“Empowering the Energy Sector with AI: Forecasting Well Bottom Hole Temperature with Machine Learning Techniques on Geophysical Data”

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Introduction

- BHT is the temperature of fluids or rocks at the bottom of an oil or gas well.
- It is a critical parameter for determining well productivity in the oil and gas industry.
- Accurate BHT calculations are essential for optimizing drilling, completion, and production operations.
- Helps to identify reservoir properties and assist in reservoir characterization and modeling.
- Predicting BHT of new locations can save time and money by avoiding unnecessary drilling and testing operations.

Objectives

- Develop a machine learning model that accurately predicts well bottom hole temperature.
- Implement the model to reduce the need for costly and time-consuming drilling while optimizing energy sector performance.
- Utilize the model to identify trends and patterns in the data, enabling better resource allocation and management.

Data Collection

Source: These files are part of a larger dataset uploaded in support of Low Temperature Geothermal Play Fairway Analysis for the Appalachian Basin (GPFA-AB, DOE Project DEEE0006726).

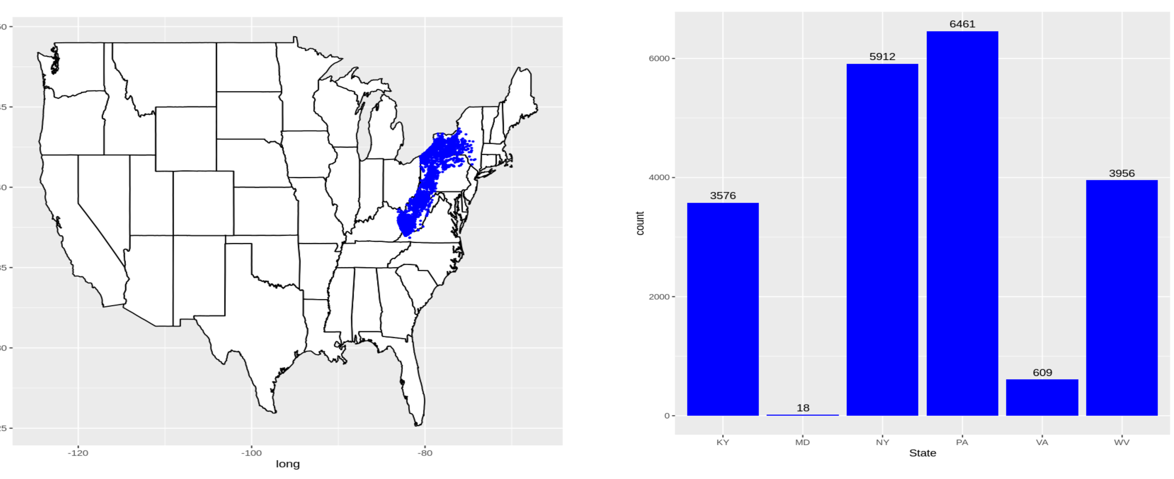

Figure 1: Locations of Wells based on State

Table 1. List of Predictor Variables used in the model

State	LatDegree	LongDegree	True vertical Depth
Reported Elevation	BHTReg	Basement Depth	Surface Temperature
Driller Total Depth	RomeID	Layer 0-18	Cond 0-18

