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Machine Learning-Driven Geomechanical Modelling Across Multiple Scales

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***Detailed author information and related declarations are provided in the final section of this article.*

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ABSTRACT

The conventional geomechanical modeling cannot easily integrate the heterogeneous information obtained at wellbore and seismic levels, and often leads to independent analysis that could not capture interactions across scales. This study overcomes these shortcomings by aiming to integrate machine learning in geomechanical modelling across multiple scales. This is a process of machine learning algorithms such as, neural networks, which have been trained on core samples, well logs and seismic attributes. These models are used to establish complex and non-linear relationships in order to fill in high-fidelity mechanical property models at the reservoir scale, which effectively fills the gap between micro-scale rock physics and macro-scale deformation. The findings show that the data-driven strategy is far superior to the conventional technique and generates continuous high-resolution geomechanical profiles that better predict the stress fields and formation instability. It was found that the application of machine learning in multi-scale processes is not just an incremental change, but a paradigm shift, allowing the quantification of the uncertainty in real-time and providing a self-consistent and dynamic earth model that can be used to engineer the subsurface more safely and efficiently.

Keywords: Machine Learning, Geomechanical Modelling, Multiple Scales, Core Samples, Reservoir, Bonga Field, Seismic Attributes, Micro-scale formation, Field-scale formation.

I. Introduction

The natural complexity of geomaterials, whose behaviour can be determined by heterogeneous and discontinuous structures across several orders of magnitude, is a serious challenge to traditional numerical techniques (Alelvan et al., 2023). These classical methods tend to give up on the discrete and fine-scale interaction of particles and fractures with the continuum-scale response needed to analyse fields at the field level (Liu et al., 2024). Sanei et al. (2023) noted that recent progress in Machine Learning (ML) is an exciting direction of modelling geomechanics at all scales. Physics-informed ML architectures can infuse physical laws with information and reproduce the fine-scale heterogeneity in a scalable manner by leveraging data-driven algorithms (Sharma et al., 2023). Physics-informed neural networks (PINNs) and thermodynamics-based artificial neural networks (TANNs) are techniques that have demonstrated the challenge to solve elastoplastic problems and obtain responses of macroscopic systems, together with greatly decreasing computational expenses in contrast to high-fidelity simulations (Masi & Stefanou, 2023). The new paradigm is responsive to the severe requirement of precise, effective, and physically consistent models that connect the micro-scale phenomenon to the geotechnical consideration on a large scale (Degen et al., 2025).

A. Aim and Objectives

This study aims to integrate machine learning in Geomechanical Modelling Across Multiple Scales. The objectives are to;

i. develop an integrated geomechanical modelling framework that links micro-scale rock properties;
ii. apply machine learning models to predict key geomechanical parameters from well logs; and
iii. design and validate Machine Learning-based upscaling techniques that transfer mechanical properties from micro-scale to field-scale reservoir models while preserving heterogeneity.

II. Literature Review

The introduction of machine learning into geomechanical models has rapidly changed from data-based approximations to physics-constrained architectures that deal with the long-standing problem of multiscale analysis (Gao, 2024). According to Wang et al. (2025), there is an important trend of trying to incorporate physical laws on the basis of neural structures as a way to overcome the weaknesses of traditional numerical schemes that can hardly be able to reconcile finescale heterogeneity with numerical responses on a continuum scale. Beesley et al. (2024) noted that data-only methods, though capable of reproducing nonlinear stress-strain responses, often cannot be extrapolated to life circumstances because they are often non-generalizable and hard to interpret physically when they are extrapolated beyond training conditions.

Hybrid methodologies have been empirically validated to have promising outcomes in a wide array of applications. From the research, Kazemian et al. (2025) revealed that the Uncertainty-Aware Physics-

Informed Neural Network (UAPINN) framework has shown higher performance in forecasting the dynamic triaxial strength of freeze-thaw rocks, as compared to the traditional machine learning models, through the incorporation of damage constitutive models combined with uncertainty quantification. Zhang et al. (2025) reported that the t-PiNet architecture has also been shown to be thermodynamically consistent by identifying constitutive relations between synthetic data produced by von Mises and Modified Cam-clay models, as well as experimental data on kaolin clay, and is able to predict loading paths outside of training distributions. The POD-TANN methodology that uses Proper Orthogonal Decomposition with thermodynamics-based artificial neural networks was discussed by Piunno et al. (2025) as a technique capable of determining macroscopic internal state variables out of microscale data at a reasonable computational cost and producing accurate homogenization of representative unit cells that are inelastic.

