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# Research on Fracture Prediction Method Based on Multi-Source Information Fusion

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## Abstract

Machine learning is a good method for predicting fracture by integrating multi-source information. Post-stack seismic attributes are commonly used to predict medium to large fractures, while pre-stack seismic attributes are proven to be more sensitive to small and micro sized fractures through forward modeling. Using machine learning algorithm to fuse information from different scales to predict fracture can greatly improve the accuracy of fracture prediction. On the basis of *in-situ* stress prediction, the paper conducted post-stack seismic attribute analysis and pre-stack seismic attribute analysis, further studied on the sensitivity of seismic attributes to fracture and selected sensitive attributes, used the sensitivity log of wellbore fractures as the target log for learning, ultimately obtained a comprehensive body of fracture. Through blind well verification, the prediction results match well with the we1l data and the prediction results is highly consistent with the production data. The results of fracture prediction are reliable, and the research method has certain reference significance for fracture prediction.

## Keywords

*In-Situ* Stress, Fracture Prediction, Seismic Attribute, Machine Learning

## 1. Introduction

With the continuous deepening of exploration and development, fractured oil and gas reservoirs have gradually become an important part of oil and gas exploration and development, and the proven reserves are constantly increasing. Therefore, effectively predicting the development of fracture is of great significance for the development and subsequent transformation of fractured oil and gas reservoirs. At present, there are various methods for predicting fracture, including seismic, logging, etc. Among them, using seismic data for fracture prediction is a very important field. There are two main methods for predicting fracture using seismic data, those based on pre-stack data and those based on post-stack seismic data.

The commonly used methods for predicting post-stack fracture include ant tracking, discontinuity attributes and curvature attributes, which are the most commonly used post-stack seismic attributes. Ant body attribute is a fracture automatic tracking technology invented by Schlumberger Corporation. It was first proposed by Dorigo et al. (1991) as a biomimetic optimization algorithm, inspired by the phenomenon of ant colonies selecting the shortest path during foraging. Pedersen (2002) first proposed an ant tracking fracture recognition method, provided an ant tracking process, and applied it to actual data; Aqrawi (2011) combined improved 3D Sobel filtering and dip filtering methods with ant algorithm to achieve accurate interpretation of small faults and fracture. Curvature characterizes the degree of curvature of a formation, and the larger the curvature, the easier it is for fracture to develop. Therefore, curvature can be used to predict the range of fracture development.

The pre-stack fracture prediction method is mainly based on the anisotropy of fracture for research. Rüger (1996, 1997, 1998) has continuously published important theories on HTI media, providing formulas for the reflection and transmission coefficients of anisotropic interfaces to vary with azimuth and offset, and establishing the theoretical basis for pre-stack fracture detection. Downton & Roure (2010) improved the prediction algorithm to improve the accuracy of predicting fracture using azimuth gathers; Jenner (2012) studied the theory of Azimuth AVO and demonstrated its application in fracture prediction. Sun et al. (2014) proposed an optimized method for detecting azimuthal anisotropic fracture.

Fractures are complex aggregates, and the development scales of different fracture vary greatly. To accurately predict fracture, it is necessary to comprehensively apply logging, pre-stack seismic, post-stack seismic, and stress field data as much as possible. Artificial intelligence algorithms are effective tools for multi-attribute fusion. The ten commonly used machine learning methods include decision trees, random forests, logistic regression, support vector machines, K-nearest neighbors, K-means, Adaboost, Naive Bayes, artificial neural networks, and deep learning (Chen & Zhu, 2007). With the development of petroleum geophysical exploration technology, supervised machine learning methods such as artificial neural networks and support vector machines have been widely used in logging technology and seismic exploration, mainly to solve classification and regression problems encountered in the exploration process (Xie, Liu, Liu et al., 2017).

## 2. Overview of Research Ideas and Methods

In the process of fracture prediction research (**Figure 1**), the first step is to predict the tectonic stress field, which controls the formation and development of fracture. Under the control of constructing a stress field, sensitive attributes of post-stack fracture, such as ant body attributes, curvature attributes, discontinuity attributes, etc., are selected. Regarding the pre-stack seismic attributes, the anisotropic attributes sensitive to fracture can be obtained through forward modeling, such as the difference in far and near frequency attributes and azimuth frequency attributes. Different attribute bodies represent different fracture scales, and a single attribute cannot fully characterize the distribution of fracture. Using machine learning methods to fuse the selected attributes, ultimately forming a high-precision fracture development intensity volume.

