Subsurface Natural Fracture Modelling and Prediction on Igneous Rocks of "U" Geothermal Field, Utah

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Abstract

United States of America has a promising geothermal energy potential, especially in the "U" Geothermal Field, around Roosevelt Hot Springs, Utah with a reservoir temperature around 216°C to 286°C. Geothermal system needs fractures as a considerable aspect in geothermal system evaluation. Fracture formed by the geological condition in the area, so it can affect the characteristic of the fractures. This research aims to analyze the structural geology condition, fracture characteristic, fracture prediction accuracy, and the comparison of the fracture prediction result with the fracture model. To achieve it, there are some data processing steps, such as seismic data interpretation, building seismic attributes, building implicit fracture model, and predicting fracture occurrence using Support Vector Machine (SVM) method which is one of the machine learning methods. The research shows the structural geology condition in the study area consists of east – west trending normal faults and north – south trending reverse faults. The fracture in the study area has a dominant trend of north – south with the intensity ranging from 0 to 3. High fracture intensity zone can be found around faults and curvatures. The fracture prediction using SVM method produces an accuracy value of 73%. Overall, the fracture prediction result is good enough, although there are some zones which have a poor result when it compared to the implicit fracture model.

Keywords: *Fracture; Fracture Modelling; Geothermal; Machine Learning; Utah*

1. Introduction

Geothermal is a renewable energy that has been developed in many countries including the United States of America (USA) [1]. According to S&P Global Platts research, USA has 5,4 GW projected geothermal installed capacity in 2025, which marked that the country has a promising prospect on this kind of energy [2]. One of the regions that has a good potential is the Roosevelt Hot Springs geothermal field in Milford, Utah, USA, where its reservoir has a temperature around 216°C to 286°C [3]. This geothermal field is the object on this research.

Subsurface fracture existence becomes one of the aspects that need to be noticed in a geothermal system. Fracture can determine the geothermal fluid flow from the heat source into the reservoir. Therefore, the comprehension of fracture on geothermal system is crucial to be learned [4].

One of the ways to have an understanding about subsurface fracture on geothermal system is by making a fracture model that represent subsurface fracture. This model can provide some information, such as distribution, intensity, orientation, etc. On the modelling process, a fracture model can use machine learning method to predict the fracture existence on a location that has no fracture acquisition data. This kind of machine learning method is tested to be researched in this research.

This research aims to analyse the structural geology condition, fracture characteristic, and modelled the subsurface fracture of the research area. Furthermore, this research also uses machine learning to predict fracture existence in a well that has no fracture data. The result of the fracture prediction is compared to the fracture model to determine whether it has a good or a poor prediction result.

It is assumed that the fracture modelling method is a better method than the fracture prediction method by using machine learning.

2. Literature Review

Literature review will discuss about geological condition of the research area, fault and fracture, well logs, seismic method, implicit fracture modelling, and machine learning.

2.1 Geological Condition of The Research Area

The research area is located near Mineral Mountain, Utah. It is a part of the basin – range region of Utah and highly controlled by geological structures [5]. It composed of metamorphic, sedimentary, and intrusive igneous rocks. The metamorphic rocks deposited in the Precambrian and composed of gneiss, quartzite, and schist. The sedimentary rocks on this location deposited in Palaeozoic. Then, the intrusive igneous rocks are composed of granitoid in a shape of batholith, which deposited in Oligocene to Miocene [6]. The geological map and the geological cross section of the research area can be seen in Figure 1.

There is a geothermal system in the research area that proven by the existence of hot spring and other thermal manifestation. The geothermal system of the area is hot dry rock. The granitoid is the geothermal reservoir of the system. Based on geothermometer calculation, the reservoir temperature of the geothermal system is around 216°C to 286°C [3,7].

2.2 Fault and Fracture

Fault and fracture are discontinuity made by deformation process that overcome rock mechanical resistant. This kind of deformation is classified as brittle deformation. It may formed in macroscopic and microscopic size [8]. The existence of fault and fracture may change rock properties, such as electrical resistivity, permeability, and wave transmission velocity [9].

2.3 Well Logs

Well logs is a subsurface acquisition process to acquire rock properties around the borehole [10]. There are many kinds of well logs. Few examples of it are gamma ray log, resistivity log, and borehole image log [11]. These logs may be used to identify fracture. Fracture can be identified in gamma ray and resistivity log by anomalous reading on the log [12]. Borehole image log may identify fracture directly through the borehole images [13].