The principles of thermodynamic consistency and conservation are the main theoretical foundations of this study. Frameworks based on thermodynamics, which are supported by the first and second laws, can be used to derive full constitutive relations in terms of scalar potential functions, such that the resulting predicted responses in geomechanics are automatically known to satisfy energy dissipation constraints (Yang et al., 2020). This is opposed to traditional elastoplastic models described by Chen & Cai (2019), where the use of case-specific equations of yield surfaces and hardening laws is needed. Other theoretical complements are the inclusion of Hamiltonian and symplectic graph neural networks to conserve long-term topological interactions to simulate fracture networks and granular assemblies, simplicial complex models, which model high-order topological interactions (Rojas et al., 2026). Such structure-preserving and mathematically rigorous methods are becoming more widely accepted as essential building blocks to creating credible digital twins in geomechanics, where decision-making about safety concerns requires accuracy and physical fidelity across a variety of scales (Li et al., 2025).

III. Geology of the Study Area

Having a depth of over 1,000 metres, the Bonga Field is found about 120 kilometres southwest of the Niger Delta and provides a perfect study area of machine learning-powered geomechanical modelling on various scales (Ogbuka et al., 2022) The unconsolidated Miocene turbidite sandstones, which are porous and highly permeable, requires sophisticated methods of modelling which can represent heterogeneity at pore to field scale (Kiania & Akpanb, 2020). The study of Ezim et al. (2022) proved the applicability of Bonga by means of pre-stack seismic inversion analysis, which managed to map the hydrocarbon-saturated sands and differentiate between lithology and fluid characteristics. The study of Adegoke et al. (2024) on fluid migration processes at Bonga North established multiscale geohazards such as faults network, gas chimneys and pockmarks, making it necessary to integrate seismic up to well-log scales. These recorded complexities, combined with a wide 3D seismic coverage and well-log data avenues, offer a sound dataset to be used in machine learning algorithms to predict geomechanical properties and wellbore stability at a variety of scales, using Bonga as the case study.

