SP295031

APPLICATION OF MACHINE LEARNING AND DEEP LEARNING IN GEOSTATISTICS FOR 3D RESERVOIR PREDICTION

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INTRODUCTION

- 3D geological property prediction has always been of critical importance for **accurate estimation of reserve volumes** and other **engineering properties for long term reservoir management**.
- In practical situation, development of statistical tools (Machine Learning, Deep Learning and ANNs) for propagation of properties is considered of great importance since it saves time, human efforts and costs of drilling.
- Comparative analysis of lithologies using results of various geostatistical interpolation methods, machine learning models and their hybrid models has shown significant improvements in the field of reservoir property prediction.

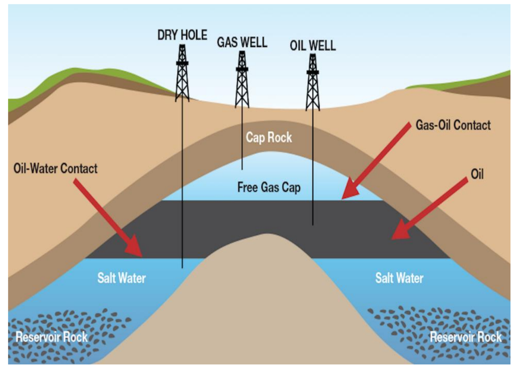


Figure 1. Reservoir Diagram

PROBLEM STATEMENT:

- Traditionally, geostatistical methods have been the main stay for the prediction of geological properties in the spatial domain. However, it had much limitation in handling complex situation and data-dimensionality.
- **The goal of this study is to examine the performance of conventional geostatistical interpolation techniques, regression machine learning methods and their combination** in terms of accuracy and time.

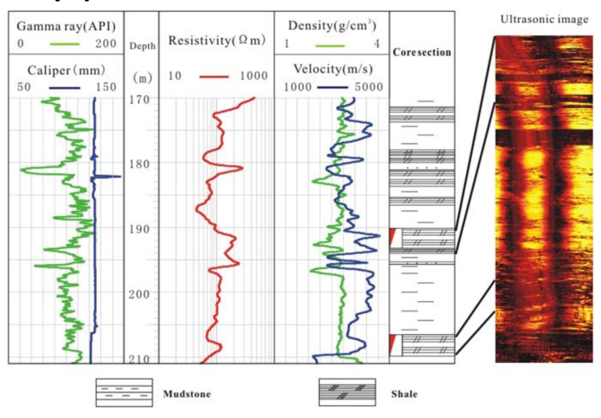


Figure 2. Systematic Wireline Logging

METHODOLOGY AND WORKFLOW:

- Geostatistical Methods:
  - Ordinary Kriging
  - Universal Kriging
  - Inverse Distance Interpolation
- Machine Learning Regression Methods
  - Decision Tree
  - Random Forest
  - AdaBoost + DT
  - Gradient Boosting + DT
  - Support Vector Regressor
- Hybrid Approaches:
  - OK + AdaBoost
  - OK + SVR
  - OK + Random Forest
  - IDW + Kriging
  - IDW + Boosting
  - IDW + SVR
  - IDW + Random Forest
- Artificial Neural Networks

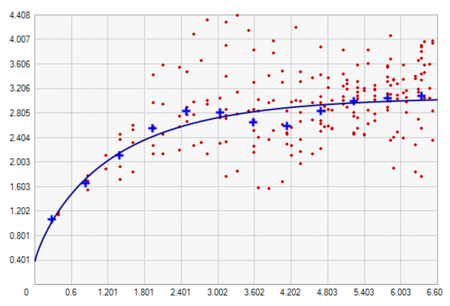


Figure 3. Generic Variogram, used to identify spatial correlation

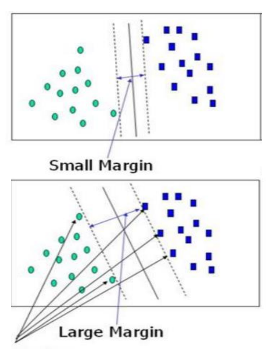


Figure 4. SVM, depiction of the optimal hyperplane which maximizes the margin between variable of training data

