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Prediction of natural fracture network patterns using feature engineering and machine learning approaches

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Abstract:
In this paper, we present a study of machine learning algorithms for predicting patterns of natural fracture network. The dataset used originates from the Teapot Dome field, USA. Initially, fracture azimuths were categorized into eight classes, each representing a 45-degree segment. Various machine learning models were then employed, ranging from traditional boosting algorithms to more recent approaches to predict the fracture classes. The K-Nearest Neighbors (KNN) algorithm was used to produce the best initial results with an accuracy of approximately 70%. After applying data augmentation techniques, we improved the model performance, achieving an accuracy of 88%. In addition, with feature engineering, we achieve 98%. This work highlights the potential of machine learning models in predicting fracture paths, contributing to the broader application of ML in the geomechanical model.

1. Introduction

Fracture networks play a critical role in several geoscientific fields, including petroleum engineering, mining, and hydrogeology. A comprehensive understanding of these networks is crucial for optimizing the extraction and transportation of subsurface resources. Accurate characterization of fractures significantly enhances the efficiency of resource extraction processes, such as hydraulic fracturing, and is vital for predicting reservoir behavior. In particular, reliable prediction of fracture distribution can maximize resource recovery while minimizing operational risks and costs.

In the past, heavily statistics-based methods such as multiple-point statistics (MPS) and other geostatistical methods have been used to analyze fracture paths and their distribution. Although they provided some insight into the nature of fractures, they lacked the ability to capture higher-order spatial relationships, particularly those physically related, such as the influence of global and local stress fields on fracture propagation.

To address these drawbacks, machine learning (ML) algorithms were introduced as a complement to MPS. After being trained on rich datasets with geostatistical information, ML models demonstrated the ability to capture the intricate nature of fractures and their propagation (Srivastava et al., 2004; Chandna and Srinivasan, 2022, 2023; Amanbek et al., 2023; Freites et al., 2023; Merembayev and Amanbek, 2023). This established that ML models can significantly improve our understanding and accurate prediction of fracture paths.

For example, in the study by Chandna and Srinivasan (2022), ML models were combined with MPS to improve the precision of fracture prediction using the Teapot Dome dataset. This dataset, derived from FMI logs near well 67-1-x-10 in the Tensleep Formation, includes detailed fracture geometry and stress data. The study divided the area around fracture tips into eight equal segments of 45 degrees each and employed a triangular mesh to extract critical input

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parameters, such as normal stresses in the x and y directions, and shear stress. The propagation of the fracture was simulated using a probability distribution within predefined angle classes, determining movement along the grid based on the most probable adjacent class. The approach, validated with a voting classifier of SVM, random forests, and gradient-boosted trees, achieved an 80% accuracy through 10-fold cross-validation.

Although this study demonstrated the successful integration of machine learning and MPS for modeling fracture behavior, further research has expanded the application of ML models for fracture network prediction in porous media. In Merembayev and Amanbek (2023), the authors used LightGBM to predict fracture networks in porous media based on geological data from Kazakhstan. The model accurately estimated fracture parameters, including azimuth angles, showing promise for use in less-explored subsurface regions. However, challenges remain, particularly in comparing the performance of different ML models and optimizing feature engineering from complex geological datasets.

To address these challenges, Valera et al. (2018) introduced a machine-learning surrogate model using Gaussian Process Regression to predict breakthrough times in discrete fracture networks (DFNs). This model was trained on a limited set of DFN simulation data and achieved predictions within 20%-30% of high-fidelity simulations while also quantifying uncertainty using Bayesian inference. Although this approach demonstrated a good balance between computational efficiency and accuracy, its scalability to more extensive fracture networks with higher complexity remains a topic for further investigation.

Alternative approaches have also been explored to enhance fracture property estimation. For instance, Feng et al. (2024) proposed using Markov Chain Monte Carlo (MCMC) algorithms to estimate fracture density and aspect ratio in reservoirs based on seismic data. Their novel use of a training image to model spatial fracture distribution improved prediction accuracy, though the computational cost of MCMC methods-particularly the extended Metropolis approach-remains a significant barrier for larger datasets, with processing times extending up to three weeks.