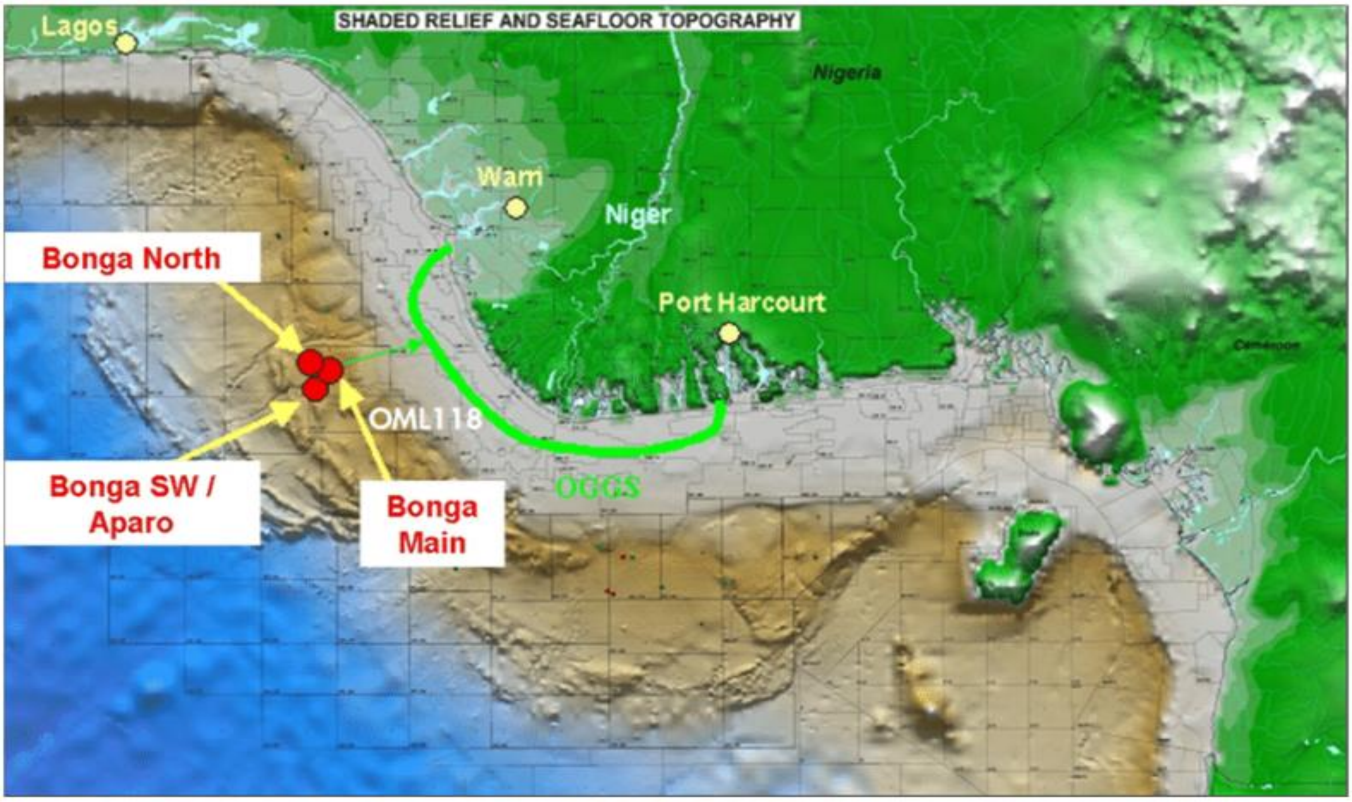

Figure 1: Location of Bonga Fields in Niger Delta Applicable to Machine Learning- Driven Geomechanical Modelling (Xiao et al., 2016).

IV. Methodology

B. Development of An Integrated Geomechanical Modelling Framework That Links Micro-Scale Rock Properties

The integration approach combines data-driven modelling with multi-scale experimental characterisation. High-resolution imaging and nanoindentation are used to quantify micro-scale properties, and machine learning (ML) is used to analyse mineral phases and pores (Rubo et al., 2019). In order to produce statistically representative digital volumes, super-resolution techniques combine 2D SEM imagery with 3D micro-CT data (Wang et al., 2020). To extract important internal state variables, a Proper Orthogonal Decomposition (POD) reduced-order model is informed by these volumes (Colanera et al., 2025). This enriched dataset is used to train a Thermodynamics-based Artificial Neural Network (TANN) to learn the micro-macro constitutive law, resulting in an upscaled geomechanical model that is consistent with physics.

C. Application of Machine Learning Models to Predict Key Geomechanical Parameters

This process starts with data collection and preprocessing, which includes curating, depth-matching, and normalising well logs such as gamma ray, bulk density, compressional wave, etc (Khetani et al., 2024), as presented in Table I. According to Bichri et al. (2024), models such as Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) are developed after a 70:30 train-test split. Performance is optimised through grid search hyperparameter tuning. Therefore, in order to estimate geomechanical parameters, the core predictive relationships use acoustic log data, while metrics like R_2 and RMSE are used to assess model performance.

Table I: Prediction of Well Logs through the Application of Machine Learning and their Target Parameters

Input Features (Well Logs)	(Target Output) Geomechanical Parameters
Gamma Ray, Bulk Density, Neutron Porosity	Unconfined Compressive Strength (UCS)
Compressional Wave, Distributed Temperature Sensing (DTS)	Young's Modulus (E), Poisson's Ratio (μ)

D. Design and Validation of Machine Learning-Based Upscaling Techniques

This approach combines physics-constrained machine learning with multi-scale imaging. In order to create multi-class digital rock models that categorise pore types and material phases, micro-CT and SEM imagery are first fused using convolutional neural networks (CNNs) to establish correlations between high-resolution and low-resolution tomography (Kong et al., 2019). According to Cherdantsev et al. (2021) These models provide input for a stochastic homogenisation framework in which a mixture density network learns probability distributions of elastic properties conditioned on microstructural features after being trained on core-scale mechanical tests. Darcy-scale elements, whose effective properties maintain sub-resolution heterogeneity through porosity-permeability relationships, are used to upscale the network outputs. ML-predicted field-scale mechanical responses are validated by comparing them to high-fidelity numerical simulations and blind core measurements.