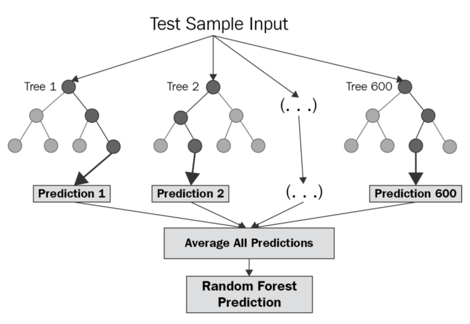


Figure 5. Random Tree Based Visualization

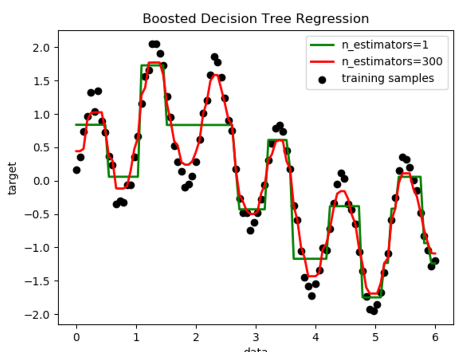


Figure 6. Boosted Decision Tree Regressor performance plotted for no. of estimators

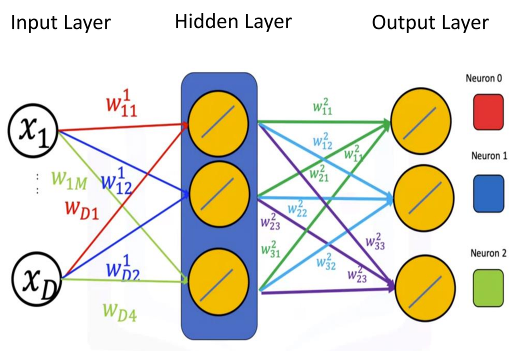


Figure 7. Single Layered Artificial Neural Network

Workflow for ML approaches:

Data Pre-processing
- Integration of Data from all Well-logs with respective lat-long values
- Useful Feature Extraction (RHOB.RAW values)
- Data Partition into training dataset and testing dataset

Model Building and Validation
- Different ML approaches are applied first
- Using Grid Search CV, the model parameters are selected

Volumetric Visualization
- 3D Graphs Plots

Predictions
- Applied on Test Set
- Compared Results between actual and estimated values

Workflow for Artificial Neural Networks:

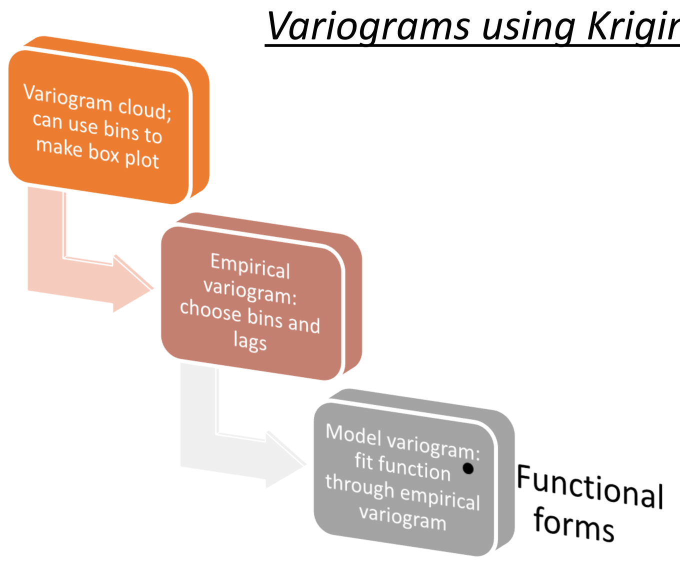
Building the Torch Dataset
- Defining Normalised Depth
- Data loader with batch size = 16