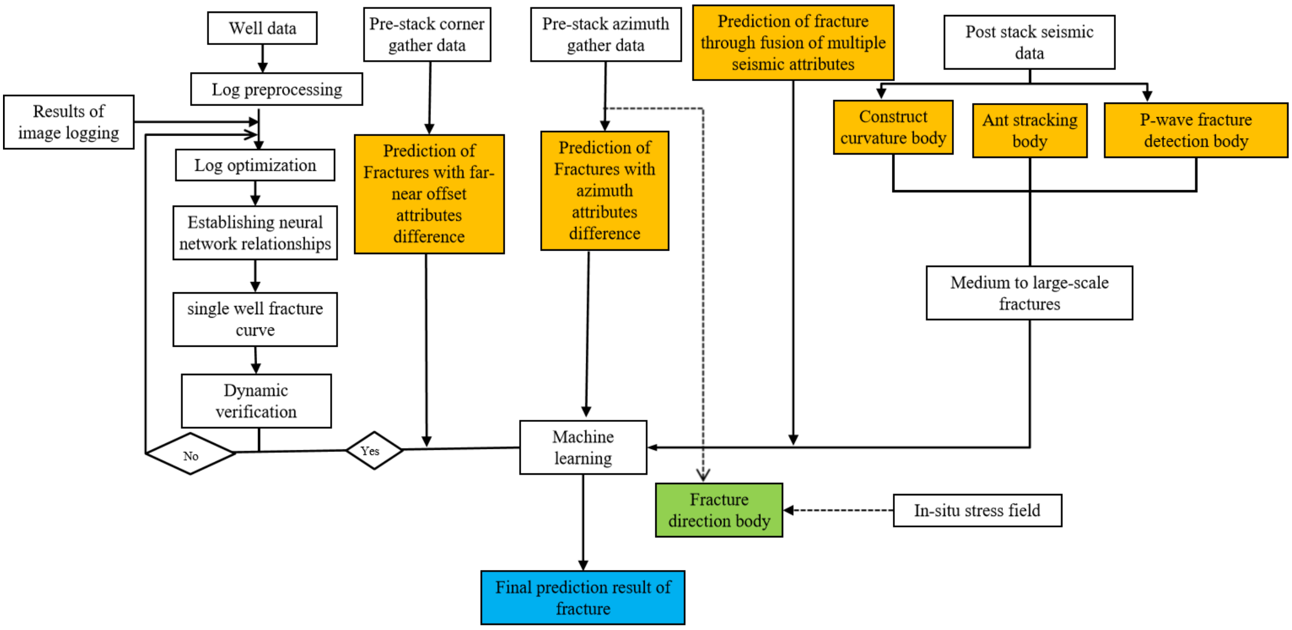



**Figure 1.** Technical roadmap for paper research.

## 2.1. *In-Situ* Stress Fields Simulation

The principle of using seismic for stress field simulation is to comprehensively study the correlation between fracture development and formation thickness, lithology, porosity, structure, etc., and use thin plate theory to simulate the stress field. Specifically, it is to use pre-stack seismic inversion to obtain reservoir thickness, lithology, Lame constant, and shear modulus, while analyzing seismic discontinuity to obtain fault development systems. Integrate these parameters for stress field numerical simulation. This method comprehensively considers more geological factors, making the simulation results more accurate.

## 2.2. Fracture Prediction Using Anisotropic Properties

Theoretical studies have shown that the presence of faults, fracture, etc. can cause scattering of seismic waves and attenuation of seismic energy (Zhu et al., 2001). High frequency energy decays rapidly, and after seismic waves pass through fracture, the entire frequency band will shift towards the low frequency band due to attenuation. Calculate the difference between amplitude and frequency at the far and near offset distances at the same azimuth angle. The more developed the fracture, the greater the attenuation, and the greater the difference between the far and near offset distances. Therefore, the difference in distance offset can be used for fracture prediction.

Similarly, utilizing the differences in attributes at different azimuth angles can also be used for fracture prediction. In the vertical direction of fracture development, seismic attenuation is the fastest. The more developed the fracture, the faster the seismic attenuation. Subtract the amplitude or frequency of different azimuth angles, and the larger the difference, the more fracture will develop.

#### 2.2.1. Relationship between Azimuth Attributes Differences and Fracture Development

Establish a forward model in the fracture development section and obtain the forward results. The amplitude changes with the azimuth and incidence angles. When the incidence angle is less than 40˚, the incidence angle remains unchanged. As the azimuth angle increases, the amplitude increases, and the difference caused by the azimuth angle becomes larger and larger as the incidence angle increases (**Figure 2**). The incidence angle of the pre-stack seismic data in the study area is 27˚, therefore, the difference in azimuth attributes is highly sensitive to the development of fracture.

