Facies Classification Modeling – Deployment

Final Machine Learning Project - Sekolah Data Pacmann

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Outline

1. Problem Definition & Goals
2. Project Timeline
3. Data Preparation
4. Data Preprocessing
5. Feature Engineering
6. Modeling
7. Model Evaluation
8. Front End and Back End Services
9. Pytest
10. Deployment

Problem Definition & Goals

Problem Definition

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Business Problems

- **Oil and Gas companies** need to translate **well measurement data** into lithofacies layer to **better understand** the condition of the **reservoir** being drilled.
- **Manually interpreting** well measurement data that are exponentially growing in volume by reservoir **geologists or geophysicists** must be **subjective** to some extent, leading to **increased uncertainties.**
- Facies definition is sometimes very **time-consuming** activity and **expensive.**

Business Solution

- **Classification of Lithofacies** can be achieved by using **supervised machine learning technique**. This supervised technique used **lithofacies labeled data** to understand the patterns and then **label other data lithofacies** based on trained lithofacies patterns
- In this **research and deployment** we will construct **supervised machine learning** model to **classify lithofacies** using **well-measurement data** to reduce cost and tackle the uncertainty of manual interpretation

Goals

- **The goal** of this project is to find the **best-supervised machine learning algorithm** for lithofacies classification, and then deploy the pre-application to the server to predict the lithofacies from the well-measurement data

Machine Learning Metrics

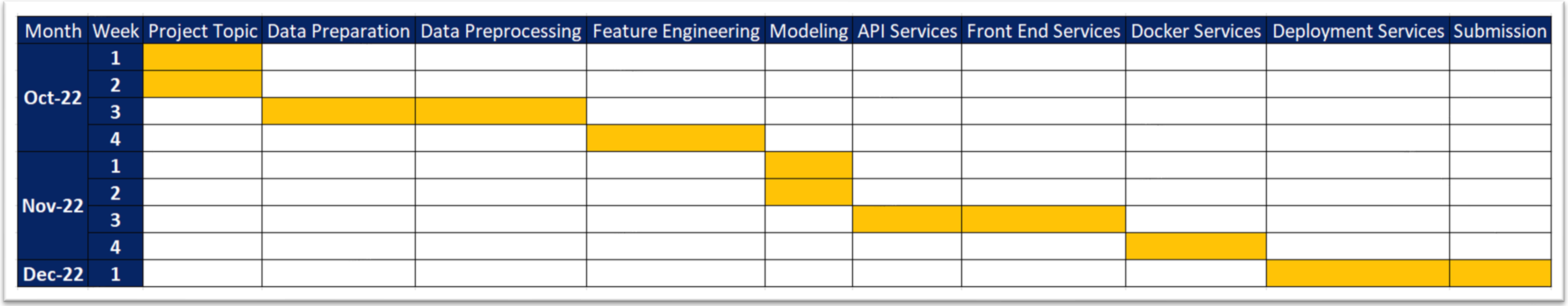
1. **Accuracy** 0.5 – 0.6 — How well does the model predicts the true positive and true negative labels from the data input
2. **Adjacent Accuracy** 0.6-0.8 — How well does the model predicts the adjacent facies of the labels
3. **CV Score** 0.5-0.6 — How is the model performance through training and validation data
4. **ROC-AUC Value** 0.8-0.9 — How well the model can separate the True Positive and False Positive

Business Metrics

1. **Cost** — Cost that was spent to interpret the well measurement data
2. **Work Execution Time** — Time spent to interpret the well measurement data

Project Timeline

Project Timeline



- **Project Timeline :** October Week 1 – December Week 1
- **Project Steps :** Topic ➔ Data Preparation ➔ Data Processing ➔ Feature Engineering ➔ Modeling ➔ API Services ➔ Front End Services ➔ Docker Services ➔ Deployment ➔ Submision and Reporting

Project Tools

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Developing ML	Front End & Back End	Deployment
pandas	FastAPI	aws
NumPy	uvicorn	docker
jupyter	Streamlit	
Imbalanced learn		
dmlc XGBoost		
scikit learn		

Data Preparation

Dataset

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- Dataset are from [Machine Learning Competition in 2016]
- Dataset comprises **11 columns** and **4149 rows**
- There are **3 categorical data**: Facies, Formation, and Well Name
- There are **7 numerical data**: Depth, GR, ILD_log10, Delta-PHI, PHIND, PE, NM_M, RELPOS
- Numerical data consist of **5 Wireline Measurement** and **2 Geological Variable**

	Facies	Formation	Well Name	Depth	GR	ILD_log10	DeltaPHI	PHIND	PE	NM_M	RELPOS
0	CSiS	A1 SH	NOLAN	2853.5	106.813	0.533	9.339	15.222	3.500	1	1.000
1	FSiS	A1 SH	NOLAN	2854.0	100.938	0.542	8.857	15.313	3.416	1	0.977
2	FSiS	A1 SH	NOLAN	2854.5	94.375	0.553	7.097	14.583	3.195	1	0.955
3	FSiS	A1 SH	NOLAN	2855.0	89.813	0.554	7.081	14.110	2.963	1	0.932
4	FSiS	A1 SH	NOLAN	2855.5	91.563	0.560	6.733	13.189	2.979	1	0.909