2.4 Seismic Method

Seismic method is a geophysical investigation method that used seismic waves to identify subsurface objects, such as rock formation and geological structure. In seismic data processing, it is often using seismic attributes to enhance several seismic characteristics. The utilization of seismic attributes can assist in subsurface interpretation, such as facies, reservoir characterization, prospect identification, etc. [14].

2.5 Implicit Fracture Modelling

Fracture modelling is a fracture representation method based on specific characteristics [15]. Implicit fracture modelling is a fracture modelling process that assumed fracture as an object to represent certain parameter towards a volume mathematically [16]. Implicit fracture modelling needs an integration between fracture data and fracture driver data. Fracture data consists of fracture characteristics data, while fracture driver data consists of fracture formation control parameter. Fracture driver can be derived from geological, geophysical, and geomechanical data [17].

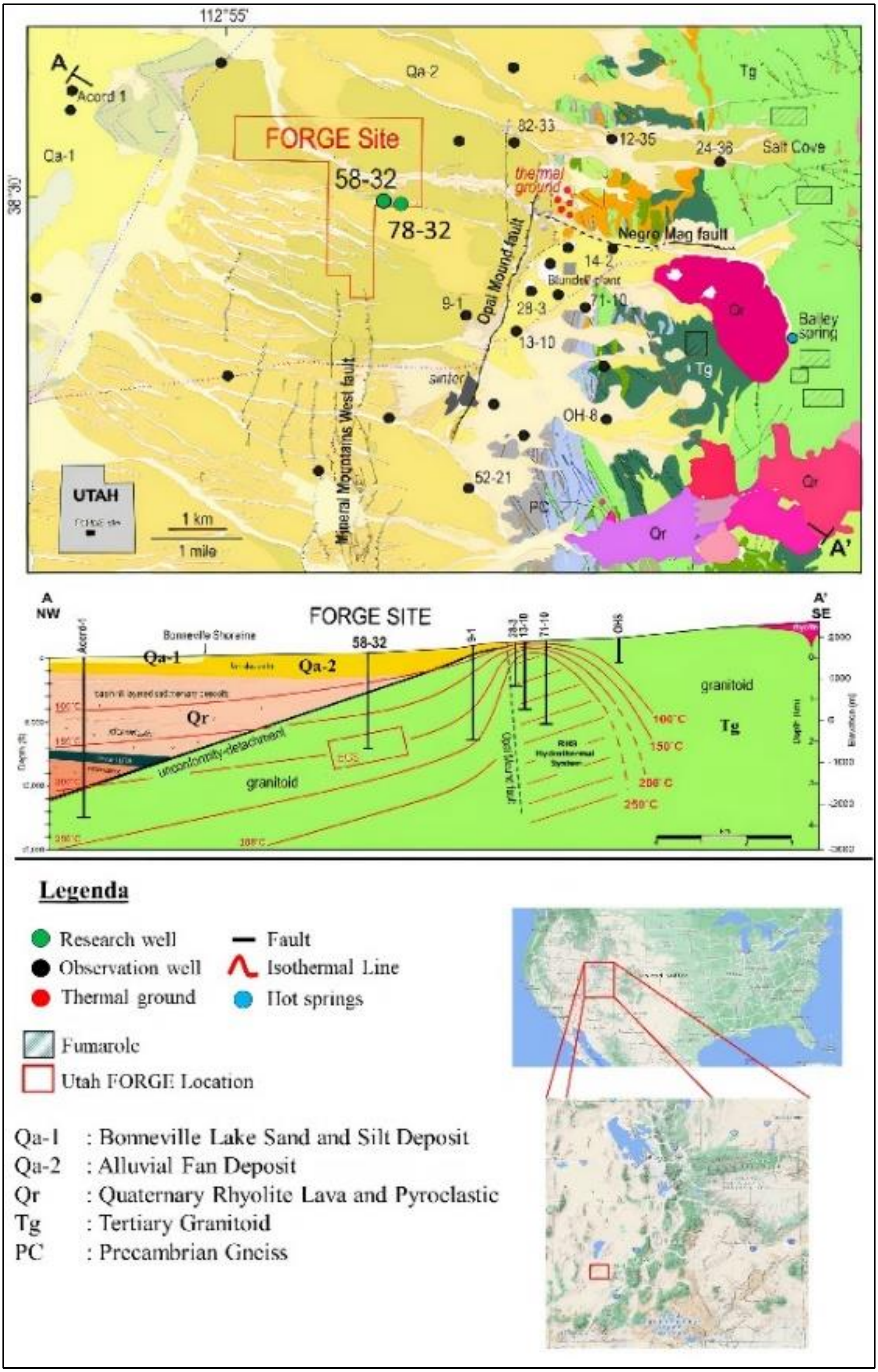


Figure 1. Geological map and cross section of research area (modified from University of Utah, 2019)

2.6 Machine Learning

Machine learning is a computational science that allow computer to learn data pattern for a specified purpose. The goal of machine learning is to implement what has been learned from the training dataset by the computer to a different dataset. One of the machine learning methods is the supervised learning method [18].