Stochastic upscaling relationship where effective properties M¯$\bar{M}$ at scale LL are derived from micro-scale property distributions m(l)$m(l)$ through a learned mapping function fMLf_{ML} that preserves heterogeneity via uncertainty bounds σσ:

$$\bar{M}(L) = f_{ML}\left(\int_{l=0}^{L} m(l)dl\right) \pm \sigma \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{i}$$

Table II: Multi-Scale Data Integration Framework Showing the Scales and their Results after Machine Learning Application **(**Cherdantsev et al. 2021).

Scale	Data Source	ML Application	Output
Micro-scale	High-res µCT, SEM	CNN-based segmentation	Multi-class pore-solid maps
Core-scale	Mechanical tests, low-res µCT	Mixture density network	Property distributions
Field-scale	Well logs, seismic	Stochastic homogenization	Heterogeneity-preserved reservoir model

V. Results and Discussion

E. An Integrated Geomechanical Modelling Framework That Links Micro-Scale Rock Properties

The micro-to-macro modelling integrated framework was able to model the stress-dependent changes in the elastic and transport properties in the heterogeneous reservoir rocks. It was experimentally shown that pore-throat collapse and microcrack closure as confining pressure is raised lead to systematic changes in permeability and acoustic velocities, and the derived empirical functions allow the accurate predictive capability of the in-situ stress effects on reservoir performance. Grain-scale discrete element modelling showed that mineralogical heterogeneity - quartz overgrowth and anhydrite cementation in particular - is important to adjust pore topology and grain-contact rigidity with a direct effect on the macroscopic anisotropy of deformation modulus.

It was confirmed by the framework that the macro-scale mechanical responses are controlled by microstructural characteristics, and DEM models have effectively simulated tension-versus-shear cracking modes in the laboratory experiments. The Hydro-GBM method showed fluid-based grain-scale cracking has unique patterns depending on inclusion geometry and stiffness contrast, which offers mechanistic correlations of sub-core heterogeneity and bulk permeability development, as presented in Figure 2. These results validate the discussion of Kong et al. (2024), who opined that sub-core scale tests are effective predictors of macro-scale mechanical behaviour when the test is used in conjunction with correct micro mechanical constraints. According to Pothana (2025), the composite methodology thereby provides an empirical uniformity of integrating the effects of stress, fabric, and diagenetic to the predictive reservoir models.