Dataset

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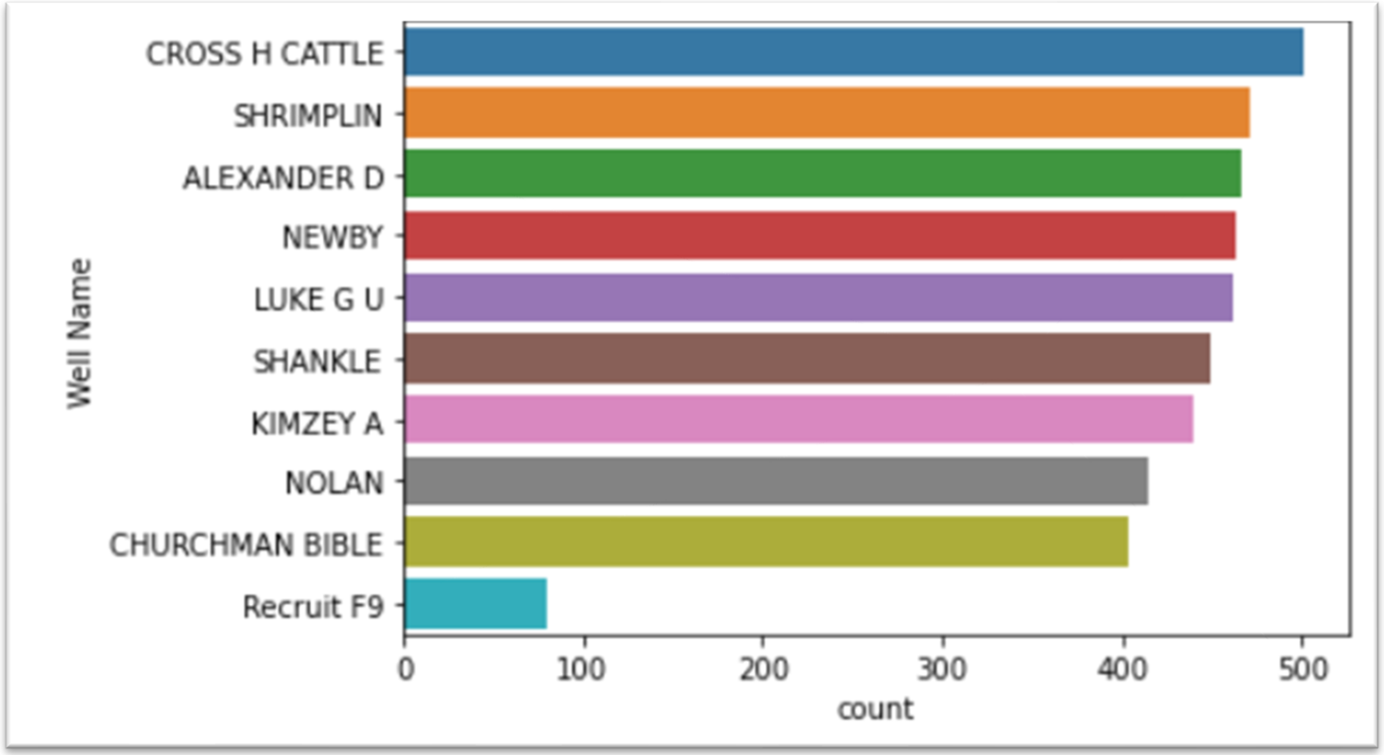
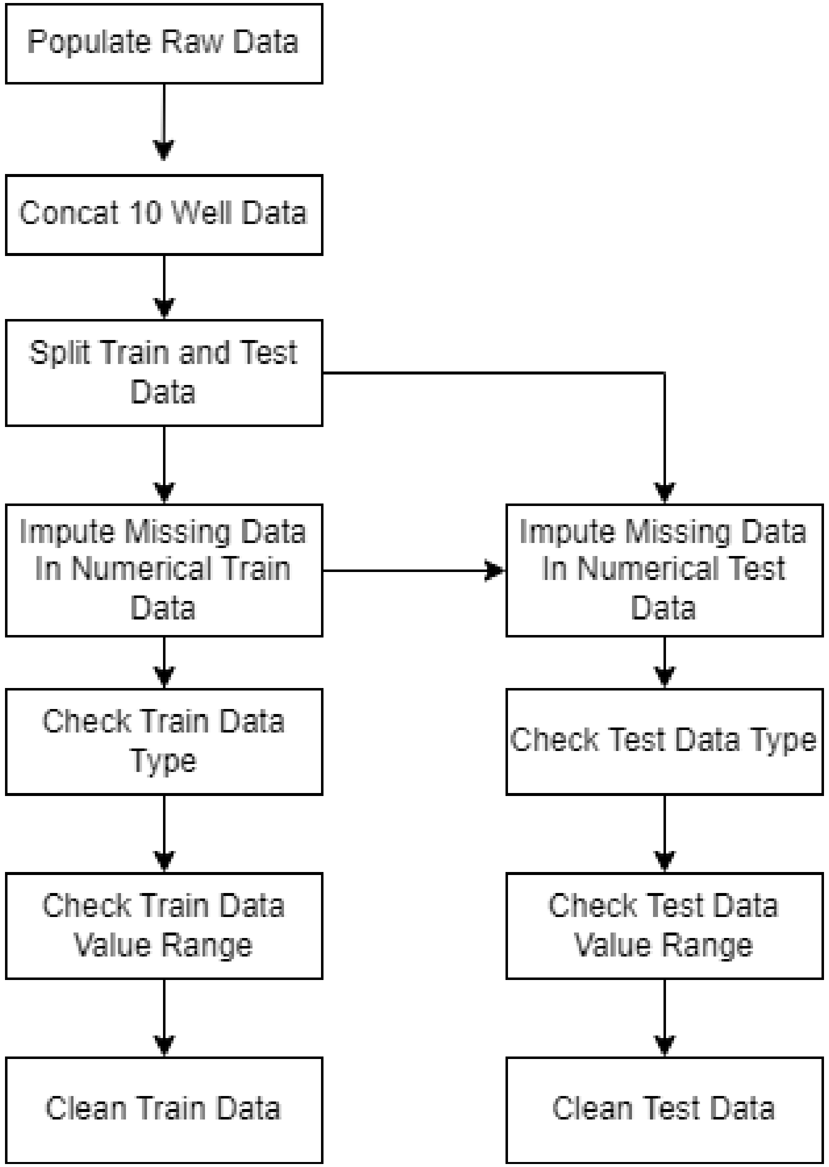


- Dataset consist of data measurement from 9 real well and 1 synthetic well (F9) to compensate category BS (Phyloid-Algae Bafflestone) in other well
- The difference on the amount of data from the real well wasn't so significant, but it is significant in the synthetic well

Data Preprocessing

Data Preprocessing



- Raw data is comprised of 10 CSV files that represent the well measurement from 10 different well
- Well 'CHURCHMAN BIBLE' was used to become the test data well, and the rest of the 9 well data serve as train data
- There are missing value in numerical data, and then it's imputed by mean value for every label categories
- Every data in train data and test data checked for data type and important range value