Supervised learning is a machine learning method that allow computer to learn data pattern from a labelled training dataset. The label is assumed as the answer to the dataset parameter. One of the algorithms usually used in this method is the Support Vector Machine (SVM). The algorithm may be used to classify data with significant difference [18].

3. Research Methods

There are 2 wells that is used in this research. The first well is well 58-32 and the second well is well 78-32. The availability of petrophysical well log data in both well can be seen in Table 1. Besides well log data, there is a 3D seismic data that also been used in this research. The target zone of this research is the granitoid rocks which acts as the reservoir for the geothermal system in the area [3].

Table 1. Well log availability.
(v: available, x: not available)

Well	Well Log Types			
	Fracture	Gamma Ray		Conductivity
		γ-ray	High Resolution γ-ray	
58-32	v	v	v	v
78-32	x	v	v	v

In this research, fracture modelling and fracture prediction were carried out. The workflow diagram can be seen in Figure 2.

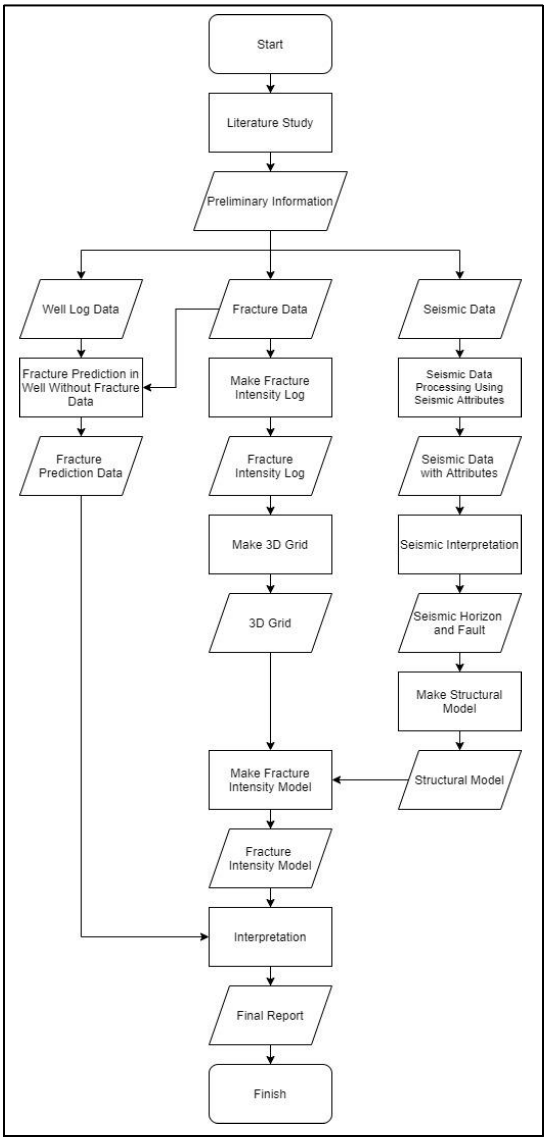


Figure 2. The research workflow diagram

The first step that need to be done is conducting literature study about the study area to gain some early insights about the area. Next, data collection phase is conducted from gdr.openei.org website. After that, the data collected is analysed by using implicit fracture modelling to gain fracture intensity model and by using machine learning to gain fracture prediction on well. After analysing the data, the analysis result is interpreted and written in the final report.

