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DETECTION OF FRACTURES USING TRADITIONAL WELL LOG DATA AND COMBINATION OF MACHINE LEARNING TECHNIQUES

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Abstract - *Fractures significantly impact hydrocarbon flow and reservoir permeability, making their detection crucial for reservoir development, production assessment, and quality evaluation. This study identifies fracture zones using conventional well log data, consisting of two main steps. First, it analyzes well log responses to detect fracture zones, distinguishing fractured from non-fractured regions. Second, it applies a Support Vector Machine (SVM) classification to predict fracture zones based on these log responses. The well logs used include RHOB, DRHO, NPHI, DT, CALI, and PEF, which are commonly available for most wells. Current technologies like Borehole televiewer and core analysis, while effective, are expensive and time-consuming, highlighting the importance of log data for fracture detection. This study demonstrates the effectiveness of the SVM model on two wells, achieving a prediction accuracy of over 95%. The model's performance is consistent across balanced, unbalanced, scaled, and unscaled data, indicating its robustness and applicability in fracture detection.*

***Key Words*: Fracture Detection, Well Log Analysis, Support Vector Machine (SVM), Hydrocarbon Flow, Reservoir Quality, Machine Learning.**

1.INTRODUCTION

1.1 Background

Fractures in underground formations have a significant role in fluid flow such as gas and oil. Without identifying the fracture and understanding its propagation in the reservoir, it is impossible to analyse and comprehend the behavioural traits of the reservoir and it does not lead to reliable results. In reservoir fluid flow, fracture have both positive and negative effects [1]. By making additional flow channels in the formation, fracture can help to transport hydrocarbon to the well bore. On the other hand, when fractures filled with clay or shale, it may create barriers to hydrocarbon flow and serve as a seal. They also affect the stability of engineered structures and excavations. Fracture may have also impact on the stability of excavation and designed structures. Additionally, fracture detection can minimize drilling costs and reduce environmental impacts by avoiding unnecessary drilling decreasing the risk of well bore damage.

Fractured zones can be detected through indirect or direct method. Various data sources, such as seismic sources, well logs, well tests, drilling mud histories and rock cores can be used to detect fracture zones. Formation Micro- Scanner (FMS), Borehole Televiewer (BHTV) etc. are used for high resolution images in bore hole to direct fracture detection. Conventional well log, well tests and other data are used as indirect methods to identify fracture zones [1].

Among these, one of the most common method for locating fractures in reservoir rock is to use conventional well log. As, well log which include, calliper (CAL), gamma ray (GR), sonic interval transit time (DT or AC), neutron porosity log (NPHI), density (RHOB), resistivity log etc. provide a continuous and in-situ measurements of rock properties, conventional well log data are commonly used for fracture identification. Fractures have typically some indirect and direct influence on the response of log these log data. Conventional well log measures several rock properties such as, density, resistivity, neutron porosity, sonic velocity etc. Fracture can be detected from changes in these properties, for example decreasing density, increasing sonic velocity etc. [2]. Using Machine Learning approach adding a novel step in identifying fracture zone in the reservoir. A machine learning system generates prediction models using previous data and learns from it to anticipate the results for new data. As various logs have different response to the fractured and non-fractured zones, these responses can be used for training a machine to discriminate fractured and non-fractured zones. In machine learning technique, detection of fractured zone in the formation by using conventional log data is a complex non-linear classification problem [2]. Because in the presence of fracture responses of these conventional log are complicated. Its need to combine all log response to do classification.