Methodology

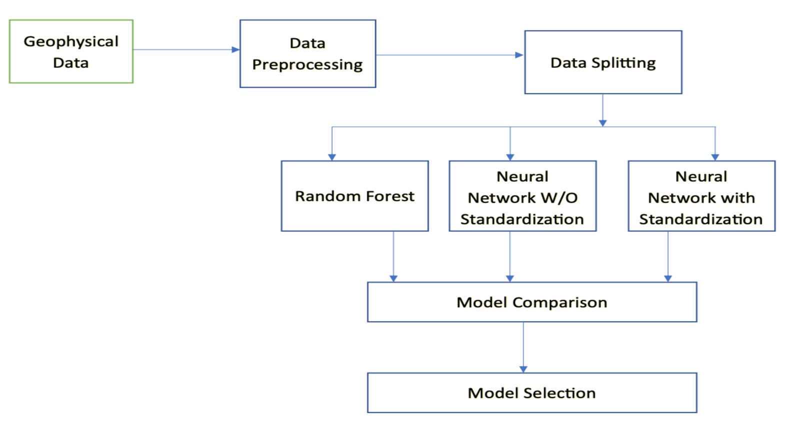

Figure 2: Block Diagram for the Forecasting Well Bottom Hole Temperature

Result 1: Random Forest

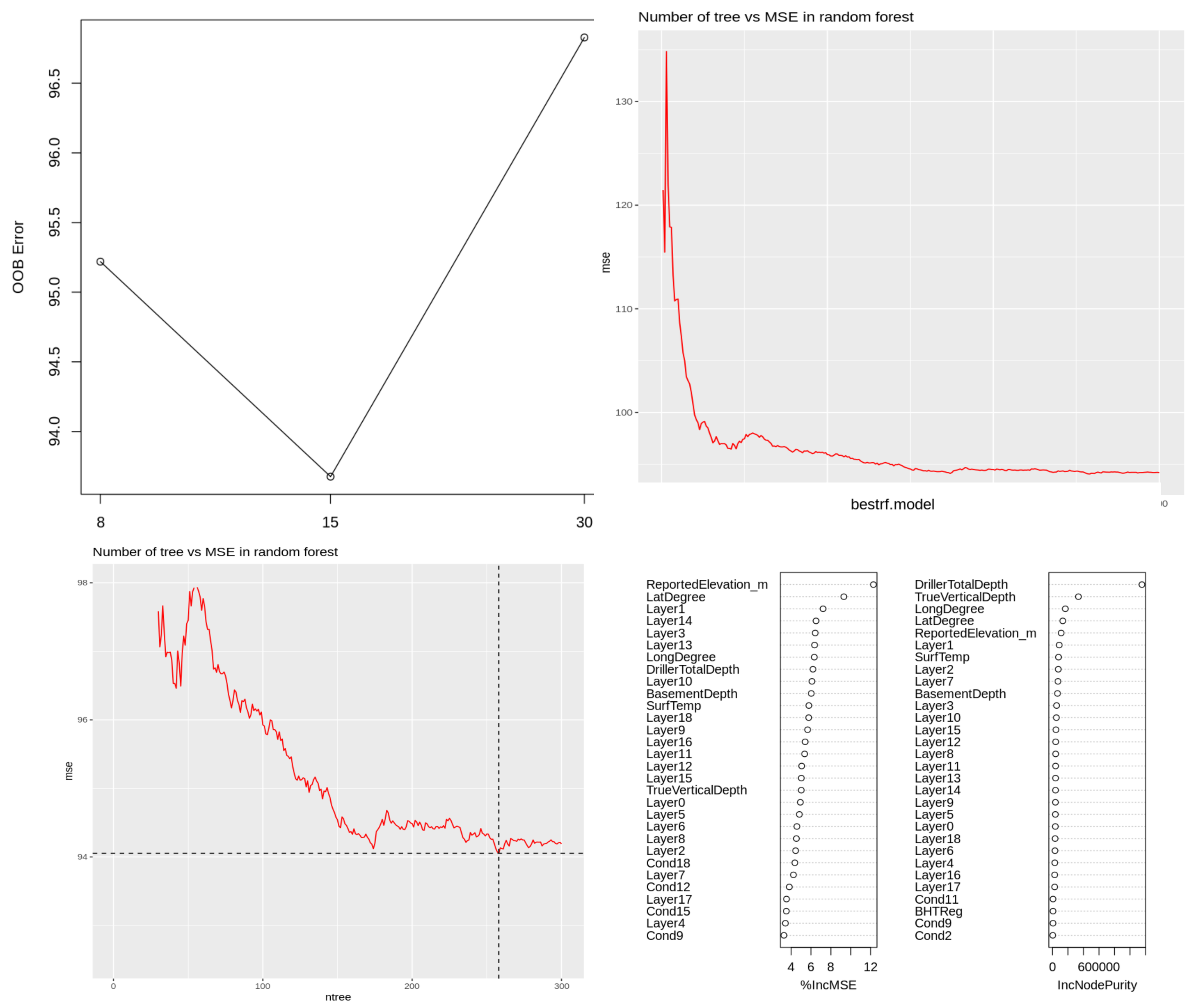

Figure 3. Deciding the optimal number of predictor variables for a decision tree. The ideal number of trees is discovered to be 258 when the mean squared error (MSE) is compared with the selection of random trees. This procedure also identifies the most significant predictor variables.