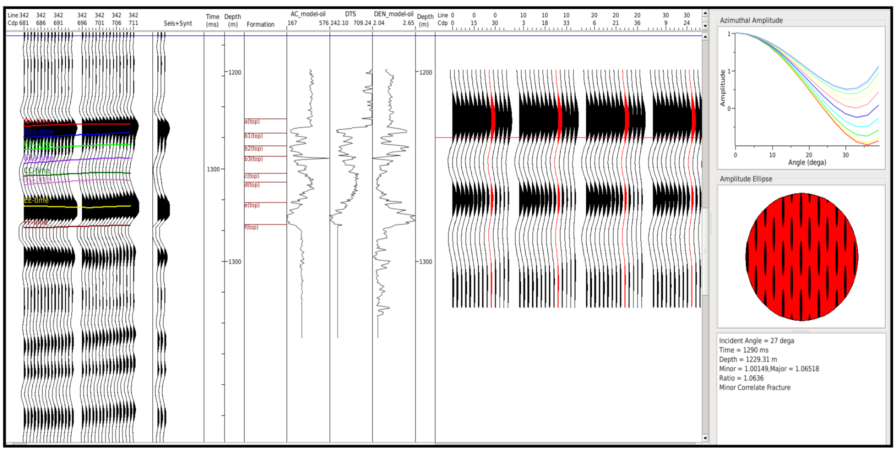
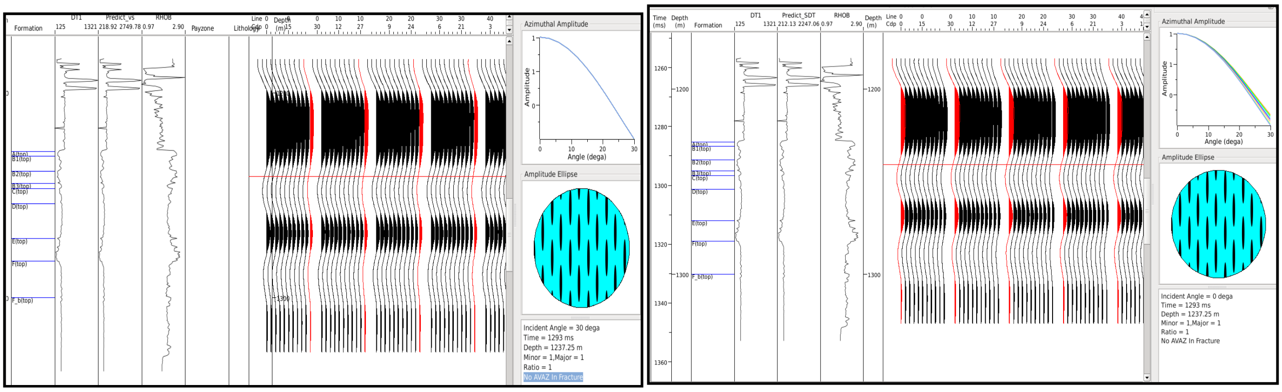



**Figure 2.** Forward modeling results of directional attributes.

#### 2.2.2. Relationship between Far-Near Offset Attributes Difference and Fracture Development

It had been established two geological models with different fracture density to investigate the impact of fracture development on the difference in far-near attributes. Model A has a fracture density of 0%, while Model B has a fracture development density of 15%. The seismic amplitude intensity at the far and near offset of model A remains unchanged. For model B, the offset distance influences the amplitude intensity a lot. As the offset distance increases, the difference gradually increases. Therefore, in the case of fixed azimuth, the difference at the far and near offset is directly proportional to the distance, and the higher of the fracture density, the greater the difference in far and near offset attributes (**Figure 3**).



(a) (b)

**Figure 3.** Forward modeling results of far and near biased attributes of reservoirs with different fracture intensities. (a) seismic forward modeling with 0% fracture strength; (b) seismic forward modeling with 15% fracture strength.

### 2.2.3. Sensitivity Analysis of Different Attributes

Different attributes have different sensitivities to azimuthal anisotropy, and 10 different attributes were extracted for analysis (**Figure 4**), indicating that seismic amplitude and frequency are more sensitive to fracture. Therefore, fracture prediction can be performed using attributes such as azimuth amplitude attribute difference, azimuth frequency attribute difference, and far near offset frequency attribute difference.

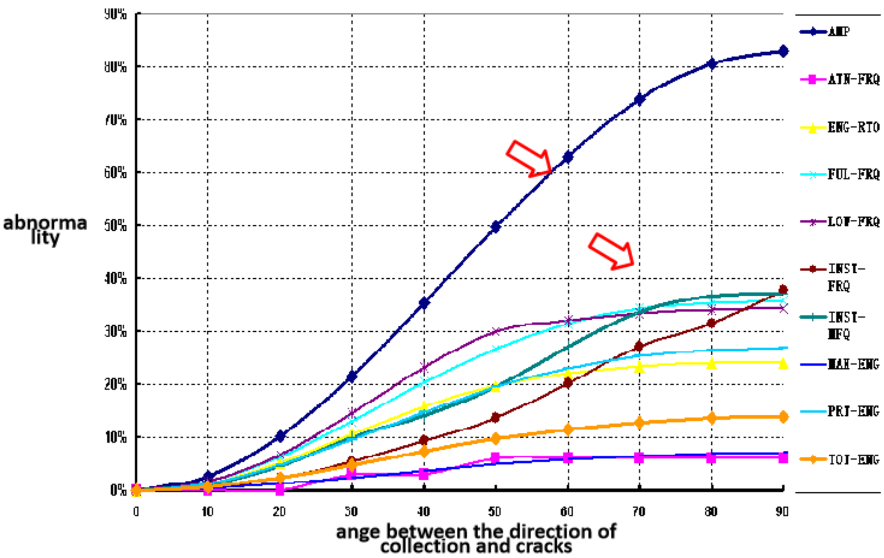



**Figure 4.** Forward modeling results of sensitivity for different attributes.

## 2.3. Machine Learning Fusion Based Multi-Source Information

There are significant differences in the sensitivity of different post-stack seismic attributes and pre-stack seismic attributes to fracture of different scales. The ant body attributes represent larger scale macroscopic fracture, while the curvature of the structure represents mesoscale fracture, while pre-stack seismic are more sensitive to micro fracture. By using machine learning algorithms to fuse attributes of various scales, the resulting fracture development body is more consistent with the actual situation. The main processes of machine learning include:

1) Data preparation and organization

It is necessary to collect and integrate data from different sources in order to prepare for data-driven approaches. After data integration, it is necessary to select suitable data for specific project purposes. The collected data is usually not clean and may contain errors, missing values, noise, or inconsistent data. Different methods need to be applied to the selected data, such as deleting incorrect data, completing missing data, removing noise, and unifying inconsistencies, to eliminate these anomalies.