1.2 Context

Conventional well logs including gamma ray, resistivity, and sonic logs etc. have traditionally been used for fracture identification, though these have some limitations. Machine learning approach has now emerged as an advanced tool for detecting fracture, as it can make use vast amount of well log data to find patterns and relationships that are challenging for humans to recognize. In This paper, it will be explored the use of machine learning algorithms in order to fracture detection by using conventional well log data. At first the paper will provide an overview of conventional well logs and detect fracture by analysing graphical discontinuation due to fracture. After that it will introduce the idea of machine learning and applicability to fracture detection. North-sea well log data will be used for identification of fracture that is collected from an online source. First, these log data(.las) will plotted into PETREL software to create graphical view and then detection of the fractured zones will be done by analysing the log response to fracture. Then finally implication of the machine learning technique to fracture zone detection by using support vector machine (SVM) will be analysed. As a large amount of well log data will be used for the detection process in SVM, it is a great challenge to reach at a better accuracy. Because of less amounts of fracture zones compared to non-fractured zones in a reservoir, there create an imbalance data set. A small amount of fractured data with respect to non-fractured data may cause biases in the classification. For better accuracy its need to make the data set balanced and compare with the imbalanced accuracy. The conclusion of the thesis paper will entail a discussion on the implications of the research outcomes for oil and gas sector. The paper will highlight the fracture detection process from conventional well log data and find the potentiality of machine learning in this field for better efficiency.

1.3 Aims and Objectives

The main purpose of the paper is to use conventional well log data for fracture detection and development of a machine learning based method. Support vector machine classifier were used for this purpose.

1. To detect fracture zones by using conventional well log in a reservoir.

2. To predict fracture zones by using machine learning approach.

3. To analyse the applicability of machine learning technique for fracture detection by using conventional well log data.

1.4 Significance and Scope

Fracture identification is one of the important parts of reservoir characterization. As it is a complex task in petroleum industry, several techniques were developed for this job. Among these approaches, fracture detection by using image logs is more reliable, because of its high resolution and advance technology. But the image log technology is very expensive and was developed during the last four decades [3]. That's why image logs were not run in the most of the wells. Core analysis is also a direct process for fracture detection. As cores are acquired from a well within a small range of depth, well log is more advantageous over core analysis. Because, well logs normally cover full depth of the well and a lot of information are collected in every reservoir during its developing phase. As conventional well log data is almost available in every reservoir's well, if we can use these data for the purpose of fracture detection it will may offer a highly significant role and be beneficial. Beside this, if we can able to apply the machine learning process for underground fracture identification, it will add a revolutionary step in the petroleum industry. By trained a machine learning algorithm, it can predict fracture zones on the basis of conventional well log response to the fracture. We can apply this trained algorithm for different wells and gain idea about fracture zones without analysing or applying the other detection methods. It reduces cost and complexity with minimizing the environmental impact. The thesis has a broad scope, as it involves the machine learning approach to a specific geological issue. It involves proficiency in machine learning methods and data analysis, as well as a thorough understanding of the geology and petrophysics of subsurface formations. This thesis may enhance the applicability of machine learning in other reservoir evaluation sectors.[4]

All things considered, a thesis on fracture identification integrating conventional well log with machine learning has the potential to significantly.