Fracture modelling process was carried out using Petrel 2017. This process used implicit fracture modelling method to create fracture intensity model. The model can be made by integrating seismic interpretation data in form of structural model, fracture intensity log from well 58-32, and fracture driver data that derived from seismic attributes. The seismic attributes used as the fracture driver are Variance, 3D Edge Detection, 3D Curvature, Ant Track, and Dip Illumination. The fracture driver was used to correlate the fracture intensity log to the whole research area.

Fracture modelling began with interpreting the seismic data to obtain fault and horizon interpretation. This interpretation was used to make the structural model of the area. Then, the fracture intensity log was produced from the fracture log. The fracture intensity log was processed further by conducting upscaling process, so it can be used in the model later as one of the modelling parameters. The other modelling parameter was the seismic attributes, and it was processed after the fracture intensity log upscaling process. Next, the implicit fracture modelling can be done by using petrophysical modelling menu.

Fracture prediction process was carried out using Google Colaboratory. This process used supervised learning method with Support Vector Machine (SVM) as its algorithm. The prediction can be done by training the computer to seek for fracture occurrence pattern by using petrophysical well log data of well 58-32 that has been labelled with the fracture data from well 58-32 in every depth in the log as the training datasets. After the computer has been trained, the computer would be able to predict fracture occurrence in well 78-32 by seeking the pattern in the petrophysical well log of well 78-32.

Fracture prediction process began with importing the machine learning code database, such as panda, numpy, sklearn, etc. Then, the fracture data and its parameter, which is the petrophysical well log data is imported to the software. After that, the fracture data and its parameters were analysed to find out how well the correlation between them. Next, the data was split into 2 groups. The first group is training dataset with 80% portion of the whole data and the second one is the testing dataset with 20% portion of the whole data. After splitting the data, the computer was trained to make some classifications, whether there was a fracture or not in certain depth. The classification accuracy can be observed by making the confusion matrix. Finally, the process of predicting the presence of fractures can be carried out.

4. Results and Discussion

4.1 Fracture Data Interpretation

Based on the fracture data on well 58-32, there are three kinds of fractures, i.e., conductive, resistive, and induced fracture. The fracture types were already interpreted from the borehole image log. The borehole image log can be seen in Figure 3.

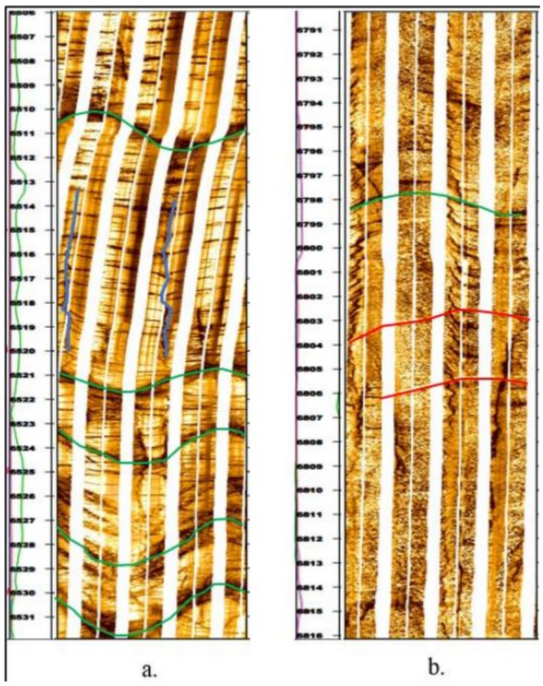


Figure 3. Borehole image log interpretation on 6505 – 6530 feet (a) and 6790 – 6816 feet (b) that shows conductive fracture (green line), resistive fracture (red line), and induced fracture (blue line).

Induced fracture is not used in this research because it is not formed naturally like conductive and resistive fracture. The conductive and resistive fracture shares the similar north – south fracture orientation (Figure 4). The intensity of the natural fracture is around 0 to 3 fractures per feet (Figure 5).