Feature Engineering

Feature Engineering

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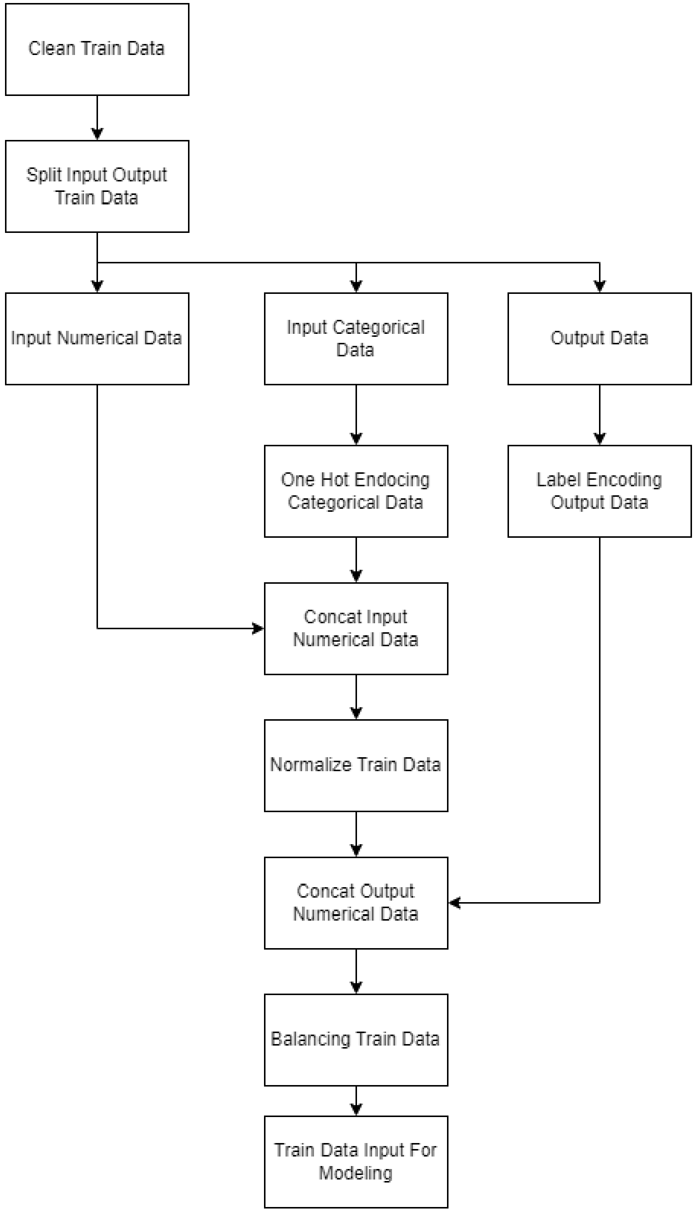
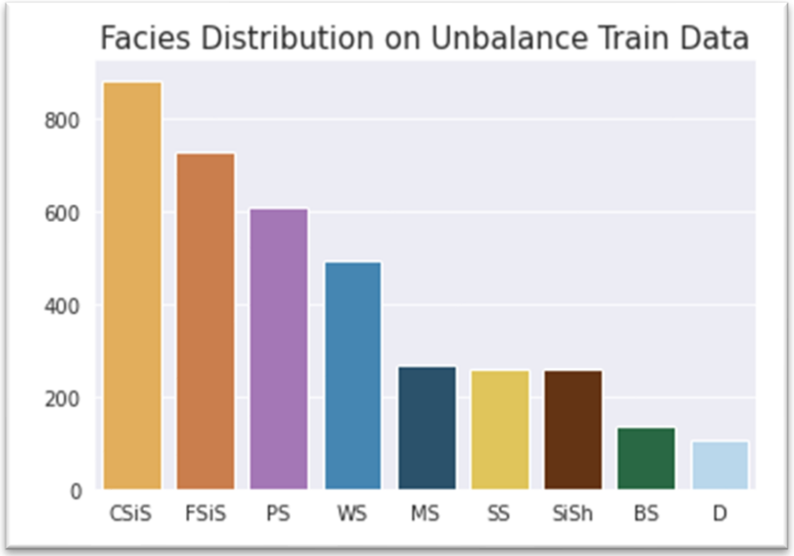


- Drop feature Formation, Well Name, Depth, and RELPOS, then split numerical, categorical, and output data
- One Hot Encoding for feature NM_M
- Label Encoding for feature output facies
- Normalize Input to have mean = 0 and standard deviation = 1
- Balancing train data using random under sampling, random over sampling, and smote

Facies	Numeric Representation
SS	0
CSiS	1
FSiS	2
SiSh	3
MS	4
WS	5
D	6
PS	7
BS	8



Dataset for Modeling

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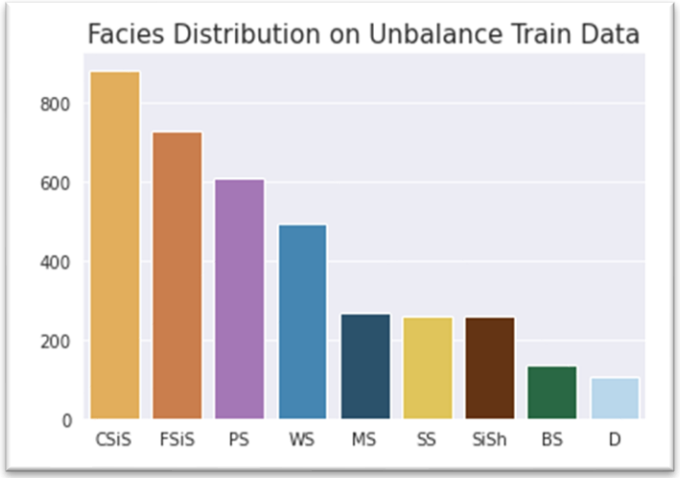
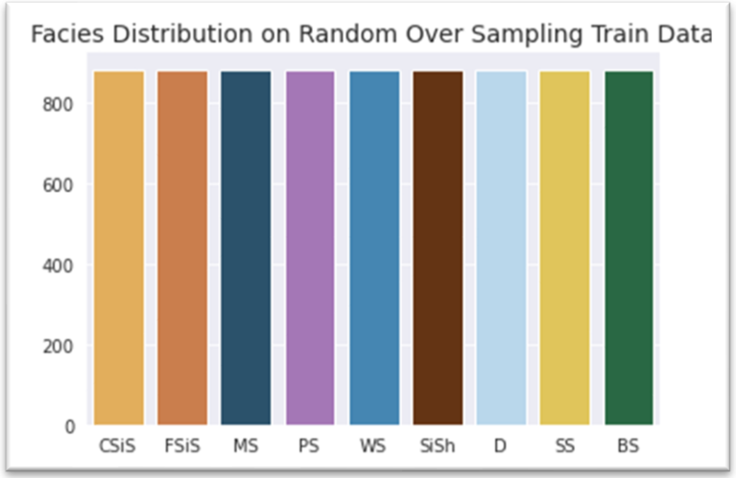
Unbalance



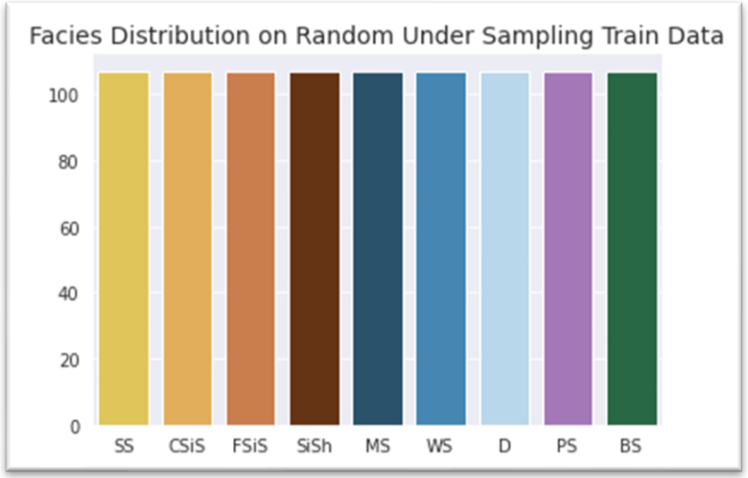
- 3745 data point for training
- Facies unbalance