2. METHODOLOGY

2.1 Workflow Diagram

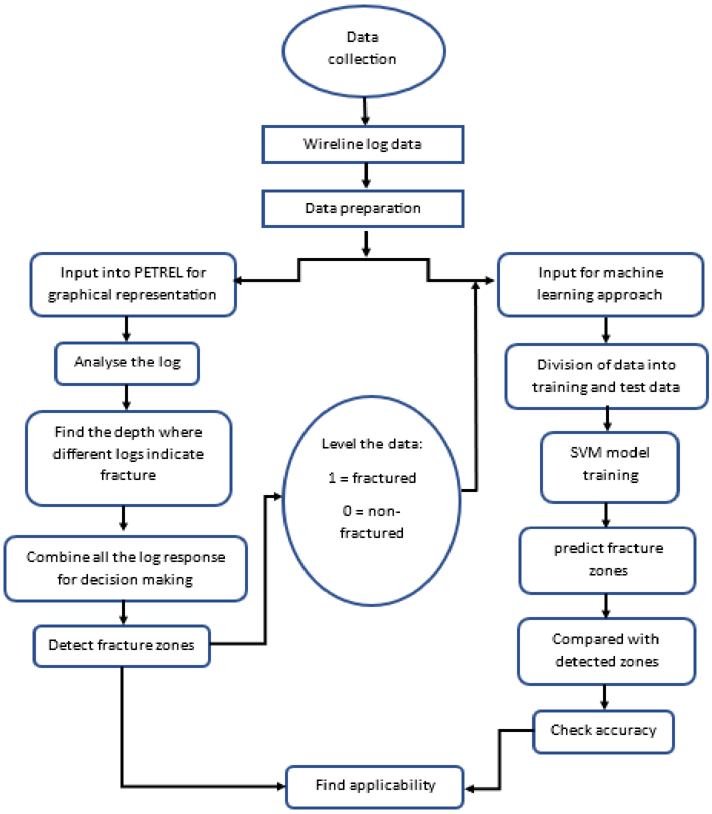

Fig-1: Workflow Diagram

2.2 Data Management

2.2.1 Data Collection

For the fracture detection process in this study, conventional well log data was utilized. The data was obtained from the GEOLINK website, which offers a comprehensive collection of well log data in .las format for research purposes. Specifically, data from 223 wells drilled in the North Sea was collected. The dataset includes various types of logs such as density, neutron porosity, photoelectric effect, gamma ray, and resistivity logs [11].

2.2.2 Data Analysis

From the extensive collection of well log data provided by GEOLINK, the analysis focused on the most common logs for fracture detection [8]. Due to the inconsistency of data availability at different depths and the varying effectiveness of logs in responding to fractures, the selected logs were density, density correction, neutron porosity, caliper, and PEF logs, as they showed better responses to fracture zones in underground formations. After evaluating the data from various wells, 'well-25_7-2' and 'well-34_7-21' were selected for the study due to their suitability for the thesis objectives.

2.2.3 Data Cleaning and Repairing

For the fracture detection task, the log data from 'well-25_7-2' was analyzed between depths of 4620 m to 4822 m, and from 'well-34_7-21' between depths of 2550 m to 2882 m. Data outside these ranges was excluded due to missing data. Abnormal data points were corrected by replacing them with average values to ensure better accuracy. Additionally, data standardization was performed using standard scalar processes in Python to normalize the data.

2.2.4 Data Pre-processing

To address data imbalance issues, two common techniques were considered: Random Over Sampling and Random Under Sampling. The Random Over Sampling technique was employed to balance the dataset by creating duplicate samples from the minority class [9].

2.3 Fracture Detection by Using Conventional Well Log

The figure below shows the different log responses to underground fractures.

Table-1: Log Response

Formation density log (RHOB)	Decrease with a sharp drop
Density correction log (DRHO)	Decrease
Neutron porosity log (NPHI)	Increased with a sharp pick
Calliper log (CALI)	Size change
Sonic log (DT)	High value with a sharp drop
Photoelectric factor log (PEF)	Increase

2.4 Fracture Prediction by SVM Classification Model

Although the SVM model can be used for both classification and regression problems, however initially it is utilized as a classification and recommended for use as classifier [3], [10]. The SVM algorithm's objective is to establish the best line or decision boundary that can divide n-dimensional space into classes, allowing us to quickly classify fresh data points in the future.

2.4.1 Mathematical Expressions

In order to understand the basics of this classification, mathematical expression of svc model are described below-

Let consider binary classification by SVC model, from Fig-3 a line that separate the positive and negative data into two classes. Equation of that line,

$$Y = mX + c$$

Now, consider a vector 'w' which parameters are 'm' and 'c'. 'w' is called weight vector orthogonal to the hyperplane.

$$w = (m, c)$$

Now to classify the input data, the decision function is-

$$D(x) = w^T x + b$$

If the value of D(x) is positive, the input data falls into positive class and if the value of D(x) is negative then input data falls into negative class.