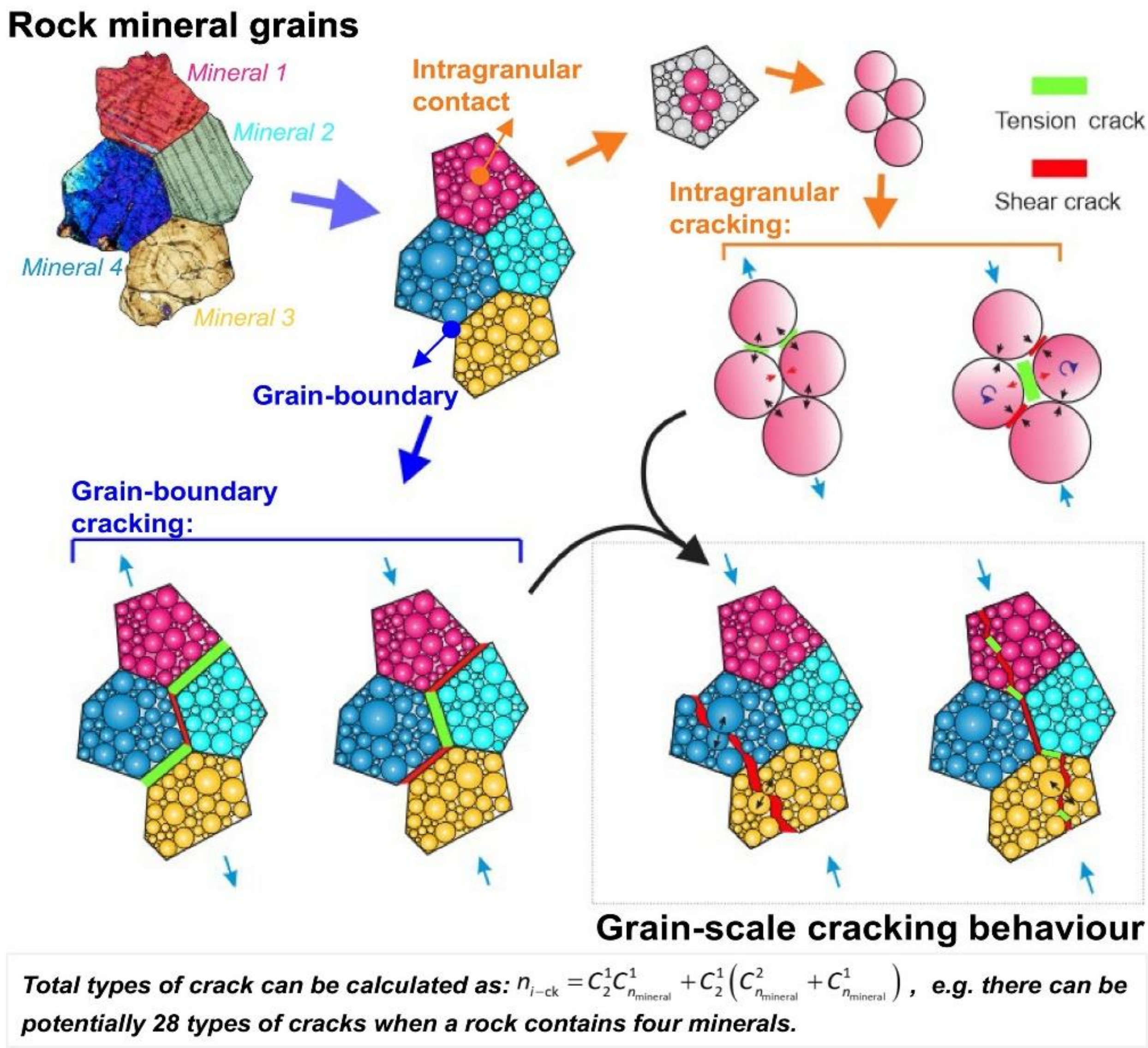

Figure 2: Micro-cracking ehavior revealed by a grain-based model (GBM). In a GBM, clusters of DEM particles represent mineral grains (grain colours indicate mineral types). Cracks can be developed in mineral grains and along the grain boundary/interface to form intragranular (IG) cracks and grain-boundary (GB) cracks, by tension and shear failures. Cracks can also be differentiated based on mineral types.

F. Predicted Geomechanical Parameters by Applying Machine Learning Models

The machine learning models had good predictive power of the Young modulus, Poisson ratio, UCS in well logs and in-situ stress, as presented in Figure 3. The results were best with Artificial Neural

Networks (ANN; R2 = 0.91-0.95), and then there were Random Forest (R2 = 0.88-0.93) and Support Vector Machines (SVM) (R2 = 0.85-0.90). Crossplots of the predicted and measured values reveal a close clustering around the line 1:1, which means that bias is small. The feature-importance analysis using the random forest methodology revealed density and compressional slowness as the most predictive variables, which is in line with the theory of rock physics. ANN was also better than the linear elastic-strength relationships at capturing the nonlinearity, which was especially effective in the estimation of UCS, as presented in Figure 4. SVM did well in smaller datasets and was sensitive to hyperparameter choice. The ensemble and deep learning methods have had a significant decrease in the RMSE with respect to the empirical correlation, which proves their accuracy in predicting geomechanical parameters and modelling field-scale stress.