Defining Training Model
- 3 Hidden Layers
- Loss Criterion : MSELoss()
- Optimizer : Adam() ,
- Calculate gradient and Back propagation
- Learning Rate = 0.001

Tuning Hyper-parameters
- Experimenting with different Learning Rates
- 4 Hidden-Layered Networks
- Increasing #neurons in 1st hidden layer

Training and Validation
- Plotting Epoch vs Loss Data
- Testing on Validation dataset
- Comparing predicted well log

Workflow for Modelling Variograms using Kriging:



DATASET

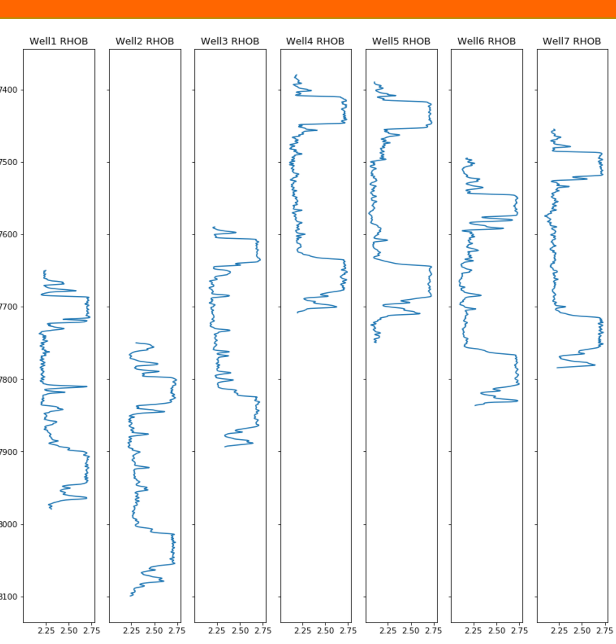


Figure 8. 2D Well Logs for RHOB (density) values

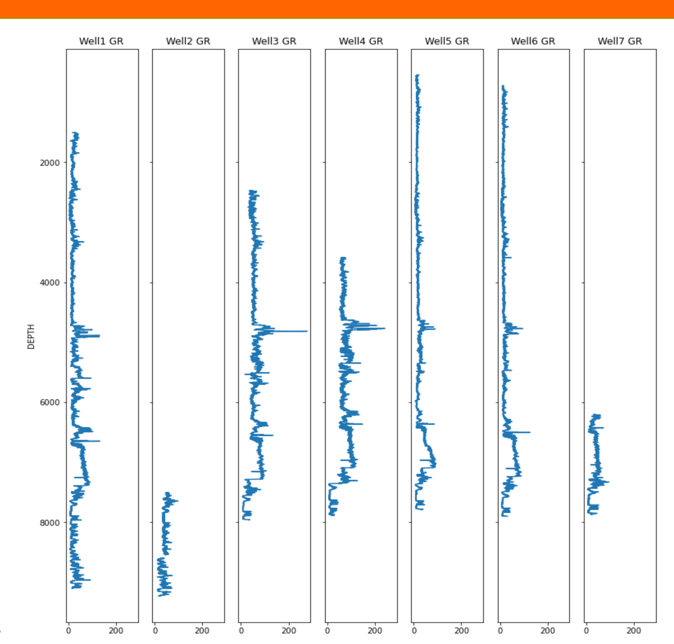


Figure 9. 2D Well Logs for GR values

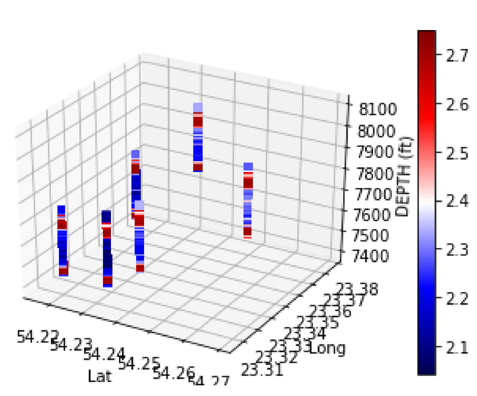


Figure 10. Spatial location of wells showing density in gm./cm3 at original depth