Now the question arises about best hyperplane selection as it can be any straight line with the different slope.

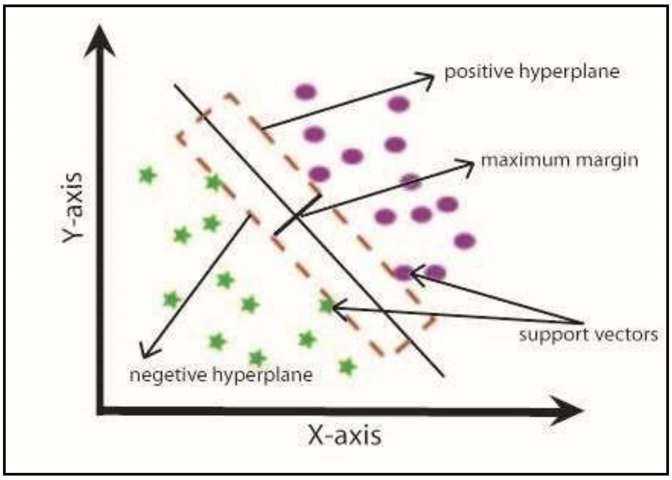

Fig-2: SVM Principle

3. RESULTS

3.1 Identify Fractured Zones

From Fig. 3, in these two zones the density and density correction log were decreased suddenly. On the other hand, neutron porosity increased rapidlyfrom its normal average value. The sonic log value was increased with a sharp pick. That means, the sound velocity was decreased and for this reason interval Transit time was increased which was an indication of fractures. At 4632.0454 m – 4632.198 m depth, the caliper log value was slightly increased, whereas at 4665.2686 m – 4667.0972 m, the caliper log showed a good indication by the bore Hole size to presence of fractures. The PEF value also increased at both zones which might be caused by entrance mud into fractures. By analyzing all the signs, it could be said that there was a fracture zone at the mentioned depth.

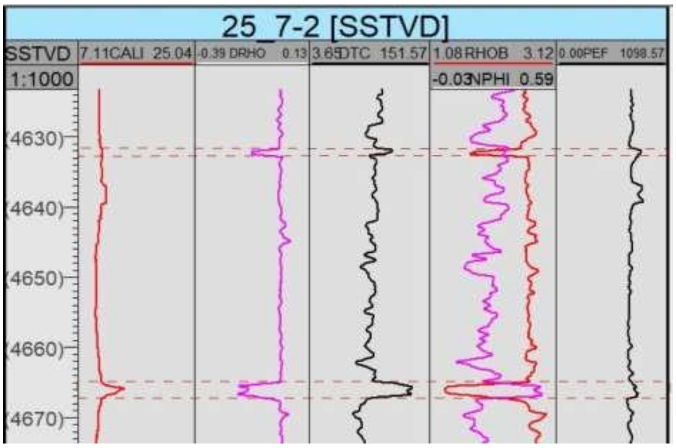

Fig-3: Fracture zones at (4632.05m – 4632.20) & (4665.27m – 4667.10m)

The neutron-density overlap in track-3 made the fracture detection process easier. As density and porosity are inversely related, the decreased density log value and increased porosity response at these two zones were good indications of fracture existence. In Fig. 4, the zone from 4698.3394 m to 4703.521 m represents a large fractured zone with better responses. The other log responses showed similar characteristics as mentioned for the previous zone with more accurate indications about fractures.