2) Data optimization and dimensionality reduction

The correlation between the selected data and the learning objectives is different, and excessive interference information can reduce the accuracy of learning. Meanwhile, duplicate data with high correlation will greatly increase workload. Perform correlation analysis on all data and remove data with low correlation and high homogeneity to the target. Ensure that the data participating in the calculation has high independence and can well reflect the required predictive attribute information.

3) Unified encoding of different information

After data cleaning and optimization, it is usually necessary to convert the data into a form suitable for data analysis and data mining, and perform data smoothing, standardization, clustering, encoding, and other processing. For example, for the classification and pre-coding of lithological data, the original shot sets collected by seismic detectors in 3D seismic acquisition may need to be processed into pre-stack common reflection point gathers, partially stacked angle gathers, or post-stack seismic data in reservoir prediction projects.

4) Data Feature Engineering

Analyzing the geological and geophysical laws contained in the data. A solid understanding and experience of theoretical knowledge, such as geology, geophysics, and reservoir engineering, is required to analyze data characteristics, which have guiding significance for establishing effective data-driven models and are an important foundation for data-driven methods.

5) Data driven model establishment

Selecting appropriate machine learning methods, and establishing descriptive or predictive data-driven models. This step is the core of a data-driven approach.

6) Model evaluation and post analysis

Evaluate and optimize the established data-driven model, conduct visual analysis on the established data-driven model, discover hidden models or patterns, and improve understanding of the model.

7) Knowledge Discovery and Decision Making

Utilize newly established data-driven models to acquire new knowledge and understanding, and use the acquired knowledge and understanding to make better decisions.

## 3. Case Study

Carbonate rocks are developed in G oilfield, and fracture are the main factor affecting production. Therefore, predicting fracture can effectively guide the next step of oilfield development and subsequent reservoir transformation. On the basis of simulating the stress field of oilfield structures, different seismic attributes were extracted before and after stacking, and imaging logging was used to establish sensitivity curves for wellbore fracture. After encoding all the data, machine learning is carried out to obtain the final fracture prediction result of the work area. Perform blind well validation on the predicted results and compare them with production data, and the predicted results are more reliable.

### 3.1. Basic Geological Characteristics of the Research Area

The structure of G oilfield is characterized by a long axis anticline in a northwest southeast direction, and the overall direction of the fault is consistent with the long axis of the anticline. The faults in the oilfield are all reverse faults, with most of them trending NW-SE. The faults extend far, with a maximum extension distance of 25 km. It leans between 65˚ and 73˚ and belongs to a high angle reverse fault. The G oilfield is mainly characterized by limited and semi limited platform sedimentation. The main lithology of the A oil group includes dolomite, sandy dolomite, gypsum dolomite, mudstone, and a small amount of gypsum and conglomerate. The main lithology of the B oil group is limestone, followed by dolomite, with a small amount of sandstone, mudstone, etc.

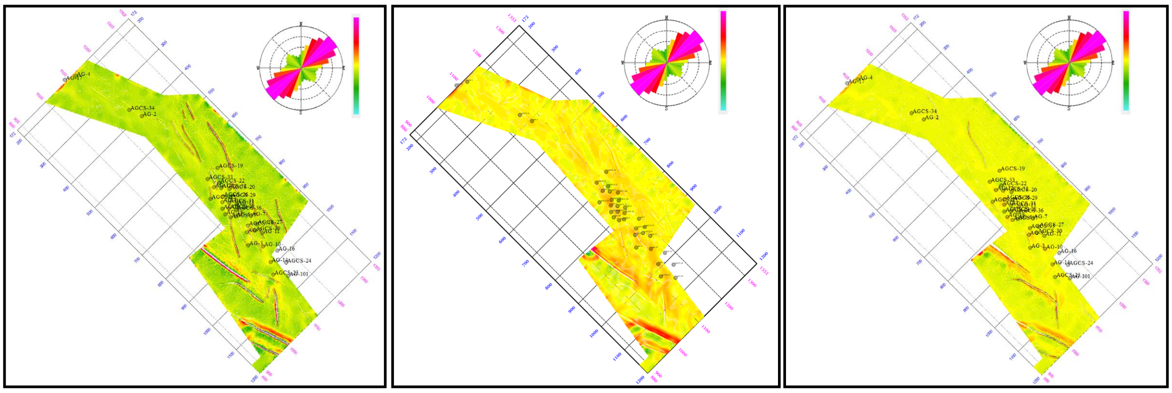
### 3.2. Simulation Results of *In-Situ* Stress Field

Simulate the structural stress field of layers A, B, and C in G oilfield. As shown in the figure below, the main direction of stress distribution in layer A is northeast, and the development of *in-situ* stress in the plane is shown in **Figure 5(a)**. The *in-situ* stress is most developed in the southern region, followed by the middle region. The main direction of stress distribution in the B-layer structure is northeast, and the development of *in-situ* stress in the plane is shown in **Figure 5(b)**. The *in-situ* stress is most developed in the southern region, followed by the middle region. The main direction of stress distribution in the C-layer structure is northeast, and the development of *in-situ* stress in the plane is shown in **Figure 5(c)**. The *in-situ* stress is most developed in the southern area. The place where *in-situ* stress develops is also the place where fractures develop, and the main direction of *in-situ* stress is generally perpendicular to the main direction of fracture development.

