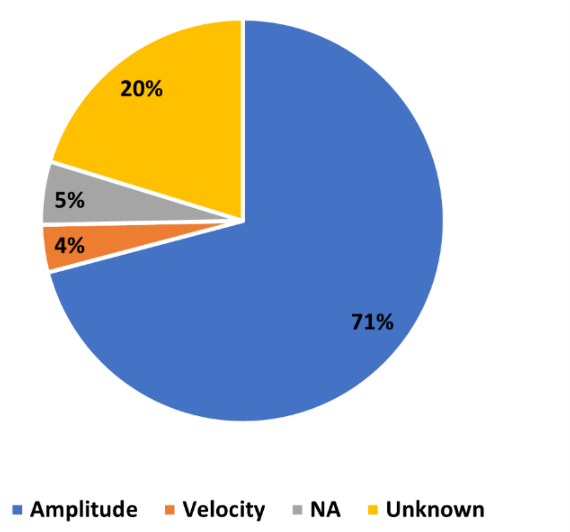

Figure 6: Type of seismic dataset

4.7.3. Machine Learning Models

Based on the selected paper, the ML model was classified. As a result of analyzing the studies, the models were categorized into a total of 6 types: Deep Neural Network (DNN), Convolutional Neural Network (CNN), Neural Network (NN), Multi-Layer Perceptron (MLP), Machine Learning (ML) methods such as decision tree, random forest, self-organizing maps (SOM), principal component analysis (PCA), Support Vector Machine (SVM), Kernel Ridge Regression (KRR), Kernel Regularized Least Squares (Kernel RLS). Figure 7 represents the classification details of the ML technique. The figure indicates the usage frequency of all models in the study. The most frequently used model was the convolutional neural network (65%).

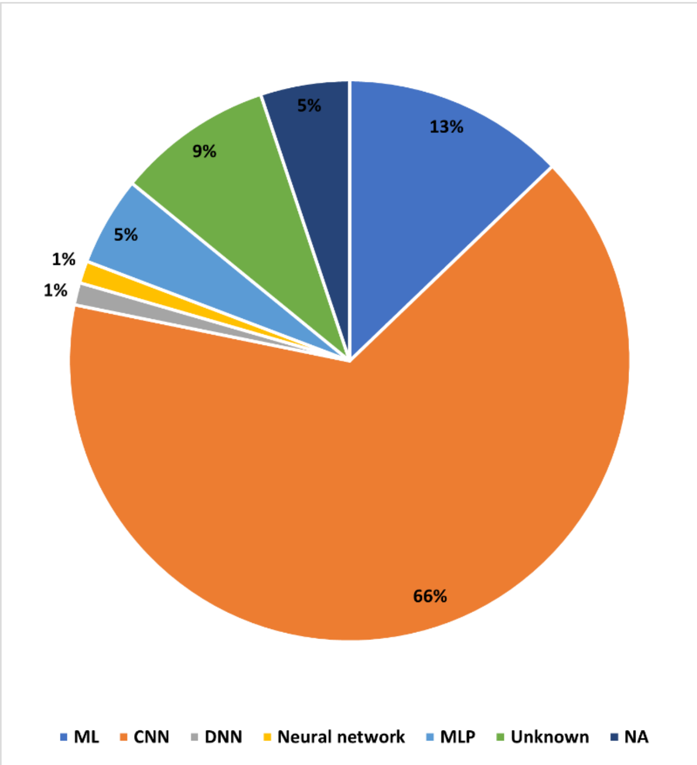

Figure 7: Usage frequencies of ML models

4.7.4. Learning mechanisms

The figure 8 below shows the distribution of studies based on the learning methods. Learning can be supervised, semi-supervised, unsupervised, and reinforcement. As it is clear, supervised learning is the most used method (55 studies).

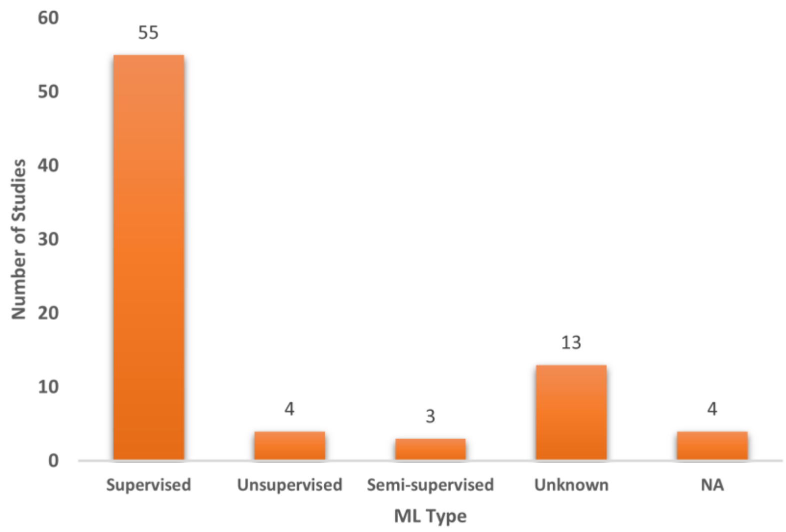

Figure 8: Type of ML algorithm

4.7.5. Deep Model Training

Shortlisting many network architectures, also known as network topologies, is the first step in model training. When dealing with image data, for building a convolutional neural network (CNN) model from scratch, at least one convolutional layer, followed by a max-pooling layer, and one fully connected layer may be the default topology choice. The figure 9 indicates the usage frequency of architectures in neural network-related studies. The most frequently used architecture was the typical one (19 studies).

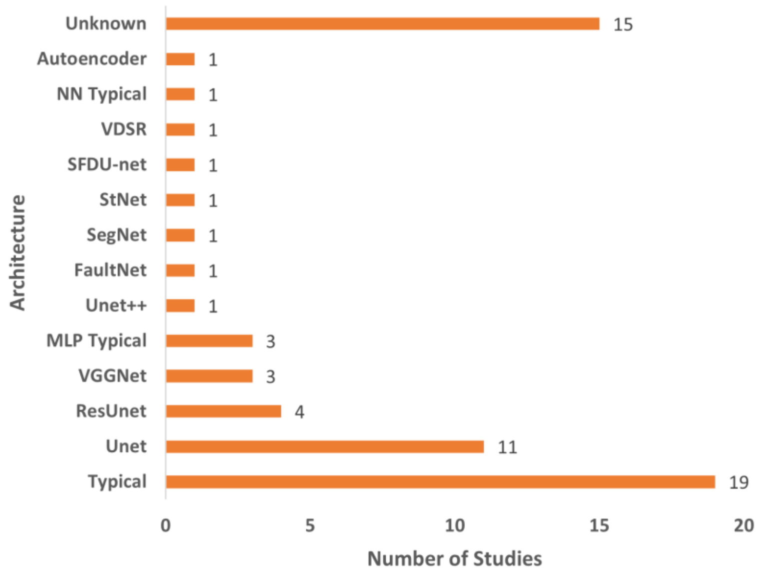

Figure 9: Neural network architectures

4.8. Conclusion

Systematic reviews were conducted to examine the current trends of machine learning techniques in fault detection and analyze previous studies in detail. The review provides an overview of the research conducted so far and assistance for future research. The answers to research questions are summarized as follows:

- Several studies have been conducted since 2010, and the highest number of studies have been conducted only in developing new ML techniques for fault detection.
- The research was conducted using convolutional neural networks (CNN) predominantly.
- The ML models were trained and evaluated primarily using real datasets.
- Since 2016, several studies have been conducted on ML techniques in fault detection, demonstrating the increased attention ML-related research has been receiving.

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