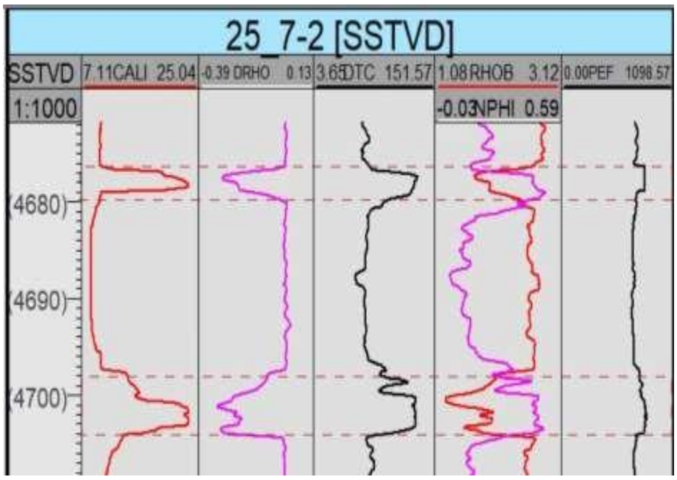

Fig-4: Fracture zones at (4676.83m – 4679.59m) & (4698.34m – 4703.52m)

At 4714.80 m - 4715.87 m, the caliper log value and PEF value showed a small increase, whereas the other zones showed a high increase. The RHOB value at each zone decreased with a sharp figure, and NPHI also increased at a high value. By analyzing these values and changes in figures, as well as the DRHO value, fractures at these zones were detected.

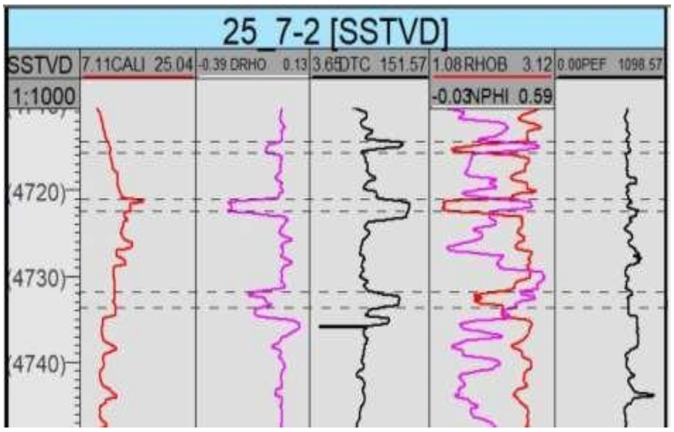

Fig-5: Fracture zones at (4714.80m – 4714.87m) & (4721.05m – 4722m) & (4732.02m – 4733.54m)

The neutron-density overlay showed a decrease in RHOB coupled with an increase in NPHI. A high value of the sonic log with cycle skipping in the selected zone indicated fractures because in open fractures or fluid-filled fractures, sound passes at a lower velocity, increasing the travel time. In this figure, the caliper log value showed a little change in borehole diameter, and considering the other log responses as well as PEF, these three zones were detected.

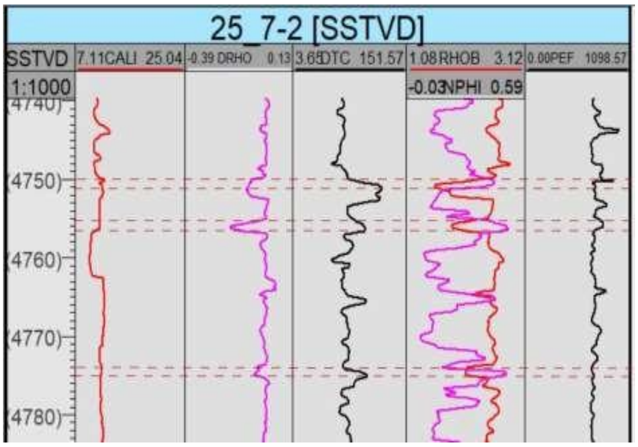

Fig-6: Fracture zones at (4750.03m – 4750.92m) & (4774.54 m – 4750.76m)

At these two depth regions, all the parameters required to denote a fracture zone were almost matched. DTC, NPH, and PEF values were increased, and DRHO and RHOB values were decreased with sharp peaks. Caliper log values for these selected two zones were a good indication of fractures.