### 3.3. Fracture Prediction Based on Post-Stack Seismic Attribute

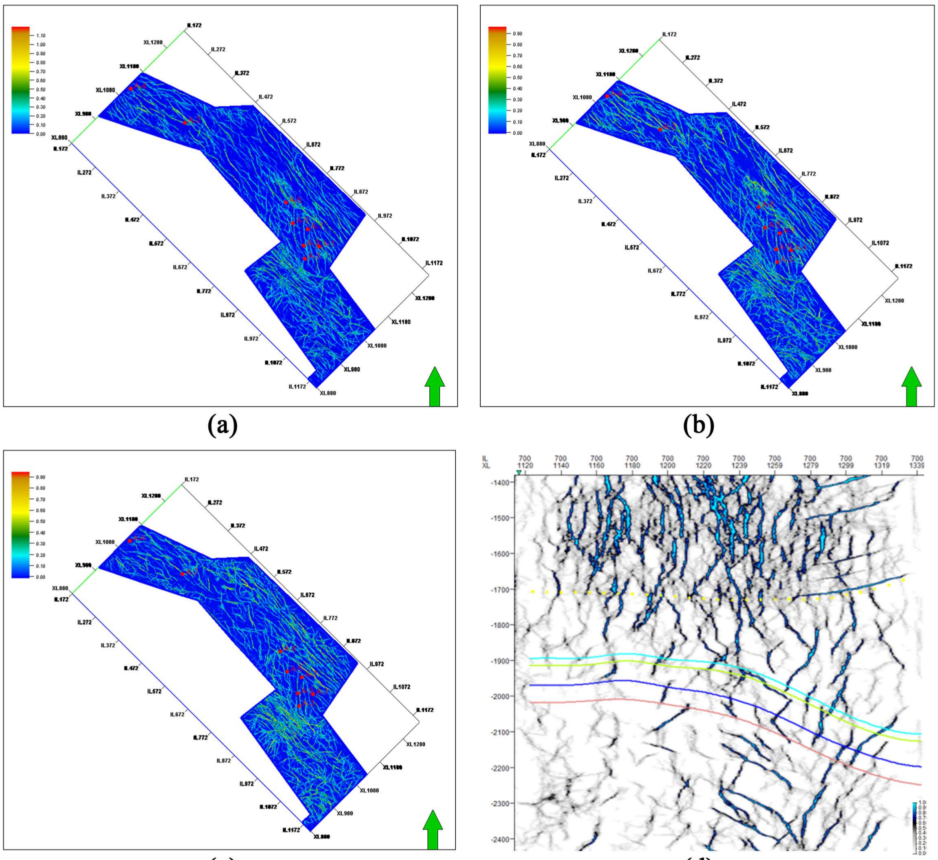
#### 3.3.1. Ant Tracking

Extracting the ant body attribute body of the research area (**Figure 6**), it can be seen that the ant body can clearly characterize the development characteristics of faults in both plane and section. The middle and southern parts of the research



(a) (b) (c)

**Figure 5.** Simulation results of *in-situ* stress field in G oilfield. (a) Simulation results of *in-situ* stress field in layer A; (b) Simulation results of *in-situ* stress field in layer B; (c) Simulation results of *in-situ* stress field in layer C.



**(a)** **(b)** **(c)** **(d)**

**Figure 6.** Prediction results of ant tracing. (a) Ant tracing result in layer A; (b) Ant tracing result in layer B; (c) Ant tracing result in layer C; (d) Ant tracing result profile.

area have relatively developed fracture, with the direction of the fracture being nearly northwest. Ant bodies have higher accuracy in characterizing larger fracture, but do not correspond to smaller scale fracture.

### 3.3.2. Discontinuity Attribute

The discontinuity attribute represents the discontinuity of a geological body in the plane, and can indirectly characterize the development of fracture. Extracting the discontinuity attributes of the study area (**Figure 7**), it can be seen that the fracture is most developed in the southern part of the study area, while the fracture in the southern part of the middle area is also relatively developed.