RESULTS & DISCUSSION

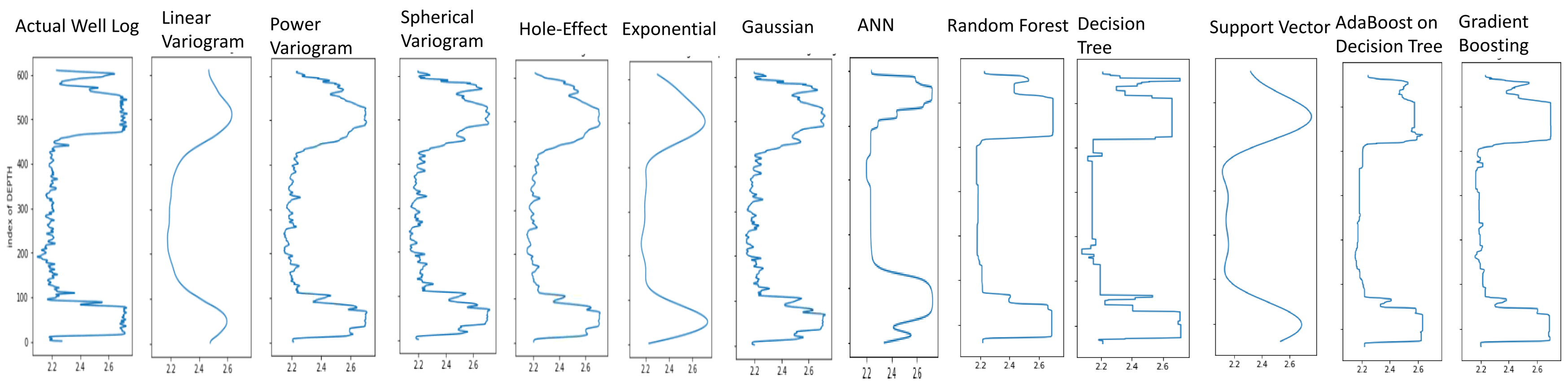


Figure 11. 2D Well Log Plots from various Models

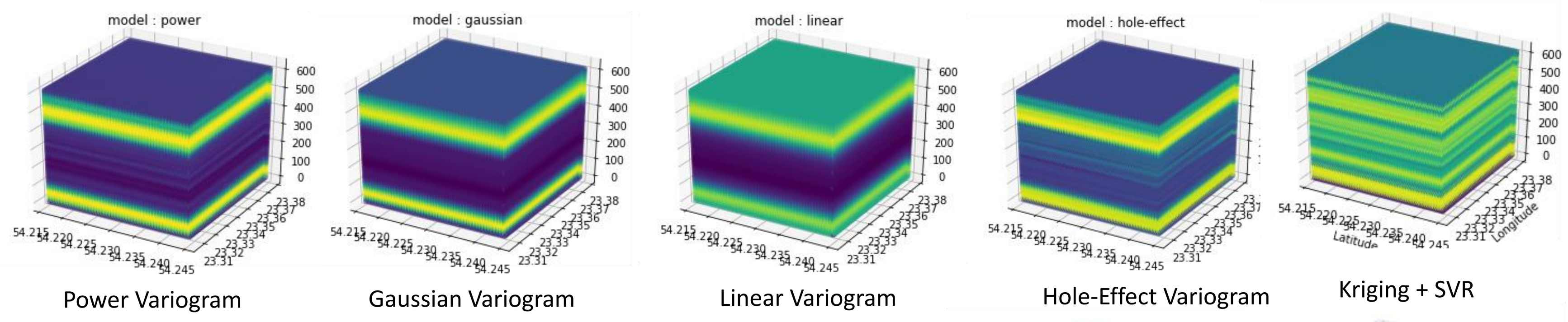


Figure 12. 3D Grid Plots from Kriging Models with different variograms and ML Regressors