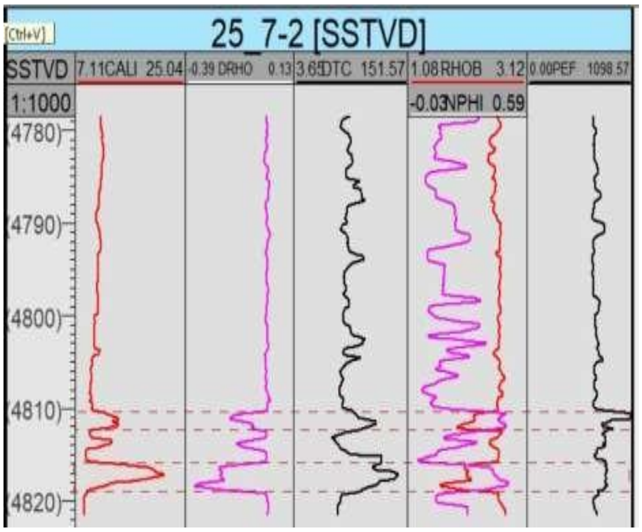

Fig-7: Fracture zones at (4810.66m – 4812.18m) & (4816.45m – 4816.45)

3.2 Cross-Plot

In order to better comprehend and analyze the classification results, a 2D cross-plot is a useful tool in SVM classification because it gives a visual representation of the data distribution, decision boundary, feature relevance, outlier detection, and model evaluation. To analyze the response of conventional well log to fractures, 2D cross-plots were made using MATLAB software. Two plots are given below:

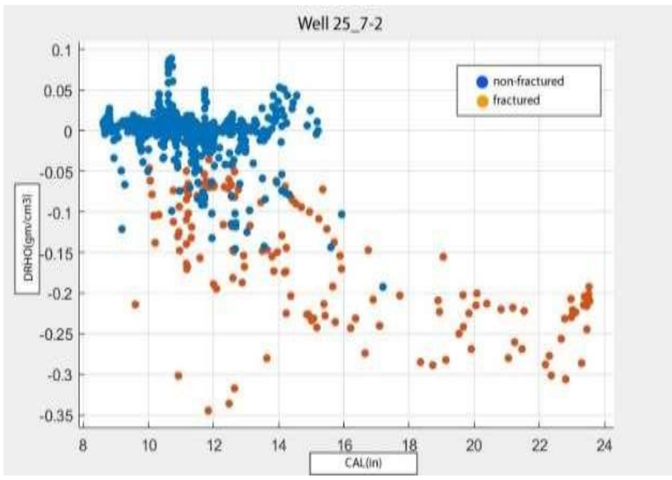

Fig-8: 2D Cross plot of DRHO vs CALI

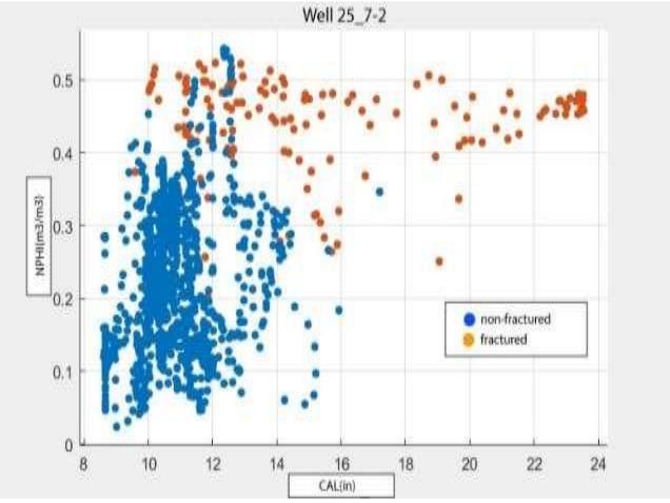

Fig-9: 2D Cross plot of NPHI vs CALI

3.3 Performance Analysis

SVM classification was used to discriminate fracture zones and non-fractured zones by using selected conventional well logs data. Accuracy was checked for both balanced and imbalanced data. Since the data was divided into two parts as test data set and train data set, accuracy was also determined by using both train and test data. Recall and precision were measured for better understanding the performance of SVM classification. Accuracy was also checked after converting the unbalanced data set into a balanced one.