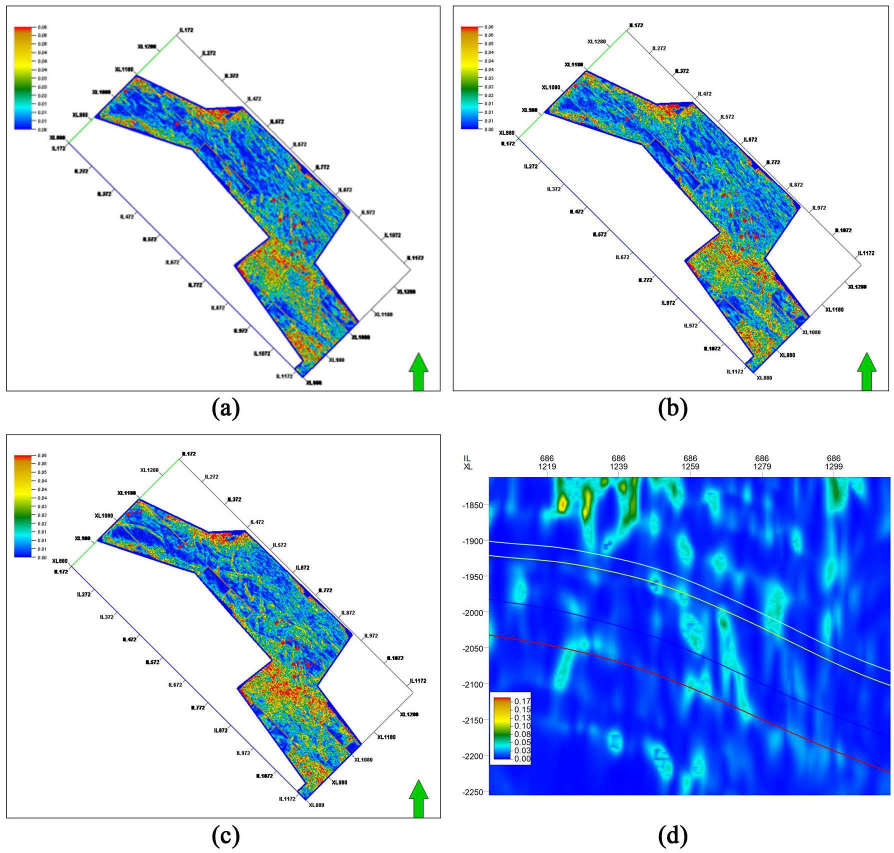


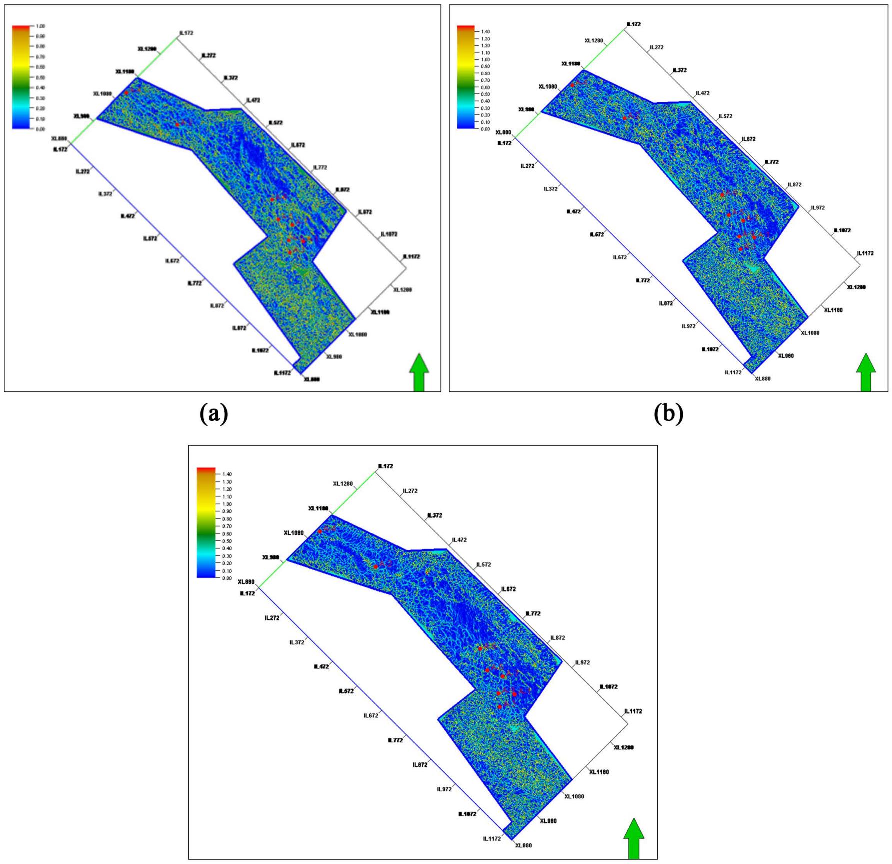

**Figure 7.** Prediction results of discontinuous attribute. (a) Discontinuous attribute in layer A; (b) Discontinuous attribute in layer B; (c) Discontinuous attribute in layer C; (d) discontinuous attribute prediction result profile.

### 3.3.3. Curvature Attribute

Stratigraphic curvature refers to the degree of curvature of a surface at a certain point. The greater the curvature (i.e., the greater the curvature), the greater the geological force applied and the more likely it is to fracture. Therefore, extracting the curvature of a certain seismic layer can characterize the location of fracture development. Extracting the curvature attribute volume of the strata in the study area, the distribution of curvature layers was obtained by constraining them with seismic layers (**Figure 8**). It can be seen that there is an abnormally large curvature value in the southern part of the study area, presenting a belt shape, indicating a high development area of faults and fracture.

## 3.4. Fracture Prediction Based on Pre-Stack Attribute

The post-stack seismic attributes mainly represent medium to large-scale fracture, and are powerless in characterizing micro-fracture. But often micro-fracture contribute more to production. The pre-stack attribute preserves more information about micro-fracture, and applies the difference in far and near frequency attributes and azimuth frequency attributes to predict micro-fracture more accurately.



(a) (b)

(c)

**Figure 8.** Prediction results of curvature attribute. (a) Curvature attribute in layer A (b) Curvature attribute in layer B; (c) Curvature attribute in layer C.

#### 3.4.1. Far-Near Offset Frequency Difference Attribute

The difference in frequency attribute between far and near is a pre-stack attribute that is more sensitive to fracture development. Extracting the difference in frequency attribute between far and near (**Figure 9**) indicates that the larger the difference, the greater the anisotropy and the more developed the fracture.