Result 2.0- Neural Network

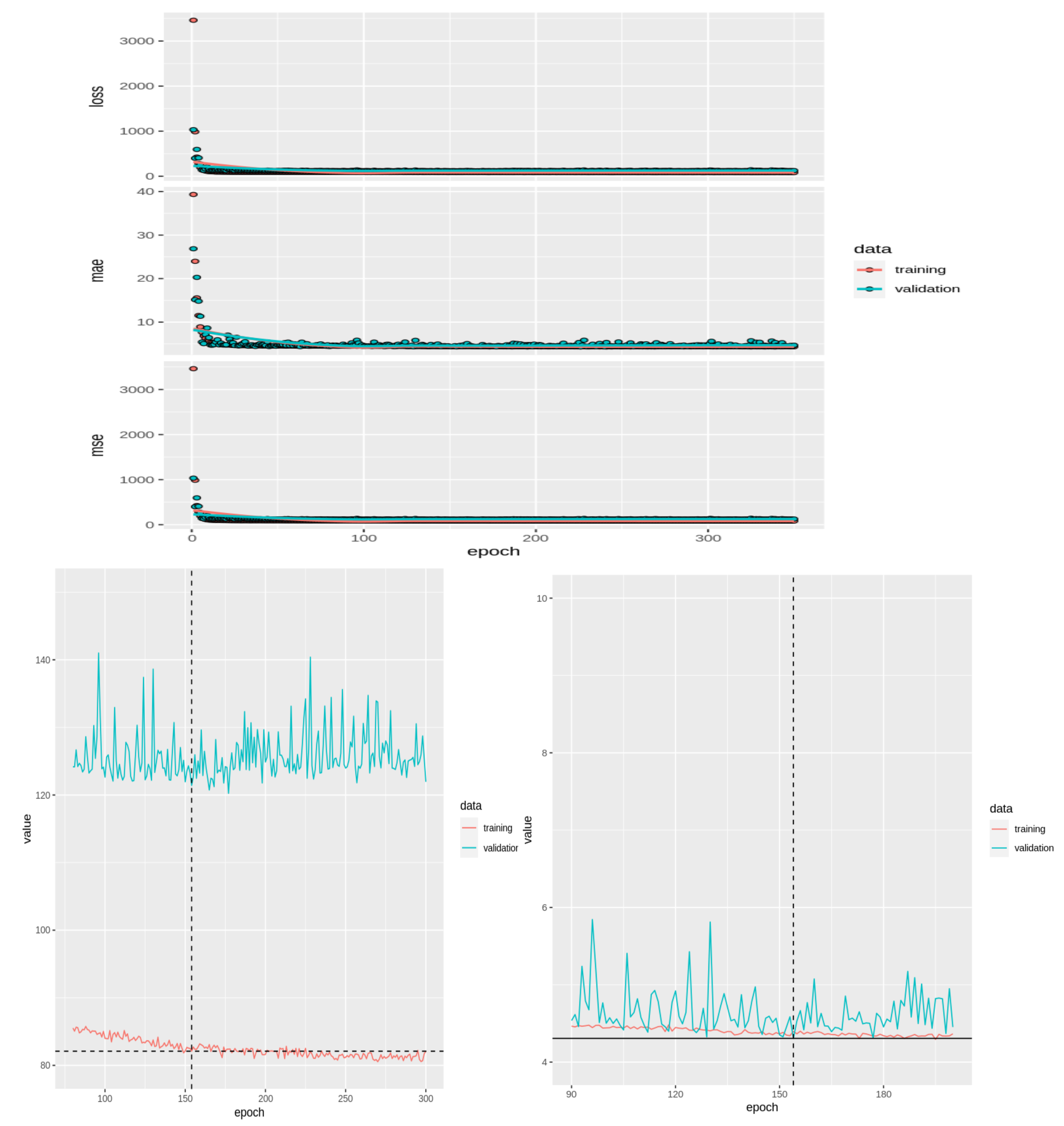

Figure 4. Deciding the optimal number of epochs based on MAE and MSE. The ideal number of epochs based on MAE is 154 and for MSE is 157. And the overall optimal epochs thus obtained is 154.