Table-2: Performance Analysis of SVM classification model

Data type			Accuracy %	Precision %
Unbalanced	Without scaling	Test	96.22	96.22
		Train	97.63	97.63
	With scaling	Test	96.98	96.98
		Train	98.01	97.99

Balanced data set (without scaling) –

Accuracy of test data: 95.09%

Accuracy of train data: 95.15%

For validation and finding the applicability of the SVC model to detect fractures, another well (34_7-21) was run through the model.

Predicted accuracy of 34_7-21 well: 95.43%

4. DISCUSSION

In this paper, we address two main tasks: detecting fracture zones using conventional well log data and evaluating the applicability of a machine learning approach for fracture detection. The approach involves applying SVM classification to well log data and testing the model's performance on another well.

Fracture detection from well log responses is complex, requiring the combination of multiple log types due to varying log characteristics for fractures. In well 25_7_21, twelve fracture zones were identified, with log responses matching theoretical characteristics described in the methodology chapter. While verification with image logs or core samples would be ideal, the high theoretical-log match suggests minimal detection errors, though some uncertainty remains regarding fracture zone width.

To apply the SVM model, we labeled fractured and non-fractured zones. Data imbalance due to a higher number of non-fractured zones compared to fractured ones was addressed using data oversampling techniques, which yielded similar accuracies for both balanced and unbalanced datasets.

For a comprehensive assessment of SVM classification, accuracy, recall, and precision for both scaled and unscaled data were compared, revealing only slight differences with high accuracy. The SVM model demonstrated high accuracy for both training and testing datasets with minimal overfitting or underfitting issues, indicating a well-balanced model complexity.

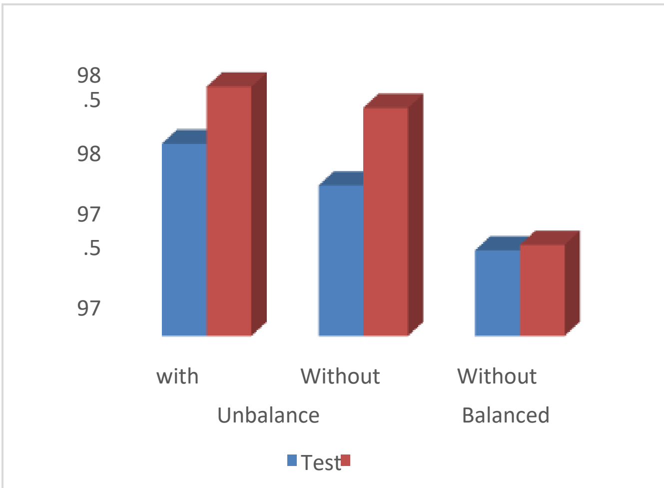

Fig-10: Comparison between train and test data

In Table-3, the fractured zones identified through conventional log analysis are compared with the zones predicted by SVM classification, with each zone's width also provided. This comprehensive presentation allows for a detailed comparison between the two fracture identification methods. By including the widths of the zones, it becomes easier to discern the accuracy and effectiveness of each method. The table aims to highlight any discrepancies or agreements between the traditional and machine learning approaches, thereby providing valuable insights into their respective performances in identifying fractured zones. This comparison is crucial for understanding the advantages and limitations of using SVM classification in fracture detection compared to conventional log methods.

The table illustrates a very small number of incorrect fracture predictions when using the SVM classifier. The classifier is able to detect all zones accurately, with only minor variations in width. This high level of accuracy suggests that the model could be effectively applied to other wells. To further assess its applicability, the trained model was tested on well 34_7-21. The results confirmed the model's robustness, as it exhibited outstanding accuracy in predicting fractures for this well as well. This successful application to a different well underscores the potential of the SVM classifier to be a reliable tool for fracture detection across various well logs. The ability of the model to maintain high accuracy across different datasets is indicative of its generalizability and effectiveness in real-world scenarios.