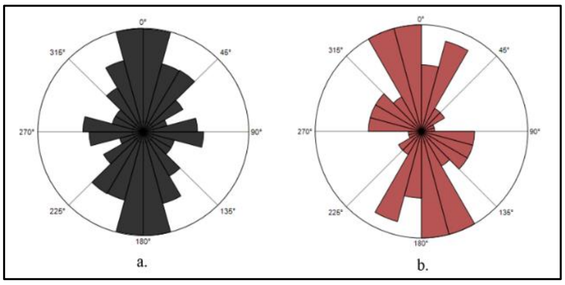


Figure 4. Stereographic projection of conductive (a) and resistive (b) fracture orientation in well 58-32

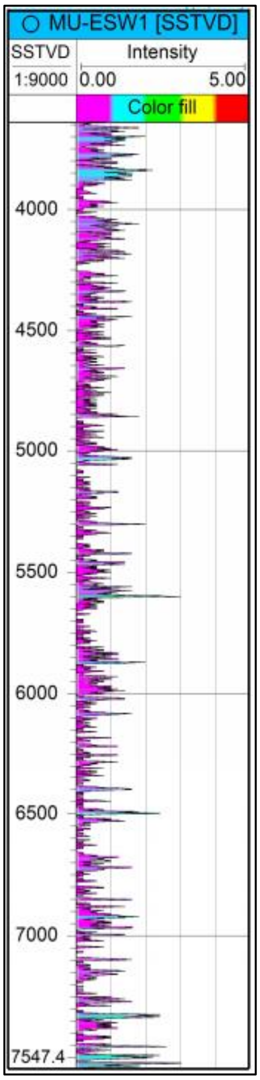


Figure 5. Natural fracture intensity log in well 58-32

4.2 Seismic Data Interpretation

Seismic interpretation which done in the granitoid area can be seen in Figure 6. From the interpretation, the seismic horizon and fault interpretation was integrated to produce a depth structure map (Figure 7). Based on the map, there is a significant difference in terms of depth between the east and the west side of the area. The east side is shallower than the west side. The difference is thought to be caused by the intrusion of the igneous rock. There is also a curvature feature shaped like a dome in the northeast side of the area that suggests an intrusion morphology. It is also supported from the geological map and cross section data (Figure 1) that shown the occurrence of granitoid outcrop in the eastern side of the area. Furthermore, the existence of fault can also influence the depth difference.

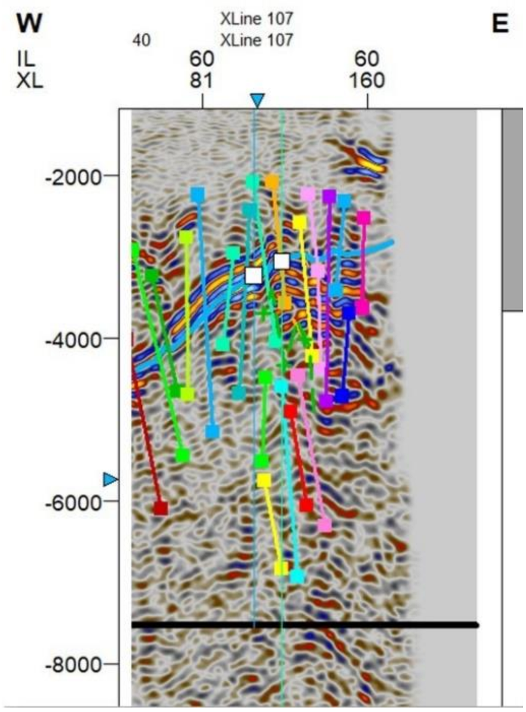


Figure 6. Seismic interpretation result.

The research area has two kinds of faults. The first one is the north – south trending reverse fault. The second one is the east – west trending normal fault. The reverse fault is thought to be formed in the Jurassic – Oligocene period due to the orogeny and uplift process. After that, in the Miocene, the normal fault was made through an extensional tectonic regime [19].

Fracture driver processing using seismic attributes shows several high valued zone. The high value may indicates high discontinuity zone. The result of the seismic attributes processing can be seen in Figure 8.

4.3 Fracture Intensity Model

The integration of the seismic attributes which acts as fracture driver with fracture intensity log produced a fracture intensity model (Figure 9). The model shows that the intensity of fracture in the research area is around 0 to 3 fractures per feet. High intensity fracture zone can be found near faults and curvature. It indicates that the fracture formation is associated with the fault and intrusion. The high intensity zone which associated with fault can be seen as a good prospect in utilizing geothermal energy from hot dry rock system. It is because hot dry rock system needs fluid injection from the surface to extract the subsurface heat, so the existence of fault and fracture may help the fluid to flow as its become the fluid pathway.