Random Over Sample



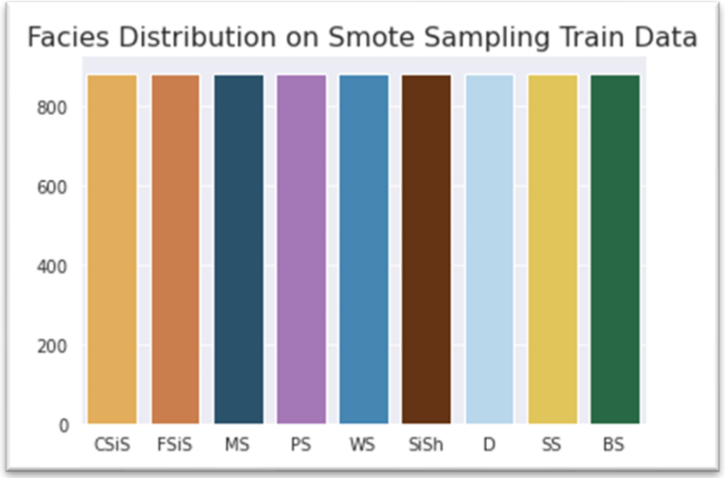
- 7956 data point for training
- Facies balance

Random Under Sample



- 963 data point for training
- Facies balance

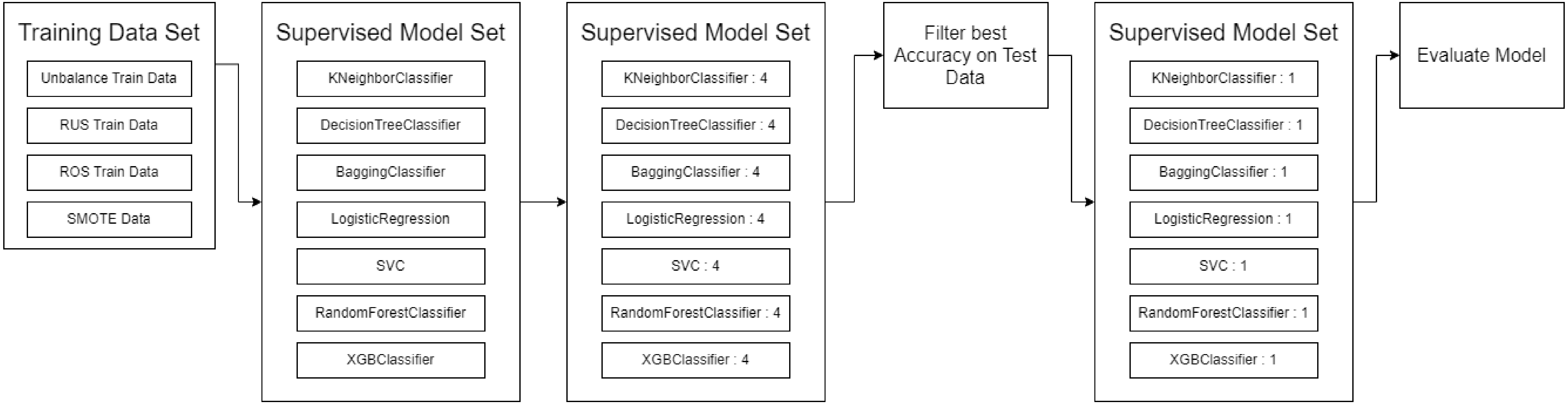
SMOTE



- 7956 data point for training
- Facies balance

Modeling

Modeling



- Seven supervised model algorithm was trained by using four training data set, that will produce 28 machine learning model
- From every algorithm will be picked one with the best accuracy on data test
- From this 7 machine learning model will be picked one the best for facies classifier

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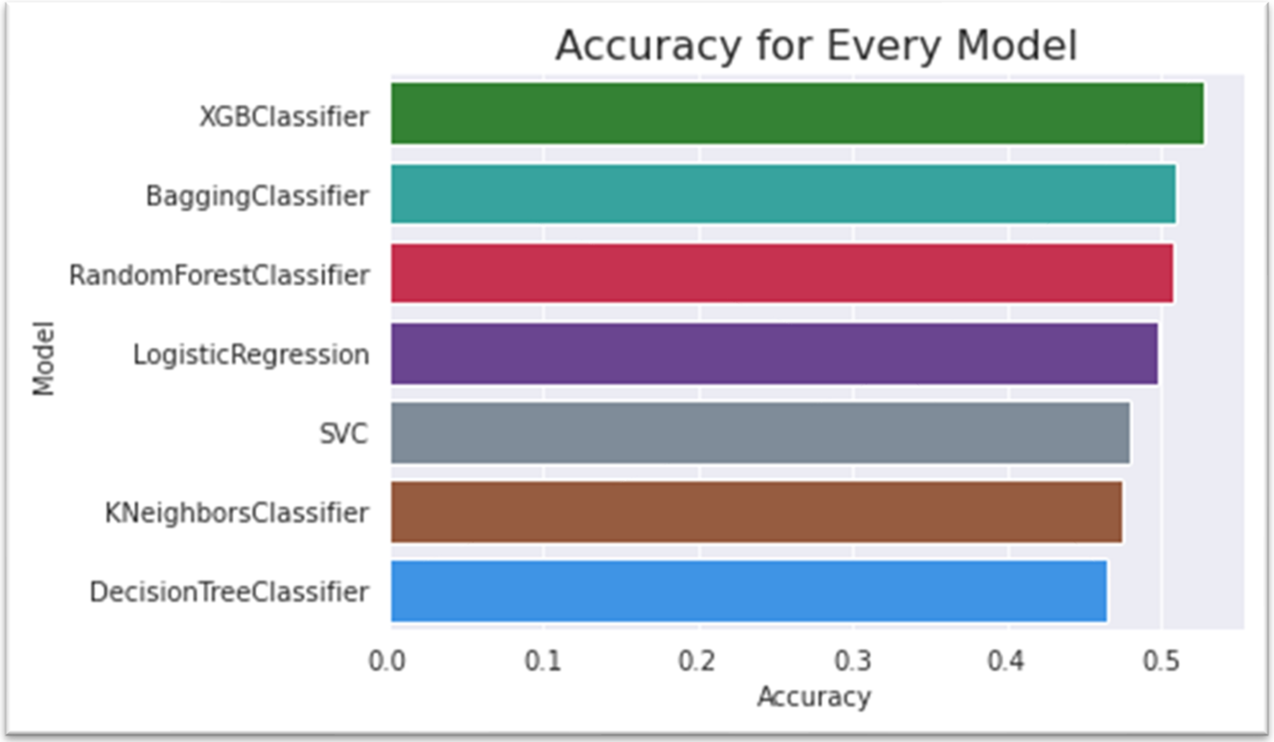
Model Evaluation

Evaluation by Accuracy Score



- All model have accuracy below 0.6
- XGBClassifier has the highest accuracy on test data (“CHURCHMAN BIBLE”) for 52.7% and Decision Tree Classifier has the smallest accuracy on test data for 46.5%