Neural network architectures, particularly deep learning models, represent another powerful tool in fracture characterization. These models can process vast datasets, model intricate subsurface structures, and make high-precision predictions in geoscience applications (Bishop and Nasrabadi, 2006; Dramsch, 2020). Recent work highlights their potential to solve complex transport flow problems in fractured porous media and to reduce uncertainty in subsurface modeling. However, challenges related to overfitting and computational demands, especially in larger fracture networks, need further exploration.

In this paper, we examine machine learning algorithms for predicting azimuth categories in fracture network models. Specifically, we explore the performance of Decision Tree, Random Forest, K-Nearest Neighbors, and Deep Neural Networks using real-world data from the Teapot Dome field, USA. To improve prediction accuracy, we incorporate augmented data into the training process and employ feature engineering techniques to assess the influence of neighboring parameters.

The rest of the paper is structured as follows: Section 2 describes the dataset used in this research, Section 3 discusses the machine learning algorithms and metrics, Section 4 presents the obtained results, and Section 5 shows the results of feature engineering and deep learning techniques. In Section 6, we discuss the overall results, and the conclusion is provided in Section 7.

2. Dataset description

Teapot Dome, located in Natrona County, Wyoming, approximately 30 miles north of Casper (Cooper et al., 2006; Schwartz, 2006), has been a notable site for geological and engineering studies since its development in 1915. Initially designated as National Petroleum Reserve number 3, the site has evolved from shallow oil extraction during the Teapot Dome scandal in the 1920s to a modern research hub for enhanced oil recovery, CO_2 sequestration, and advanced drilling technologies. Managed by RMOTC, the site provides extensive public-domain data, fostering collaboration between industry, government, and academia.

The field's fracture network has been extensively studied, particularly in the Parkman Sandstone of the Mesa Verde Formation (Cooper et al., 2006; Schwartz, 2006), where three primary fracture sets-hinge-parallel, hinge-perpendicular, and hinge-oblique-have been identified. Fig. 1 shows the location of the Teapot Dome, while Fig. 2 depicts the fracture network of the mine.

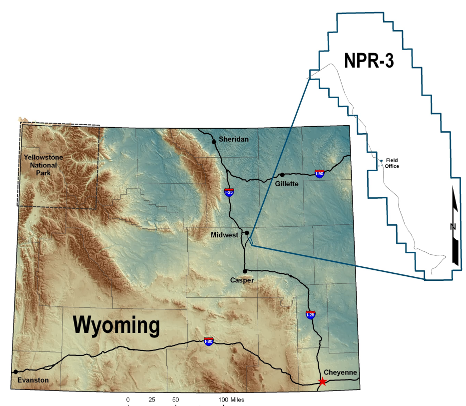

Fig. 1. Location of Teapot Dome (Cooper et al., 2006).

In this study, we use a dataset comprising 6,377 data points from Teapot Dome. Each data point includes the mid-point coordinates (mid_x, mid_y) and the azimuth (azim_frac) of a fracture segment. These fracture segments are generated by dividing larger fractures into smaller segments, with the midpoint of each segment used to determine its location and azimuth angle. The fracture network is modeled as a graph, with nodes (black circles) representing the fracture endpoints and segments (blue circles) connecting these nodes. This structure is illustrated in Fig. 3.

For this study, the azimuths of the fracture segments have been adjusted relative to the y-axis, and the 360-degree range of the azim_frac variable has been divided into eight equal classes, each spanning 45 degrees. Table 1 details the frequency of data points in each class, highlighting a significant class imbalance. Class 6, representing 26.7% of the data, is overrepresented, while Class 1, comprising only 5.2%, is underrepresented.

Table 1. Class frequencies in the dataset.

