



# Reading Report 6

A Physics-Guided Deep Learning Predictive Model for Robust Production Forecasting and Diagnostics in Unconventional Wells



# Introduction

#### Goal:

Predict well performance to improve reserves estimation and optimize production

#### Solution:

A physics-guided deep learning model that integrates well properties to forecast production

## Key Features:

Multi-task learning (forecasts production, estimates reserves, aids diagnostics) and Extended Capability to handle properties outside the training data range

## Application:

Tested on Bakken Shale Play data for robust, accurate forecasts



# **Challenge of Hydrocarbon Production**

- Problem:
  - Conventional reservoir models introduce significant errors when applied to unconventional reservoirs
- Challenges:
  - Complex fracture networks and geomechanical interactions make predictions difficult
  - Existing simulations are based on assumptions for conventional reservoirs, leading to inaccurate forecasts



# Deep Learning to the Rescue

#### Solution

A deep convolutional neural network (CNN) helps to improve predictions by:

- Simulation errors
- Oil production
- Well success rates

## Impact

- Multi-Task Learning: Tackles multiple predictions at once—saving time and improving accuracy
- Augments Traditional Models: Blends physics with data insights for way better forecasts



# **Production Prediction Model**

## Model Components

## Inputs $(I_1)$ :

Well properties ( $x \in R_{,n}$ ), processed through fully-connected layers

## **Prediction Outputs:**

- O<sub>1</sub>: 1D Convolution for simulation error prediction (oil, water, gas)
- $O_2$ : Scalar output for cumulative oil production  $(y \in R_1)$
- O<sub>3</sub>: Class label (low/mid/high performing wells)

## Training

- Implemented using Keras in Python
- Loss Functions:
  - · Mean-squared error for regression, cross-entropy for classification
- Multi-task loss optimization to improve all predictions simultaneously



# Results

#### Data Source

Bakken field data, including perforation length, proppant volume, treatment pressure, stages, and gamma-ray readings

#### Model Performance

Low prediction RMSE for the test set and scatter plots confirm strong prediction performance despite data noise

### Future Enhancements

~95% accuracy in classifying wells as low, mid, or high performers and misclassifications due to noisy data and complex relationships

## Prediction Accuracy

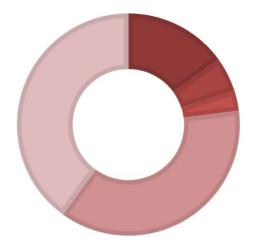
Model corrects simulation errors and effectively predicts cumulative oil production



# **Classification Results**

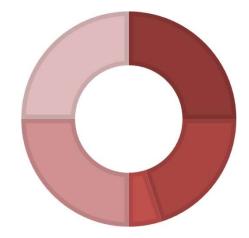
#### TRAINING DATA

- Actually C#1, Predicted C#1 Actually C#1, Predicted C#2
- Actually C#2, Predicted C#1 Actually C#2, Predicted C#2
- Actually C#3, Predicted C#3



#### **TESTING DATA**

- Actually C#1, Predicted C#1 Actually C#1, Predicted C#2
- Actually C#2, Predicted C#1 Actually C#2, Predicted C#2
- Actually C#3, Predicted C#3





# Conclusion

Research Need

Further exploration is essential for flow simulation models in tight formations

Hybrid Modeling

Combines data-driven methods with physics-based models to improve prediction accuracy

Multi-task Learning

Enhances generalization and reduces training data needs by predicting multiple metrics simultaneously

Future Work

Larger datasets and validation in complex scenarios are needed to refine the modeling approach



# **Quiz Question**

 Question: What are the reasons why traditional reservoir simulation models might not accurately predict outcomes in unconventional oil and gas resources?

### Answer:

 Conventional reservoir simulation models may introduce errors in unconventional resources due to several limitations. They often fail to account for complex fracture networks, which are common in unconventional reservoirs. Additionally, these models rely on outdated mathematical techniques that may not be suitable for the unique characteristics of these resources. Furthermore, traditional models are typically not designed for tight formations, such as those found in shale or tight gas reservoirs. Lastly, they often fail to effectively model geomechanical interactions, which are crucial for accurately predicting behavior in unconventional settings. These limitations can lead to significant inaccuracies when conventional models are applied to unconventional resources.