Evaluation by Adjacent Accuracy

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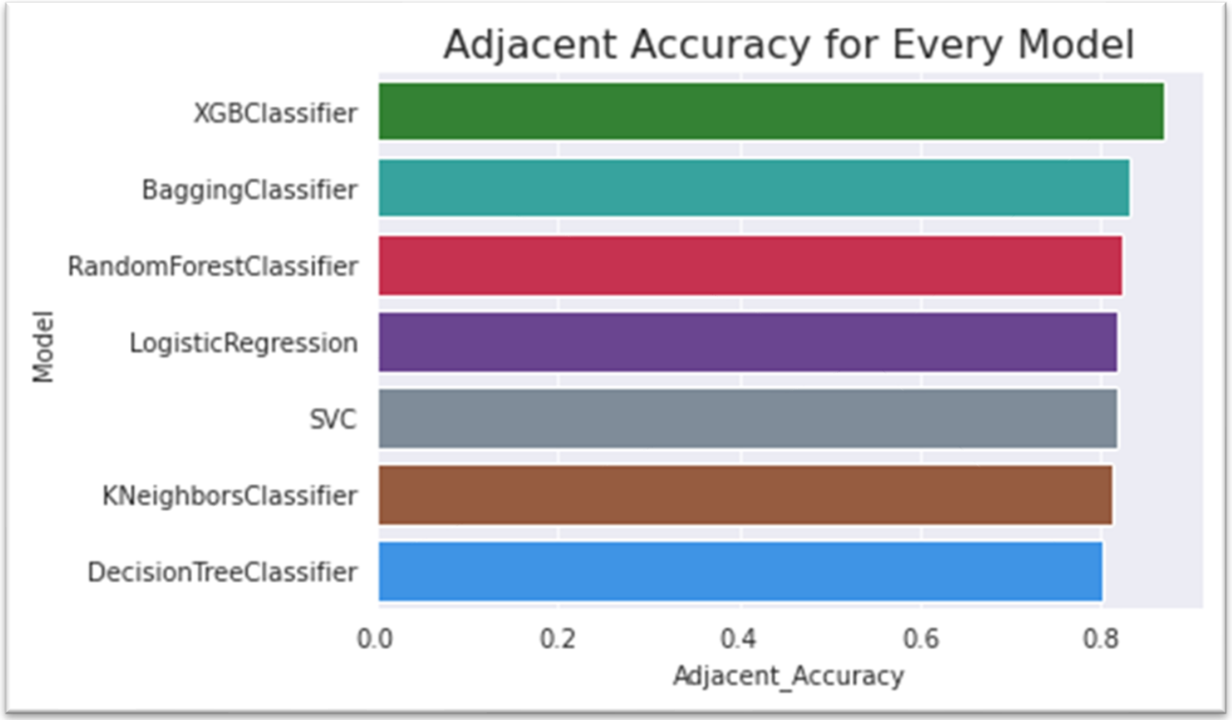

- All model have adjacent accuracy more than 0.8
- XGB Classifier again has the highest adjacent facies value for 86,8% and again Decision Tree Classifier become the model with the smallest adjacent accuracy on test data for 80,2%

Evaluation by CV Score

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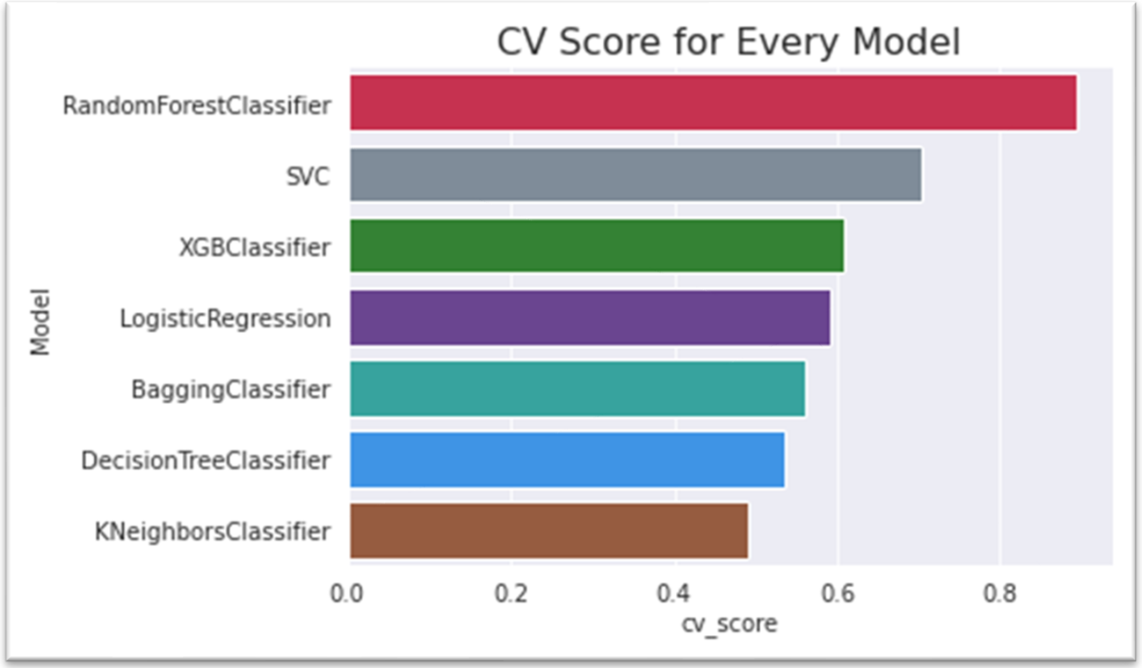
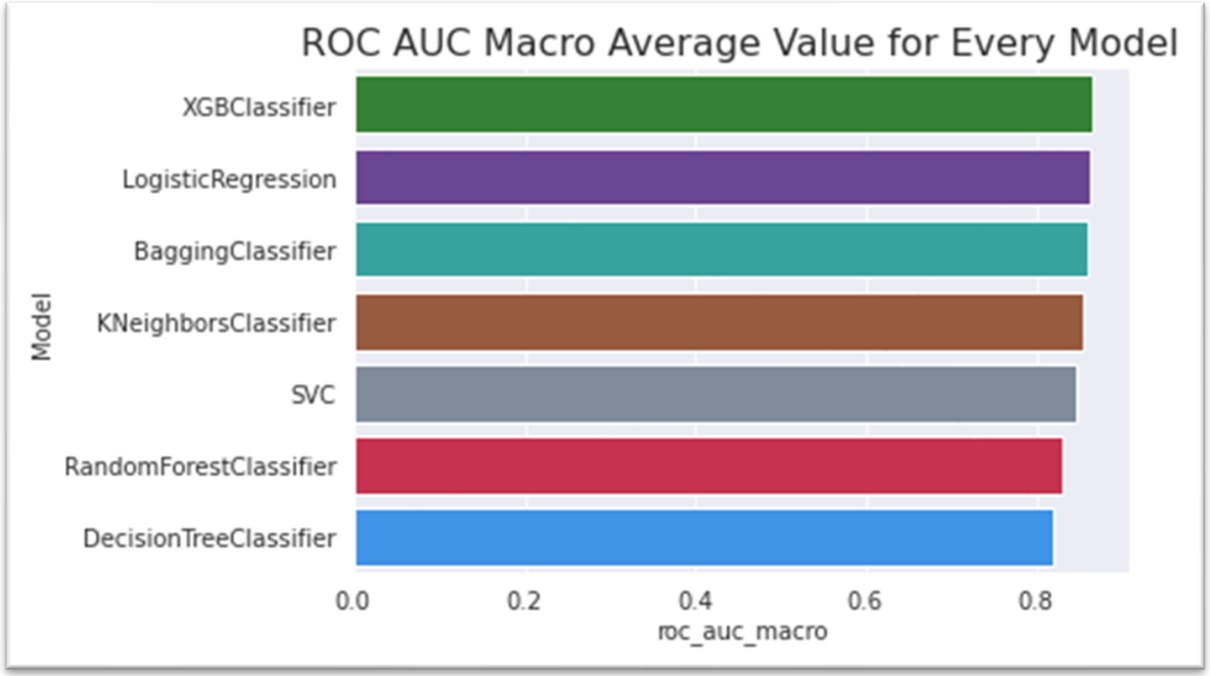
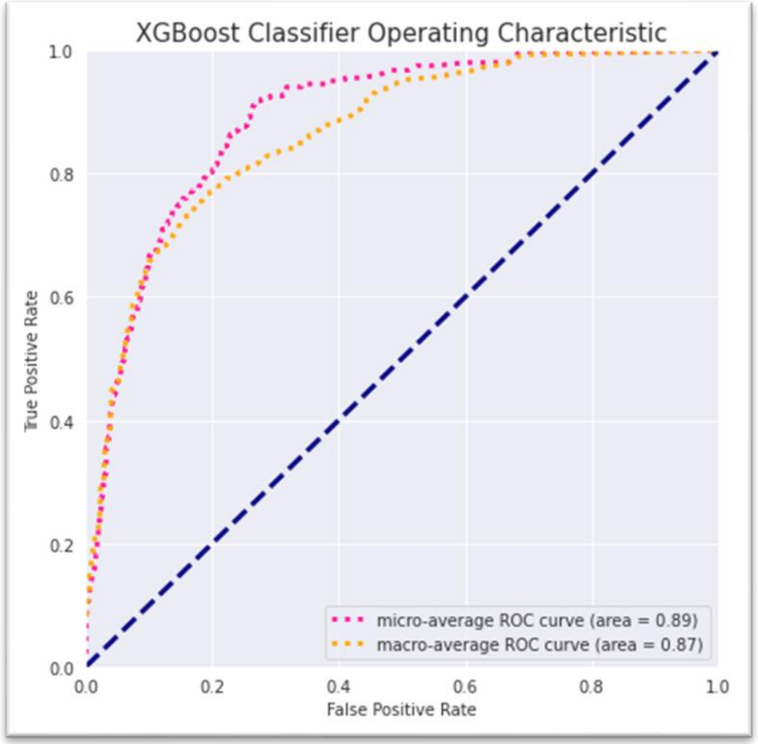