Class	Frequency	Share
0	654	0.103
1	334	0.052
2	999	0.157
3	458	0.072
4	836	0.131
5	919	0.144
6	1701	0.267
7	476	0.075

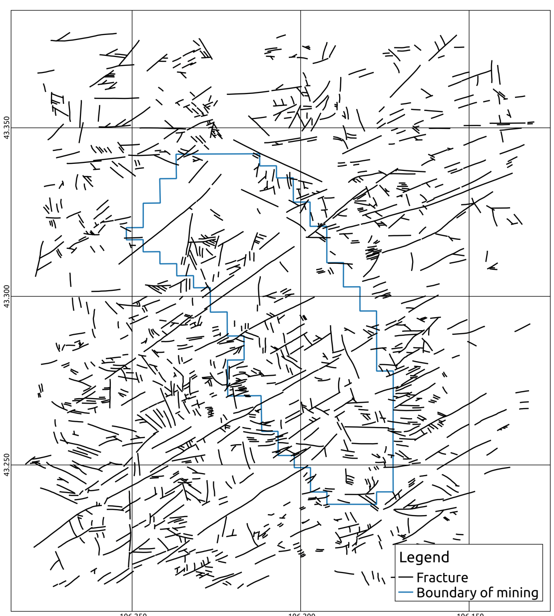

Fig. 2. Fracture network of Teapot Dome.

As illustrated in Table 1 and Fig. 4, the dataset displays a significant class imbalance, with Class 6 dominating the data distribution. This imbalance poses challenges for machine learning model performance, as models may become biased toward the overrepresented class. Therefore, techniques such as data augmentation, rebalancing, or synthetic data generation may be necessary to improve prediction accuracy and mitigate the effects of this imbalance.

3. Methodology

3.1 Data preprocessing

Due to the complexity of fracture azimuths and the lack of critical information such as stress conditions and fracture length, this problem is framed as a classification task rather than a regression problem. A regression approach would require additional data to be viable. Therefore, the primary objective is to predict the fracture azimuth class.

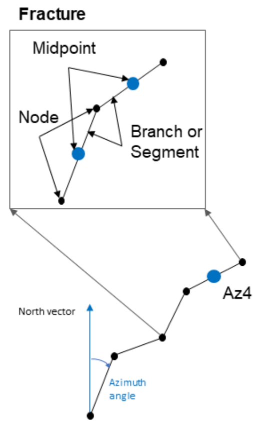

Fig. 3. Schematic showing nodes (black circles) and fracture segments (blue circles) in the fracture network.

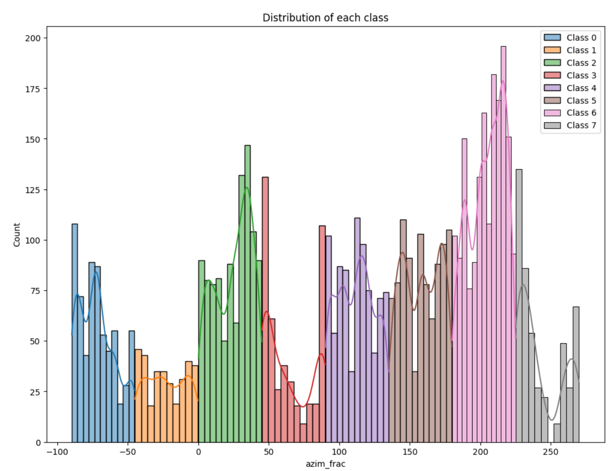

Fig. 4. Visualization of class distribution in the dataset.

3.2 Machine learning models

To address the classification task, we implemented several machine learning models, ranging from simple to more complex algorithms. The models evaluated include Multinomial Logistic Regression, Decision Trees, Random Forests, K-Nearest Neighbors (KNN), LightGBM, XGBoost, and CatBoost. The dataset was split into training (70%), validation (15%), and testing (15%) sets, yielding 4463, 957, and 957 samples, respectively.

We use the following ML models: the simplest one is Multinomial Logistic Regression, which is just an extension of logistic regression to multiple class outcomes (Nick and Campbell, 2007). Then, there are tree-based algorithms such as Decision Trees, where the tree structure is built by repeatedly dividing information, and the leaves represent classes (Rokach and Maimon, 2005). Random Forest is an extension of Decision Trees, using them multiple times on random subsets of the data and simultaneously deciding the outcomes (Breiman, 2001). Along with these, we use XGBoost (Chen et al., 2015), LightGBM (Ke et al., 2017), and CatBoost (Prokhorenkova et al., 2018), which are gradient boosting algorithms. One non-parametric algorithm, based on distance and class decisions by voting among its neighbors, is K-Nearest Neighbors (Cover and Hart, 1967). From Deep Learning, we use Dense Neural Networks, which are used to capture high-level relationships through a multi-layered structure (Bishop and Nasrabadi, 2006).