Result 2.1 - Neural Network

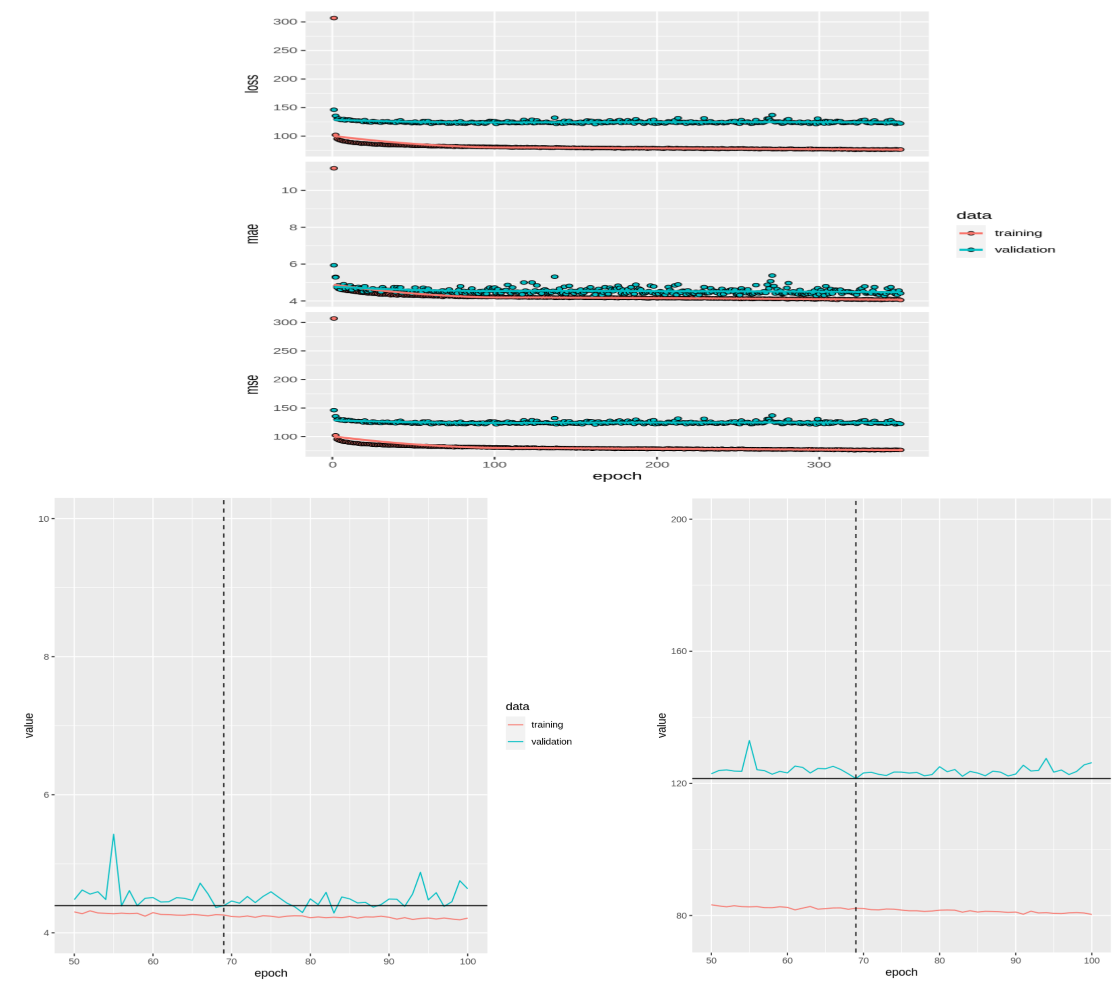

Figure 5: Deciding the optimal number of epochs based on MAE and MSE for the Neural Network with Standardized data. The ideal number of epochs based on MAE is 68 and for MSE is 69. And the overall optimal epoch thus obtained is 68.

Summary and Discussion

Table Comparision for the different models

	Random Forest	Neural Network(W/O standardization)	Nural Network (With Standardization)
Minimum Absolute Error	0.0001	0.0006	0.0002
Mean Absolute Error	4.0012	4.2177	4.2724
Max Absolute Error	81.1143	117.7012	93.775
Mean Sum of Square Error	49.4822	53.6541	55.6573
Correlation	0.8493	0.8375	0.8353

Significance and Future Enhancements

- Random forests can be used to reduce costly and time-consuming drilling operations while optimizing the energy sector performance.
- By combining different source of data like weather data and production data, it may be possible to develop more accurate and comprehensive model

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