4.4 Fracture Prediction in Well 78-32

To predict fracture existence in well 78-32 using machine learning, the correlation between the prediction parameter, which is the petrophysical well logs, and the fracture log is needed to be known. There are three kinds of petrophysical well logs that is used, i.e., gamma ray, high resolution gamma ray, and conductivity log. All logs show a negative correlation with the fracture log. It means that the occurrence of a fracture is marked by the inverse reading result of the well log if it is compared to the usual reading of the formation. For example in the conductivity log. The conductivity of an igneous rock is relatively low [20]. However, in the fractured area of the granitoid, the conductivity value of the formation is higher than usual. It indicates that the fracture may change the formation characteristics [9].

Based on the machine learning result, SVM method has a prediction accuracy of 73% (Figure 8). It indicates a respectable prediction result. Figure 9 shows the comparison of fracture occurrence in well 78-32 that derived from fracture modelling (track 2) and fracture prediction using machine learning (track 3). Track 2 is a continuous log, so it is not only showing fracture occurrence but also the intensity. Track 3 is a discrete log, so it is only showing the fracture occurrence that marked by the blue colour.

Generally, the comparison shows that the machine learning method has good prediction result, indicated by the red box. However, there are some zones that has a poor prediction, indicated by the black box. It may be caused by the limitation of available well logs that can be used as the prediction parameter.

Fracture modelling is showing its superiority if it is compared to the machine learning method. Fracture modelling can provide detailed information about the fracture feature, such as orientation and intensity, to be used in interpretation, while machine learning method cannot. However, machine learning method is superior in terms of simplicity and quickness of the process, so it may be benefited in the preliminary study to gain the first picture of the subsurface condition.