3.3 Evaluation metrics for multi-class classification

There are many ways of measuring the performance of multiclass classifiers. We use classification reports and provide loose definitions of the metrics here.

Accuracy is the proportion of correctly classified examples, while precision calculates how many positively identified examples are actually positive, and recall is the ratio of how many actual positive examples were identified correctly. The harmonic mean of precision and recall gives the F1-score. Support is the number of examples in each class. Macro averages are just the average of the chosen metric values, and the weighted average is an average where the weight of each class is taken into account. Most of the time, we emphasize the F1-score as a balanced measure between precision and recall, since our dataset is imbalanced.

In our future research, we intend to use an adaptive method for simulation of the flow and transport (Amanbek et al., 2019) with the generated fracture network and compare it with the result of the original fracture network (Amanbek et al., 2023).

4. Results

4.1 Simple models

The multinomial logistic regression yielded an accuracy of 0.2748 (27.48%) (see Table 2). This value is low and indicates the model's inability to capture the nature of the fractures.

Table 2. Classification report for multinomial logistic regression.

Class	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	91
1	0.00	0.00	0.00	42
2	0.45	0.07	0.12	146
3	0.00	0.00	0.00	78
4	0.00	0.00	0.00	128
5	0.00	0.00	0.00	147
6	0.27	0.99	0.42	256
7	0.00	0.00	0.00	69
Accuracy		0.27 (Support: 957)		
Macro Avg	0.09	0.13	0.07	957
Weighted Avg	0.14	0.27	0.13	957

The classification report shows that most metric values are zero. This might be because the relationships between the fractures are too complex and non-linear.

4.2 Advanced models

4.2.1 Decision tree model

The Decision Trees yielded an accuracy of 0.6541 (65.41%), which is significantly higher than the output of multinomial logistic regression. The metrics are fairly balanced, with class 6 showing the best result due to its high density, achieving a precision of 0.72, recall of 0.73, and an F1-score of 0.73 (see Table 3). Other classes have lower but reasonably good statistics.

Table 3. Classification report for decision tree model.

Class	Precision	Recall	F1-Score	Support
0	0.59	0.58	0.59	91
1	0.52	0.60	0.56	42
2	0.59	0.59	0.59	146
3	0.60	0.60	0.60	78
4	0.69	0.70	0.70	128
5	0.68	0.68	0.68	147
6	0.72	0.73	0.73	256
7	0.63	0.57	0.60	69
Accuracy		0.65 (Support: 957)		
Macro Avg	0.63	0.63	0.63	957
Weighted Avg	0.65	0.65	0.65	957

Overall, the results are better and more balanced; however, low-density classes like class 1 continue to challenge the model.

4.2.2 Random forest model

The Random Forest model outperforms both the decision tree and multinomial logistic regression models, achieving an accuracy of 67.18% (see Table 4). This improvement indicates that the ensemble method is better at generalizing the fracture azimuth classification task compared to a single decision tree.

For class 0, we obtained the precision and recall, which are both relatively high at 0.65 and 0.71, respectively, meaning the model correctly identifies class 0 fractures and minimizes false positives. As with previous models, class 6 has the highest support and performs well with a precision of 0.70 and recall of 0.76. This high recall indicates that the model correctly identifies most instances of class 6.

Overall, the model performs well in more frequent classes (such as class 6) and shows a more balanced performance across all classes, making it more robust than a single decision tree. However, the model still struggles with some less frequent classes (like class 1 and class 7).

Other boosting algorithms like, XGBoost, LightGBM and CatBoost gave similar results around 66%.

Table 4. Classification report for random forest model.