#### 3.4.2. Azimuth Frequency Difference Attribute

Extracting the difference in azimuth frequency attributes can characterize the differences in frequency attributes at different orientations. Extracting the difference in azimuth frequency attributes (**Figure 10**) indicates that the larger the difference, the greater the anisotropy and the more developed the fracture.

### 3.5. Fracture Prediction Based on Multi-Attribute Fusion

The types and scales of fracture development represented by attribute bodies obtained by different methods are different, each with its own advantages, disadvantages, and emphasis. Only by fusing them can a relatively complete and accurate fracture development body be obtained. Establish a fracture characteristic logging curve, use it as a sample label, use XGBoost algorithm to fuse multiple

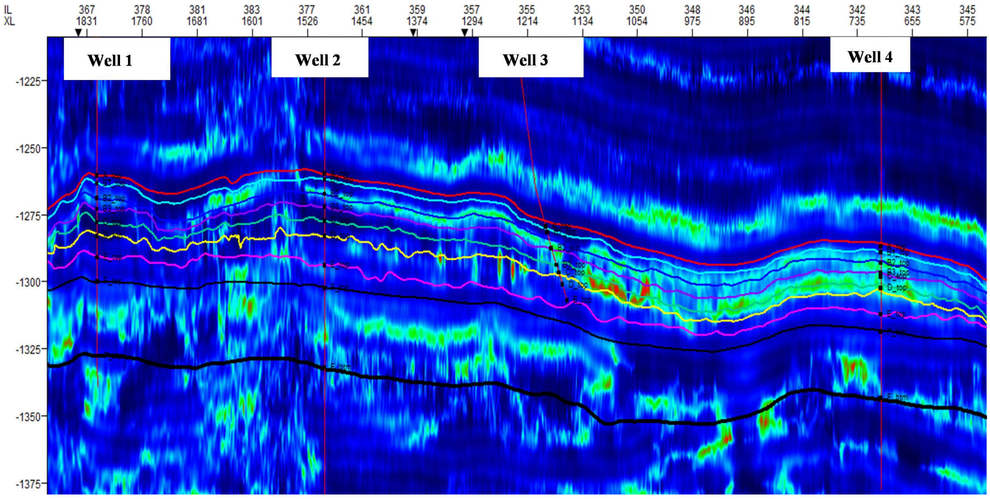



**Figure 9.** Profile of far-near frequency differences attribute.

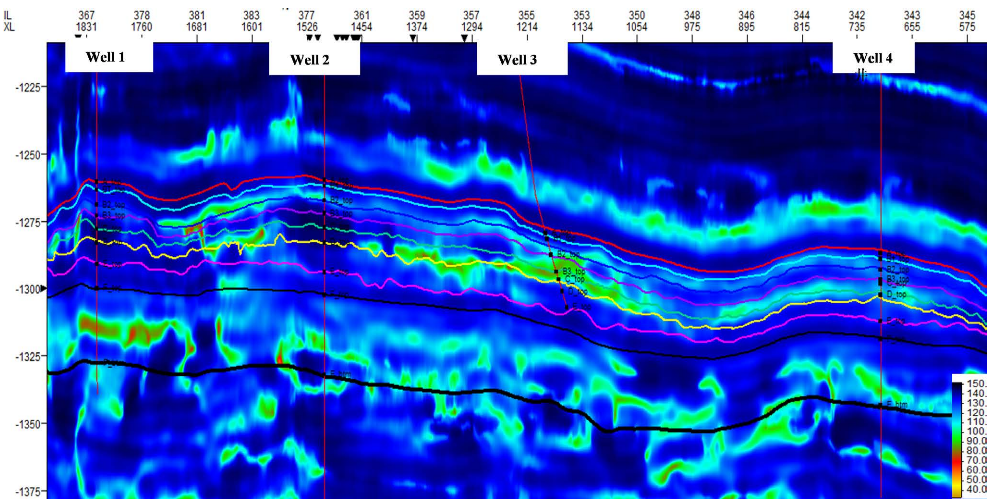
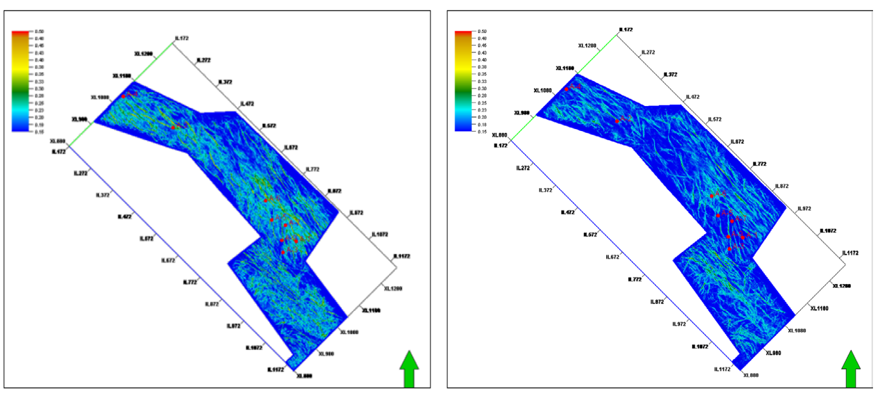
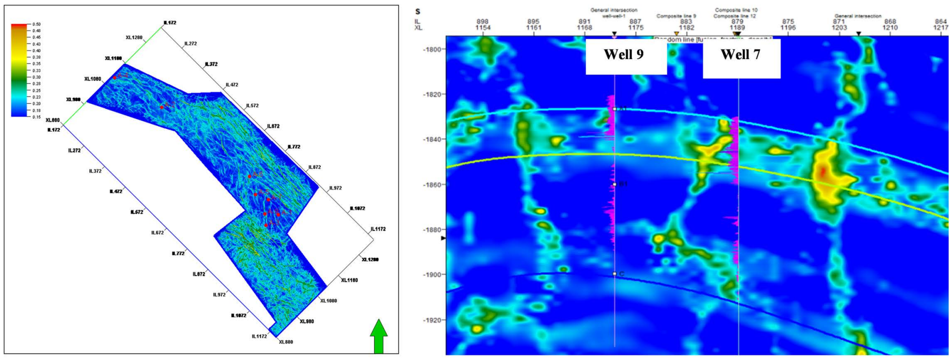