Table-3: Comparison between fracture zones predicted by SVM and detected from well log

Fracture analysis of well 25_7-2			
Predicted by SVM		Detected from log	
Zone depth(m)	Width(m)	Zone depth(m)	Width(m)
4632.04-4632.50	.46	4632.04-4632.50	0.46
4665.27-4667.10	1.83	4665.27-4667.10	1.83
4676.83-4679.44	2.61	4676.83-4679.44	2.76
4698.18-4703.52	5.34	4698.18-4703.52	5.18
4714.65-4715.87	1.22	4714.65-4715.87	1.07
4721.05-4722.88	1.83	4721.05-4722.88	1.67
4732.02-4733.39	1.37	4732.02-4733.39	1.52
4750.31-4752.29	1.98	4750.31-4752.29	0.89
4755.34-4756.56	1.22	4755.34-4756.56	0.92
4774.54-4774.10	0.44	4774.54-4774.10	1.22
Total predicted Zones:10		Total detected zones:10	

5. CONCLUSION

5.1 General

In order to discover and extract natural resources like oil, gas, and minerals, fracture networks are essential. Understanding and describing subterranean fractures aids in predicting resource distribution and developing effective extraction methods. This paper aimed to use conventional well log data for the purpose of identifying underground natural fracture zones. The fracture detection process using conventional well logs is indirect, as this technique cannot provide direct measurements of fracture zones, whereas borehole image logs can identify and represent fracture distribution.

Among all log responses to fractures, an increase in DT (sonic travel time) and neutron porosity (NPHI), along with a sharp decrease in bulk density (RHOB), are more distinctive parameters for detecting fractures. The application of machine learning has simplified this process significantly. In this thesis, SVM classification demonstrated high accuracy in predicting fractures from conventional well log data.

There is a risk of misclassifying all data as non-fractured due to the high imbalance index. However, after evaluating the results, it was found that the impact of data imbalance on accuracy is minimal. The difference between balanced and imbalanced data accuracy is only 1.13% for test data and 2.48% for training data. Data scaling is also an important task in machine learning models. Accuracy was checked for both scaled and unscaled data, revealing only a small deviation. The difference between scaled and unscaled data accuracy is 0.76% for test data and 0.38% for training data.

To better understand the model's performance, additional accuracy measurement parameters such as recall and precision were used. The differences between these performance metrics were very small for test data and showed no change for training data, which increases the acceptability of the SVM classification model. This comprehensive evaluation indicates that the SVM classifier is a reliable and effective tool for fracture detection in well log data, enhancing the process of natural resource extraction.

5.2 Key Findings

Some important findings are mentioned below:

- NPHI, RHOB, and DT serve as good indicators for detecting fracture zones.
- Errors tend to occur at the boundaries between fractured and non-fractured zones. However, since the study's objective is to identify the zones, the results are encouraging.

- There is a lower impact of the imbalance index, as the accuracy difference is not significant.
- There is minimal effect on the SVM classification model's accuracy when using scaled or unscaled data.

5.3 Practical Implications

- Since image logs are not run in every well due to high expenses, and core samples are not available for the entire depth of the well, this study will help detect fracture zones, which is an important phenomenon for every reservoir. Conventional logs are available in every well.
- Additionally, machine learning procedures can play a significant role in the petroleum industry. They can reduce costs and time, as well as improve exploration procedures.

5.4 Recommendation forFuture Study

In this paper, the main focus was on detecting fracture zones only from conventional well logs. However, there are different types of fractures and many fracture characteristics. Using conventional well logs for fracture detection has shown appreciable results. The current challenge is to determine the fracture characteristics and fracture types. Machine learning processes will help minimize many complexities in this field.

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