Class	Precision	Recall	F1-Score	Support
0	0.65	0.71	0.68	91
1	0.58	0.50	0.54	42
2	0.63	0.66	0.64	146
3	0.62	0.53	0.57	78
4	0.69	0.70	0.69	128
5	0.71	0.69	0.70	147
6	0.70	0.76	0.73	256
7	0.66	0.48	0.55	69
Accuracy		0.67 (Support: 957)		
Macro Avg	0.66	0.63	0.64	957
Weighted Avg	0.67	0.67	0.67	957

4.2.3 K-Nearest neighbors model

For class 0, precision and recall are relatively high, at 0.64 and 0.65, respectively, showing that the model effectively identifies fractures in this class. The result of class 2 is a precision of 0.67 and a recall of 0.73, which shows that this class performed well, indicating that the KNN algorithm can effectively distinguish fractures in this category. Like other models, Class 6 performed strongly, with precision and recall at 0.76 (see Table 5). This high performance is due to the larger support for this class. Despite moderate precision (0.73), recall is lower at 0.51 for class 7, which suggests that the model identifies some fractures in this class but is less successful at capturing all of them. The class imbalance likely contributes to this result. Classes 4 and 5 also performed well, with F1 scores around 0.73 and 0.75, respectively, indicating the model is adept at predicting these classes.

Table 5. Classification report for K-Nearest neighbors.

Class	Precision	Recall	F1-Score	Support
0	0.64	0.65	0.64	91
1	0.56	0.64	0.60	42
2	0.67	0.73	0.70	146
3	0.60	0.62	0.61	78
4	0.72	0.74	0.73	128
5	0.76	0.74	0.75	147
6	0.76	0.76	0.76	256
7	0.73	0.51	0.60	69
Accuracy		0.70 (Support: 957)		
Macro Avg	0.68	0.67	0.67	957
Weighted Avg	0.71	0.70	0.70	957

Overall, the K-Neighbors algorithm achieved an impressive accuracy of 70.42%, outperforming both the decision tree and Random Forest models. This higher accuracy suggests that KNN effectively captures the spatial relationships and azimuth classes of fractures, particularly for frequent classes such as Class 6, while still handling less frequent classes like Class 7 reasonably well.

4.3 Data augmentation and handling class imbalance

Given the limitations of the original dataset, including its size and the issue of class imbalance, we employed a data augmentation strategy to enhance the training process. Specifically, two new datasets of equal size to the original are generated by calculating the fracture start and end points from the midpoints provided in the dataset. The length of the fractures was set to 1,000 units, and two equidistant points were selected from each fracture's start and endpoints (see Fig. 5). After concatenating these new datasets with the original data, we re-applied the machine learning algorithms previously discussed.

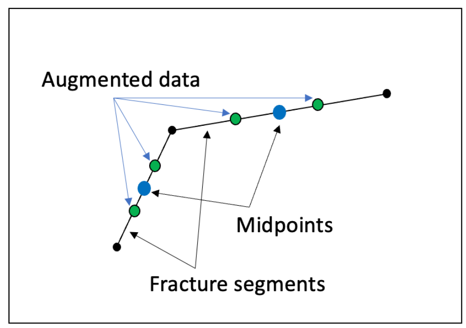

Fig. 5. Visualization of the data augmentation strategy.

Among the models tested, K-Nearest Neighbors (KNN) yielded the best performance, achieving an accuracy of 88.32%. The classification report for KNN is presented in Table 6.

The report shows that the model, after data augmentation, improved greatly, with most class statistics being greater than 0.80. As usual, class 6 outperforms other classes with a precision of 0.92, a recall of 0.94, and an F1-score of 0.93. Even with the least number of examples in class 1, its statistics are around 0.80.

Overall, the accuracy of 88% and other metric measures show that data augmentation is an effective method for increasing the model's performance. The macro-average and weighted-average metrics also reflect the model's high predictive power in general.

Even though our dataset remained imbalanced after data augmentation, excellent results are achieved. The way we equalize the number of examples in each class during data augmentation also impacts the result, depending on whether we balance the class with the fewest or the highest number of examples.

To handle class imbalance, we also used methods like the Synthetic Minority Over-sampling Technique (SMOTE) (Li et al., 2022). It generates new examples by interpolating between existing examples. We used it to oversample the training data and trained the KNN model, which was tested on the imbalanced test dataset. However, the results before data augmentation did not improve. This indicates that the relationships between the fractures are too complex, and interpolation methods like SMOTE are ineffective for our dataset.