**Figure 10.** Profile of azimuth frequency differences attribute.



(a) (b)




(c) (d)

**Figure 11.** Machine learning attribute fusion result. (a) Machine learning attribute fusion result in layer A; (b) Machine learning attribute fusion result in layer B; (c) Machine learning attribute fusion result in layer C; (d) Machine learning attribute fusion result profile.

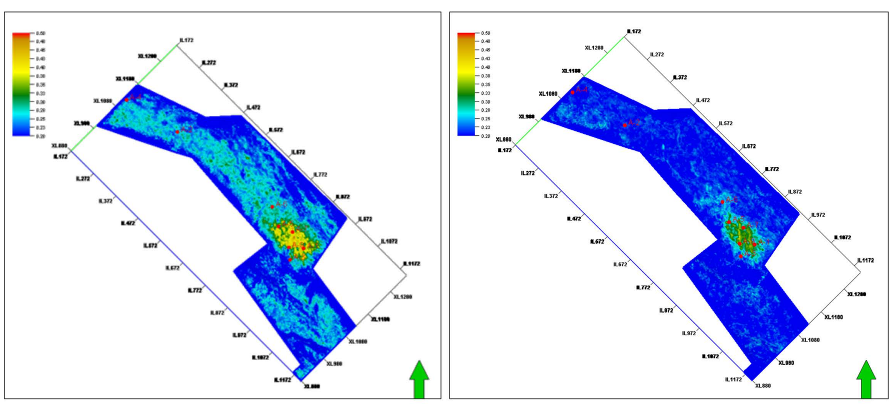
single attributes, and finally obtain the result of attribute fusion (**Figure 11**). Blind well validation was conducted, and the predicted fracture results were in good agreement with the strength curve of the fracture on the well. At the same time, compared with the stress field results, the fracture development part can correspond well to the part with higher stress. Therefore, the results of fracture prediction are good.

### 3.6. Application Effect

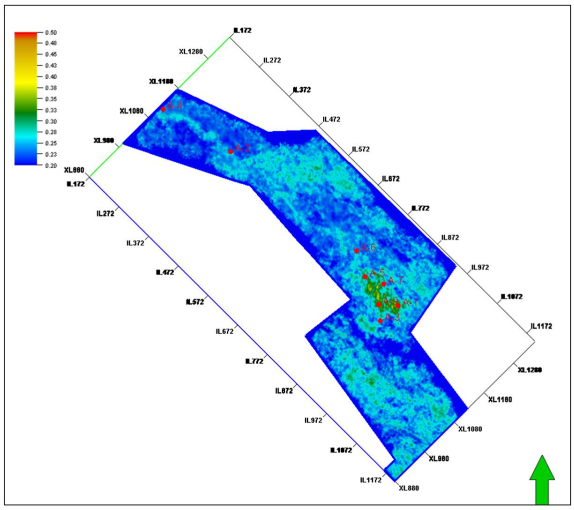
We overlayed production capacity with porosity to obtain favorable production capacity zones in the work area (**Figure 12**). It can be seen that the favorable production capacity area coincides with the predicted fracture development zone. Fractures are the main factor affecting production in this area, and the development of fracture can be further utilized to predict the favorable well positions.

## 4. Conclusions and Recommendations

1) Post-stack seismic attributes are the most commonly used method for predicting fractures, but due to the limitations of post-stack seismic, they can only be used to predict medium-large scale fractures, and their predictive ability for



(a) (b)



**(c)**

**Figure 12.** Distribution map of favorable production capacity areas. (a) Distribution map of favorable production capacity areas in layer A; (b) Distribution map of favorable production capacity areas in layer B; (c) Distribution map of favorable production capacity areas in layer C.

micro-fractures is limited.

2) Due to the development of fracture, there is strong anisotropy in the formation. Therefore, the pre-stack anisotropic attributes, such as far-near offset frequency attribute, azimuth frequency attribute, etc., can more accurately characterize micro-fractures.

3) A machine learning model based on XGBoost algorithm was constructed using multi-source seismic information such as ant tracking attribute, curvature attribute, discontinuity attribute, and pre-stack anisotropy attributes as input data, with fractures strength log on wellbore as the target curve. The obtained fracture prediction volume has high accuracy.

4) Fracture is complex, and a single source of information is difficult to accurately characterize the development of fractures. Using machine learning to synthesize multi-sources information to predict fracture can greatly improve the accuracy, and is one of the important directions for future fracture prediction.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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