- Random Forest Classifier has the highest cv-score for 89.34%, whereas KNN has the smallest cv-score for 49,1%.
- Random forest and svc have a high difference between CV score and accuracy, we can say that for this two model is overfit on train data, eventhough already pass the cross validation process.
- For acceptable CV Score XGB Classifier has the highest cv score for 60.85% whereas KNN has the smallest cv score for 49,1%.

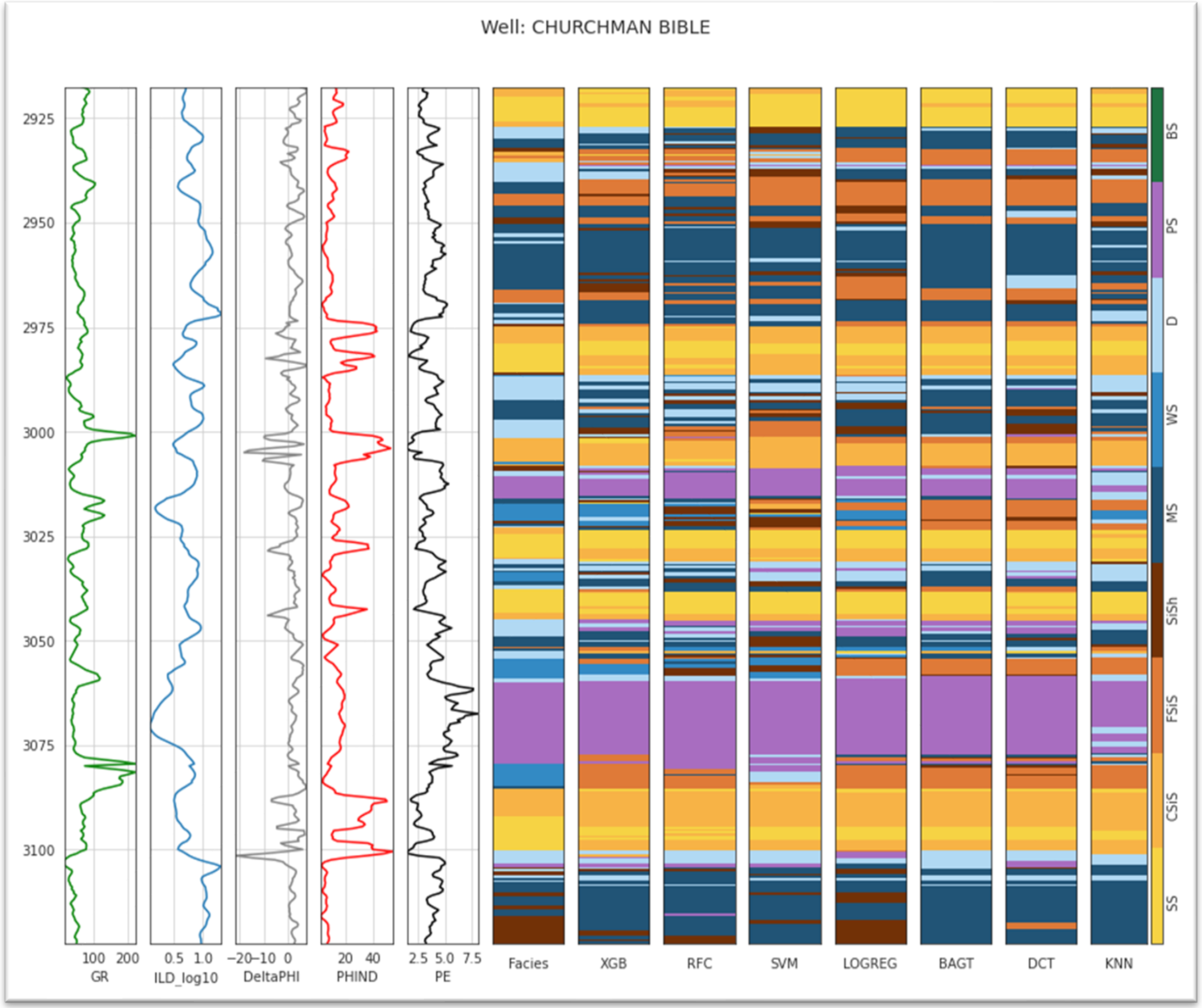
Evaluation by ROC-AUC





- All model have roc-auc more than 0.8
- XGB Classifier has the highest ROC-AUC score of 86.5% whereas Decision Tree Classifier has the smallest roc-auc score of 82%.
- For multi-class classification ROC-AUC curve was constructed by computing average TPR and FPR for every category.