Next, we aim to use feature engineering and deep learning methods to improve the existing results.

Table 6. Classification report for K-Nearest neighbors after data augmentation.

Class	Precision	Recall	F1-Score	Support
0	0.87	0.82	0.84	286
1	0.85	0.78	0.81	151
2	0.81	0.88	0.85	413
3	0.86	0.87	0.86	210
4	0.90	0.86	0.88	399
5	0.89	0.90	0.89	427
6	0.92	0.94	0.93	761
7	0.94	0.87	0.90	223
Accuracy		0.88 (Support: 2870)		
Macro Avg	0.88	0.86	0.87	2870
Weighted Avg	0.88	0.88	0.88	2870

5. Feature engineering and model performance

One way to improve the model's performance is through feature engineering, which involves generating new features from the existing dataset to enrich its information field.

We applied the KNN model to cluster our dataset into eight classes. These new classes are different from the azimuth fracture's classes, as they are based on the physical locations of the fractures.

Additionally, for each class, we identified the closest five fractures and recorded their data as new features, including the Euclidean distances to the midpoints of these five fractures. In total, there are 25 columns and several models are trained on this dataset. The results are shown in Table 7.

We also implemented a deep learning model, which achieved an accuracy of 73.98%.
To gain deeper insights into the impact of the features, we utilized SHAP (SHapley Additive exPlanations) and conducted a feature importance analysis, as shown in Fig. 6.

The feature importance analysis indicates that the azimuths of the nearest fractures, particularly the azimuths of the five closest fractures, significantly influence the class of a fracture.

Among all the models evaluated, LightGBM achieved the highest accuracy, reaching 77.84%.

We also experimented with a Dense Deep Neural Network (DNN) consisting of six hidden layers. The DNN achieved an accuracy of 82.12%, surpassing the performance of the LightGBM model, which previously held the highest accuracy at 77.84%. This indicates that the DNN was able to capture more complex patterns in the data, potentially due to its ability to model non-linear relationships more effectively. Fig. 7 shows the loss visualization across different epochs during the training process.

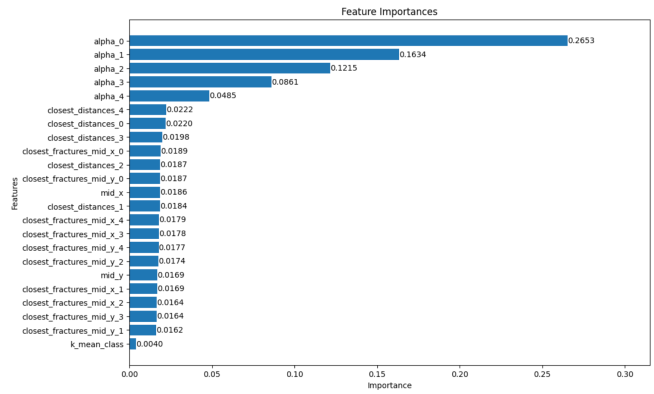

Fig. 6. Feature importance scores.

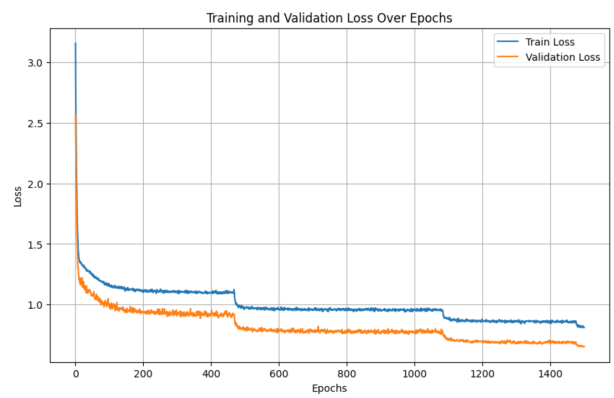

Fig. 7. Loss across training over epochs.