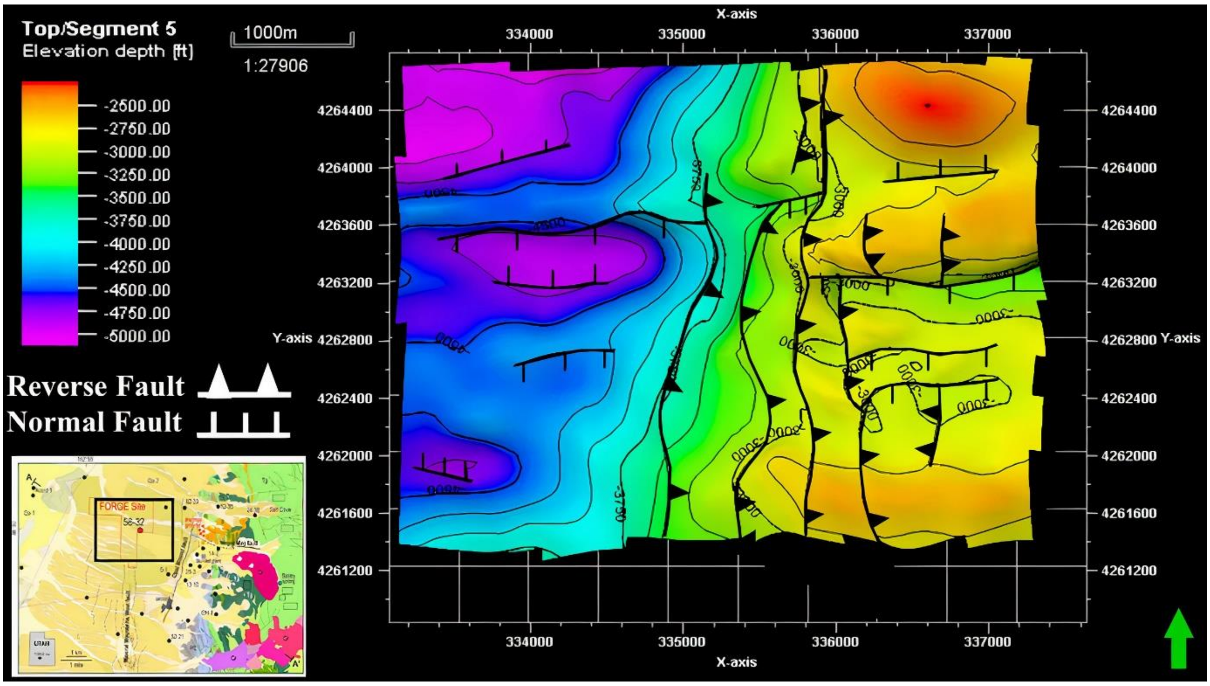


Figure 6. Depth structure map of the research area

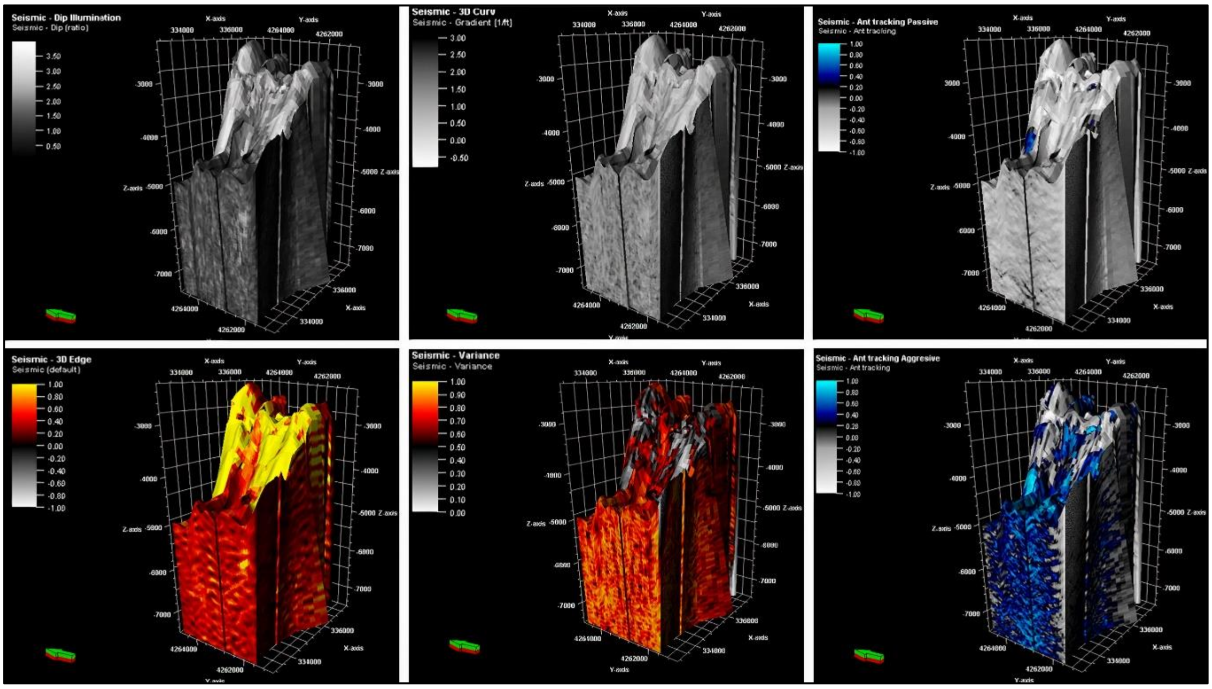


Figure 7. Seismic attributes processing result

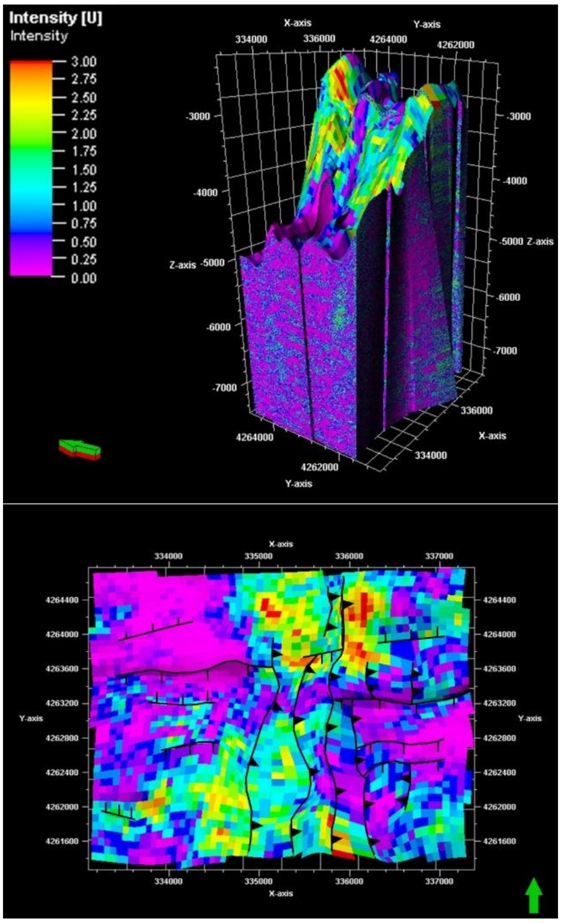
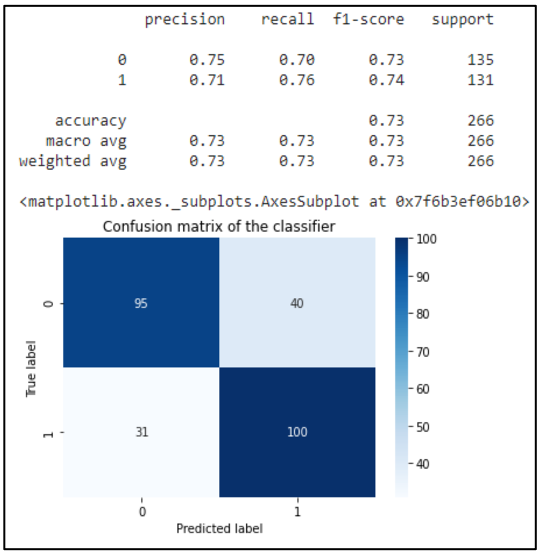


Figure 8. Fracture intensity model of the research area as it is seen from the southwest view (upper) and from the bird's view (lower).



	precision	recall	f1-score	support
0	0.75	0.70	0.73	135
1	0.71	0.76	0.74	131
accuracy			0.73	266
macro avg	0.73	0.73	0.73	266
weighted avg	0.73	0.73	0.73	266

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Figure 9. Confusion matrix of the SVM algorithm

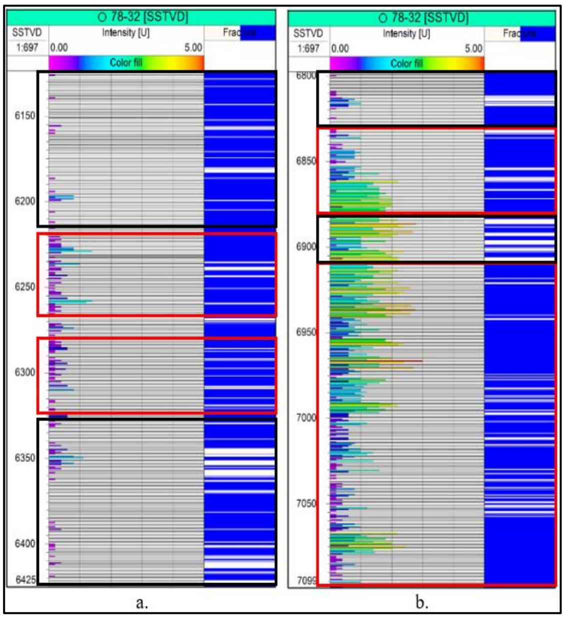

Figure 10. The fracture occurrence comparison between fracture modelling result (track 2) and machine learning result (track 3) of well 78-32 in interval 6087 - 6425 feet (a) and 6800 - 7099 feet (b)

5. Conclusion

Based on the research result, there are several conclusions, i.e.:

a. The research area has north – south trending reverse fault and east – west trending normal fault. The reverse fault was made in the Jurassic – Oligocene period caused by orogeny and uplift event, while the normal fault was made in the Miocene period caused by extensional tectonic regime
b. The research area has natural fracture with north – south trend as its dominant orientation. The intensity of the fracture ranged around 0 – 3 fractures per feet. The fracture is associated with the formation of fault and intrusion
c. The accuracy of fracture prediction using SVM algorithm reached 73%
d. Generally, the machine learning method has good prediction result, but there are some poor prediction in several zones

Acknowledgements
This research could not be done without the data provided by the U.S. Department of Energy in their Geothermal Data Repository (gdr.openei.org).

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