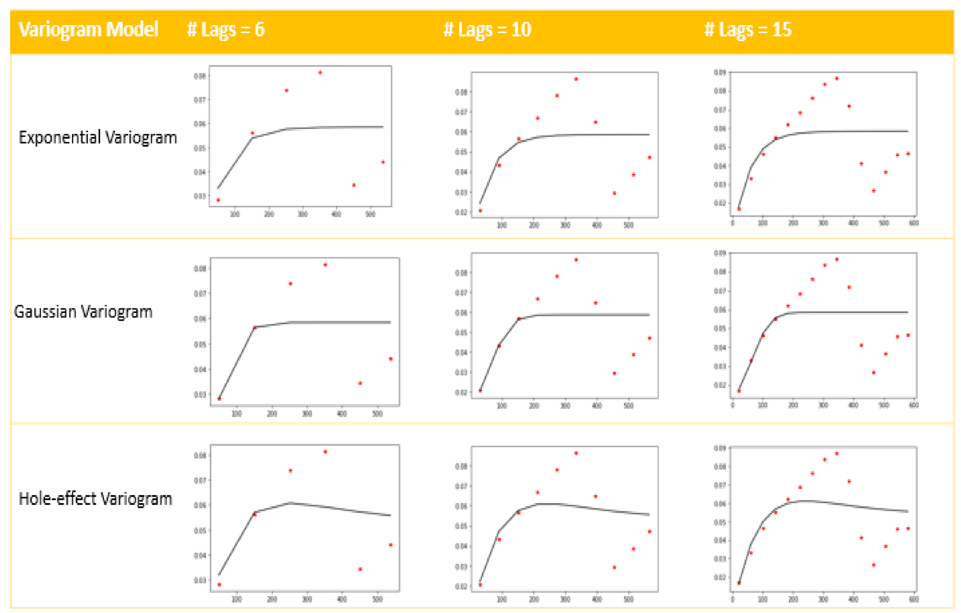
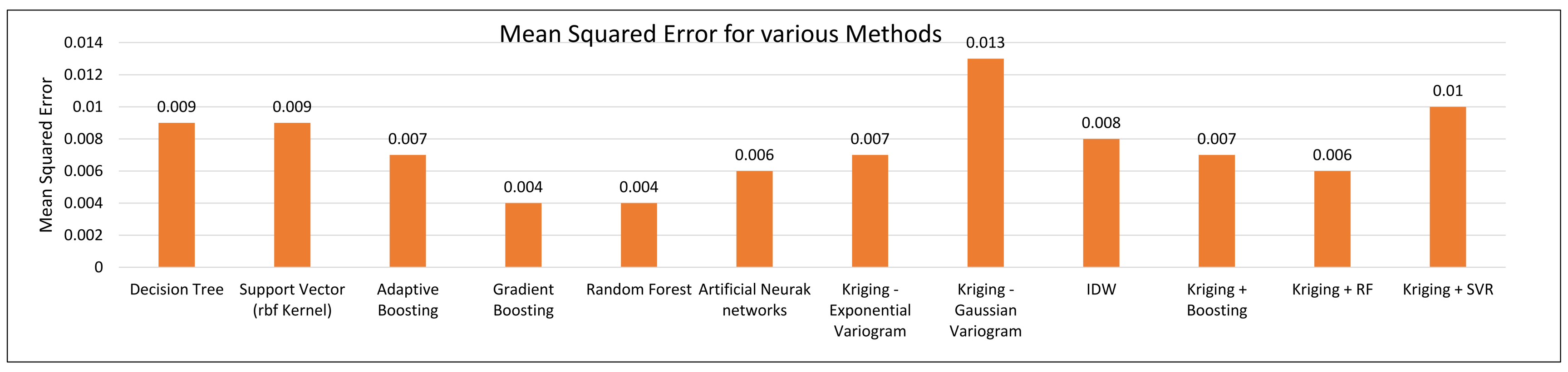
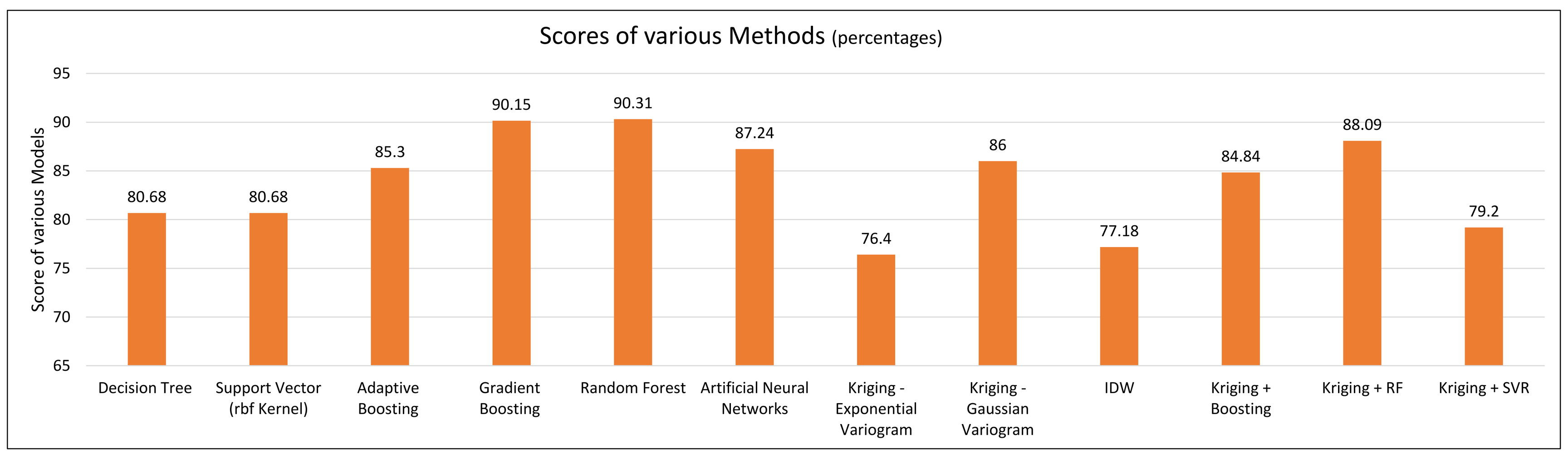