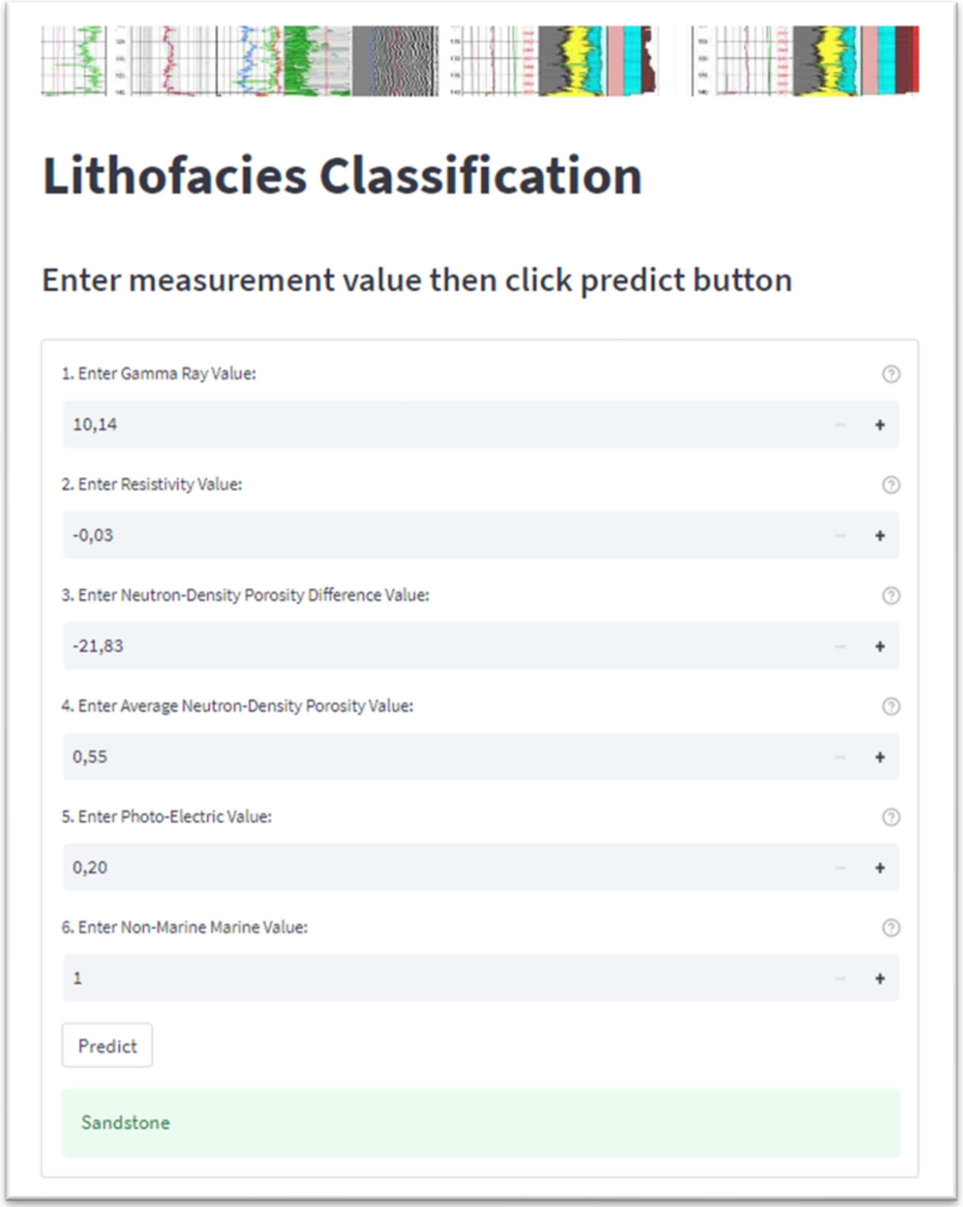
Evaluation by Prediction Result



- every model could **predict the majority of facies** when the layer doesn't variate much, like at the depth around **3075 and 2960**
- But when it comes to variative layer like in the depth around **3050 and 3100** the predicted lithofacies become **clearly different** with actual facies.
- **XGB Classifier** with the **best performance evaluated from accuracy, adjacent accuracy, cv-score, and ROC-AUC** curve could predict the lithofacies layer better than any other model.

Front End and Back End Services

Streamlit : Front End



- This project use streamlit as the front end of machine learning application
- Streamlit runs on port 8501
- Streamlit will sent api data into fast api and receive prediction result of the model

Fast API : Back End

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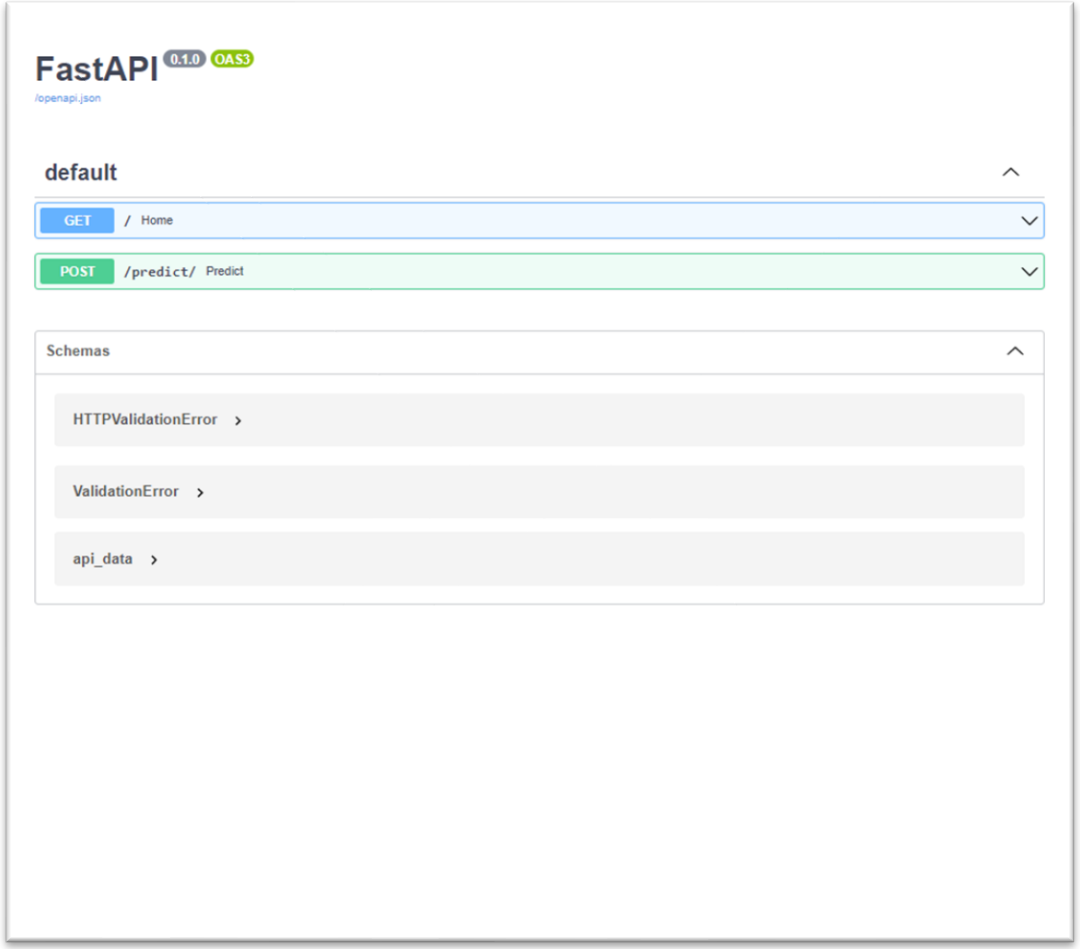