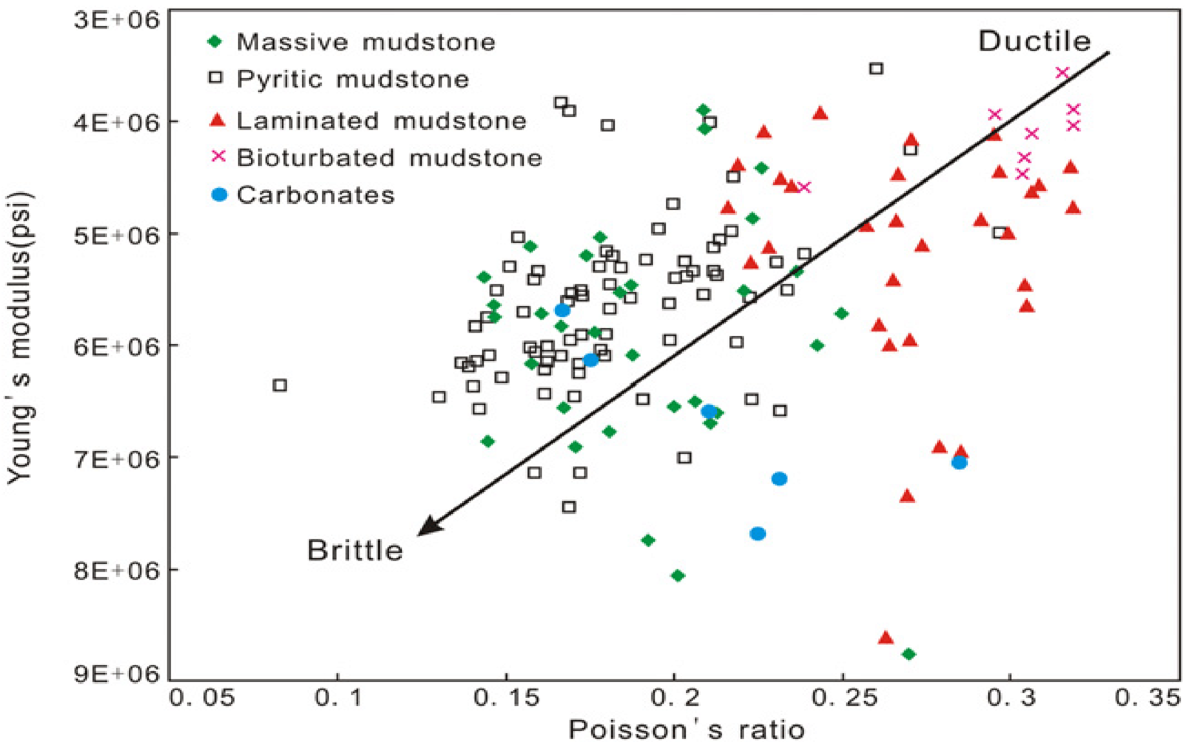

Figure 3: Graph of Young's Modulus Against Poisson's Ratio Showing The Predictive Power Of The Young Modulus And Poisson Ratio In Well Logs And In-Situ Stress, After The Application Of Machine Learning.