As seen in Fig. 7, the loss function decreases steadily over the epochs, indicating that the model is learning effectively and converging to a minimum. However, the deep learning model, despite its high accuracy, comes with the trade-offs of longer training times and higher computational requirements compared to tree-based models like LightGBM. Additionally, DNNs can be more prone to overfitting, especially with small or imbalanced datasets, but the use of regularization techniques and dropout layers in our architecture helped mitigate this issue.

In the next step, we combined data augmentation with feature engineering, resulting in a dataset with 25 columns and 19,131 data points. Of these, 13,391 data points (70%) were used for training, and the remaining 5,740 data points were split equally between test and validation sets (15% each). The performance of the models on this enhanced dataset is summarized in Table 8.

Table 8 shows that combining data augmentation with feature engineering significantly boosted the models' predictive capabilities. Both XGBoost and LightGBM reached accuracies

Table 7. Performance of models on feature-engineered dataset.

Model	Accuracy	F1-weighted average	Precision-weighted average	Recall-weighted average
Random Forest	75.44%	0.76	0.76	0.73
KNeighbors	68.33%	0.68	0.68	0.68
XGBoost	76.48%	0.76	0.76	0.76
LightGBM	77.84%	0.78	0.78	0.78
CatBoost	77.80%	0.77	0.77	0.77

Table 8. Performance of models on feature-engineered and data-augmented dataset.

Model	Accuracy	F1-macro average	Precision-macro average	Recall-macro average
XGBoost	98.08%	0.98	0.98	0.98
LightGBM	98.32%	0.98	0.98	0.98

over 98%. These findings indicate that using augmentation alongside feature engineering can effectively address the complexities of the fracture prediction task.

6. Discussion

In this research, machine learning algorithms have shown effectiveness in predicting fracture network patterns. By incorporating feature engineering and data augmentation, we observed notable improvements in the accuracy of predicting fracture azimuths. This suggests that integrating new features from geology, geophysics, geometry, and other relevant patterns could enhance the precision of the machine learning models. However, collecting this type of data is both complex and costly.

Techniques like SMOTE (Synthetic Minority Oversampling Technique) did not significantly improve, likely due to the intricate spatial relationships between data points. This finding highlights that basic oversampling methods may not adequately address class imbalance in geospatial datasets, where factors like proximity and spatial orientation are crucial.

In our research, we considered 2D fracture networks. The machine learning approach can be extended to 3D fracture networks. However, gathering 3D data may require advanced logging techniques, such as 3D seismic data or borehole imaging logs, which are more expensive and may not be as readily available as 2D data. For 3D, two angles would define the fracture orientation. Additionally, working in 3D introduces more complexity regarding data storage and computational costs. Due to their higher dimensionality, the models would need more data and time to train effectively.

7. Conclusion

We explore the application of various machine learning algorithms to predict azimuth categories in a fracture network model. Using real-world data from the Teapot Dome field in the USA, we compare the performance of several models, including Decision Trees, Random Forests, and KNN.

This paper studies various machine learning algorithms to predict categories of azimuth in the fracture network model. We use the fracture network dataset from the Teapot Dome field. The results have indicated that KNN shows the best accuracy of 70% with training of the original data. An accuracy improvement of 88% was achieved using additional augmented data for the KNN model. Additionally, by using feature engineering with data augmentation, an accuracy of 98% was achieved. From the outcome of the feature engineering investigation, it is possible to conclude that the azimuth classes of the closest five neighbors have a high impact on defining the azimuth category of the fracture segment. Future work could explore the integration of additional physical characterizations and apply these models to other datasets.

The machine learning models are powerful tools for predicting fracture networks, especially when combined with data augmentation and feature engineering. The ability to accurately predict fracture orientations has important implications for subsurface resource extraction, such as hydrocarbon production and CO_2 sequestration. Moreover, the impact of neighboring fractures on azimuth prediction highlights an opportunity for further investigation into more complex spatial relationships within fracture networks.

In our further research, we plan to apply deep learning algorithms such as the Bayesian neural network and Kolmogorov Arnold Network and extend to 3D fracture network modeling, which could provide a more comprehensive understanding of subsurface fracture patterns and their behavior.

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Conflict of interest

The authors declare no competing interest.

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