Figure 13. Variogram Models varying with no of bins [6,10,15]





Conclusions:

Kriging Algorithms and Variograms:
- Kriging algorithms gave better results for 'levelled Depth' values as compared to original depth values.
- Exponential Variogram model resulted the least mean-squared error whereas Gaussian variogram model scored the highest amongst the six models used.

Machine Learning Algorithms:
- These too estimated better properties over the 'levelled Depth' as compared to original depth attributed to variation in heights for well logs.
- Adding new features such as 'Normalised Depth' and 'length of reservoir' certainly proved to be useful.
- Random Forest performed better than others for the density estimation.

Artificial Neural Networks:
- Adam optimizer proved to be the best for training the neural network more efficiently in less time.
- The dataset requires to be worked with the normalized depth values for best results.

Combined methods is a novel approach, and proved to be highly accurate for prediction with prediction error less than the machine learning algorithms alone.

REFRENCES:

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- Static Reservoir Modeling using Geostatistics Method: a case study of the Sarvak Formation in an offshore oilfield, Rahimi and Riahi, 2020
- A parametric study of machine learning techniques in petroleum reservoir permeability prediction by integrating seismic attributes and wireline data,2019
- Artificial Intelligence Applications in Reservoir Engineering a Status Check, Ertekin and Sun, 2019

FUTURE OUTLOOK:

- Integration of Seismic data with wireline log data may results in variations for estimates by different methods. These variations can provide a deep insight into the practical situation.
- Availability of larger testing dataset can be another assets to deal with the challenges involving non-linearity of properties with original Depth values for actual well-logs.

Acknowledgement:

1. IIT Roorkee and SPARK team for the opportunity to work and learn.
2. Department of Earth Sciences for providing all the resources.