- Fast API was use as application peripheral interface for the machine learning model
- Fast API receive API data in JSON format from streamlit. Then format the data so the machine learning model could make prediction
- After prediction Fast API will sent again the data to streamlit for display

Pytest

Unit Test Function

```
======================================== test session starts ========================================
platform linux -- Python 3.9.12, pytest-7.2.0, pluggy-1.0.0
rootdir: /home/st_yudi/portfolio/07_Facies_Label_Deployment
plugins: anyio-3.6.2
collected 14 items


src/unit_test.py ..............
                                              [100%]

======================================== 14 passed in 1.08s ========================================
```

- Unit test was used to test every function in data_preprocessing.py and feature_engineering.py function as expected
- This project uses the pytest library on 14 functions in both data_preprocessing.py and feature_engineering.py and all pass the unit test

Deployment

Docker Compose

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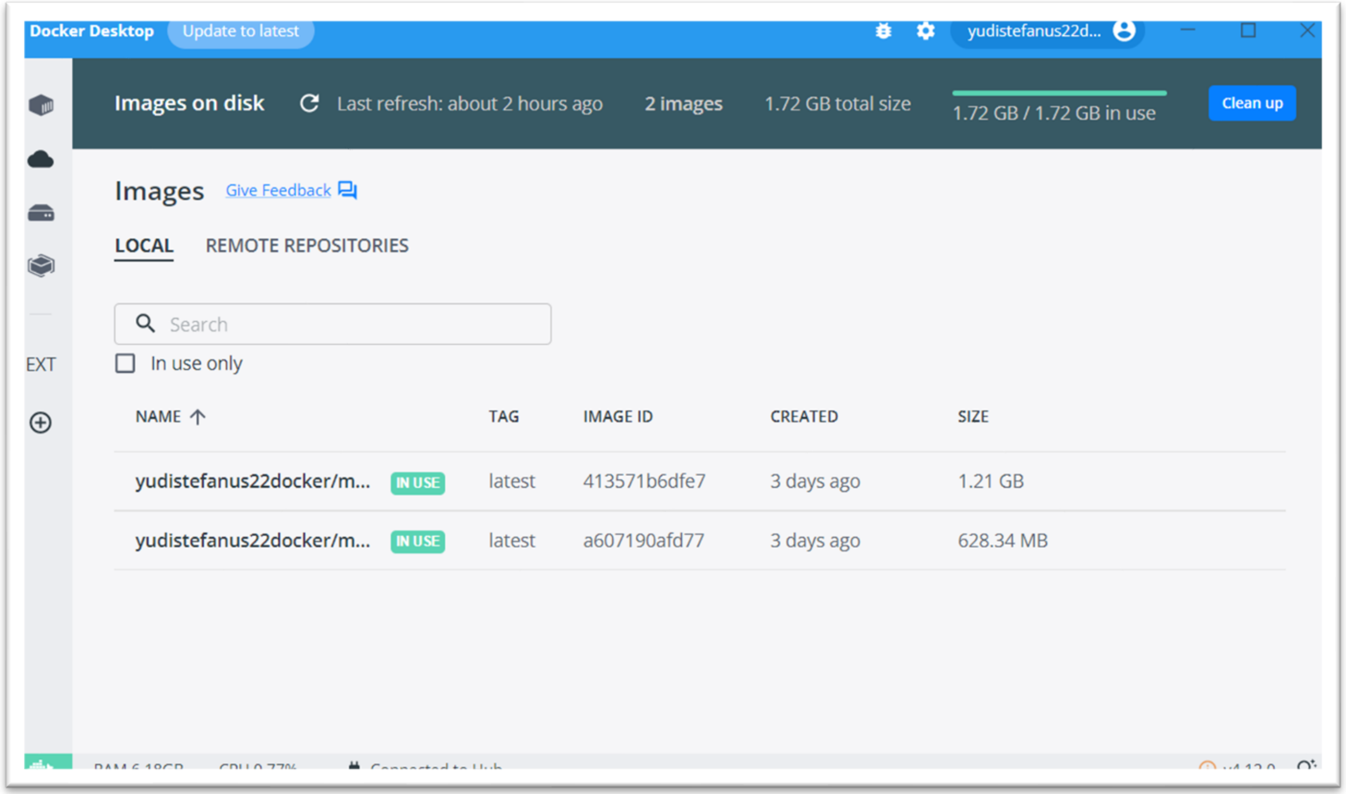

- This development use docker to run the Front end and back end services
- Docker function as a container so the front end and back end services can be run at any operating system as long as they have docker
- Front end and back end run on separate docker in a time

Reference

[1] Imamverdiyev, Y., Sukhostat, L., 2019, Lithological facies classification using deep convolutional neural network. Journal of Petroleum Science and Engineering 174 (2019) 216–228
[2] M. Gifford, C. Agah, A., 2010, Collaborative multi-agent rock facies classification from wireline well log data, Engineering Applications of Artificial Intelligence 23 (2010) 1158–1172
[3] W. Dunham, M. Malcolm, A. Kim Welford, J. 2020, Improved well log classification using semisupervised Gaussian mixture models and a new hyper-parameter selection strategy, Computers and Geosciences 140 (2020) 104501
[4] W.J. Glover P., K. Mohammed-Sajed, O., Akyiiz, C., Lorinczi, P. 2022, Clustering of facies in tight carbonates using machine learning, Marine and Petroleum Geology 144 (2022) 105828
[5] Antariksa, G. Muamar, R. Lee, J. 2022, Performance evaluation of machine learning-based classification with rock-physics analysis of geological lithofacies in Tarakan Basin, Indonesia, Journal of Petroleum Science and Engineering 208 (2022) 109250

Thank You

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For discussion

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Project Notebook and Repository

Project-Repository