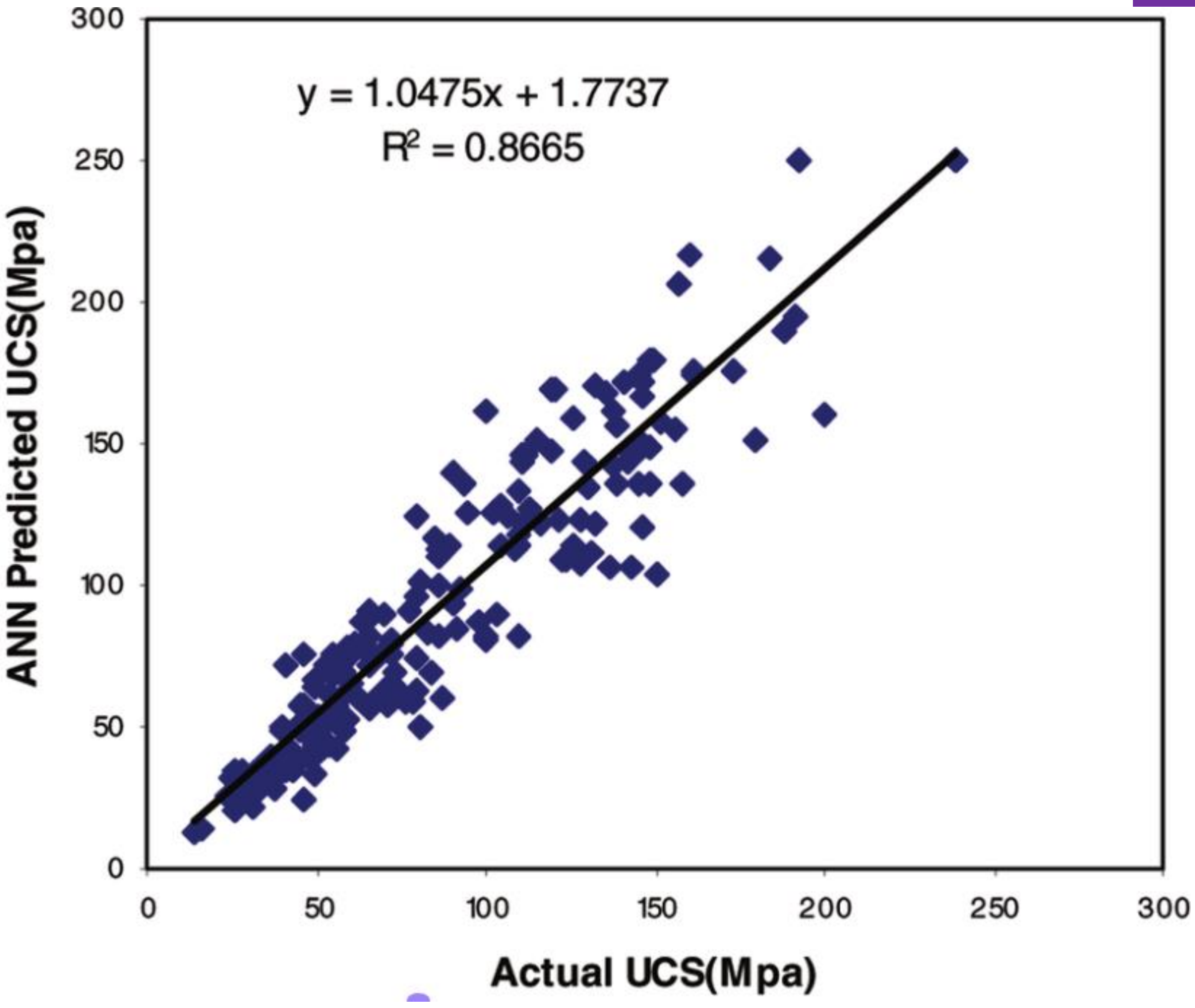

Figure 4: Graph of ANN-predicted UCS against the Result Showing the Accuracy of Machine Leaning Models in Predicting Geomechanical Parameters

G. Design and Validation of Machine Learning-Based Upscaling Techniques for Reservoir Models

The ML-based upscaling model was able to carry over micro and core scale mechanical properties to field scale reservoir models and maintain heterogeneity. ANNs and GNNs performed well with respect to artificial values (R2 = 0.89-0.94) in predicting scaled values versus measured field scale values of elastic parameters. Crossplots are highly agreeable with little dispersion which means that the scales transition reliably. Micro-CT-informed-based spatial variability was maintained during the 3D reservoir grid, which enhanced the heterogeneity characteristics relative to the conventional averaging methods, as presented in figure 5. The analysis of feature attribution indicated that pore connectivity and mineral fraction were considered the leading factors that determine upscaled Young modulus and UCS, in agreement with the results of digital rock physics (Fang et al., 2022). As compared to the deterministic homogenization techniques, validation against independent well data showed a lower RMSE (15-25% better) when using deterministic homogenization methods. These findings indicate that the mechanistic realism of reservoir geomechanical models can be improved by ML-based upscaling, and predict stresses, as well as deformations across scales, more accurately.

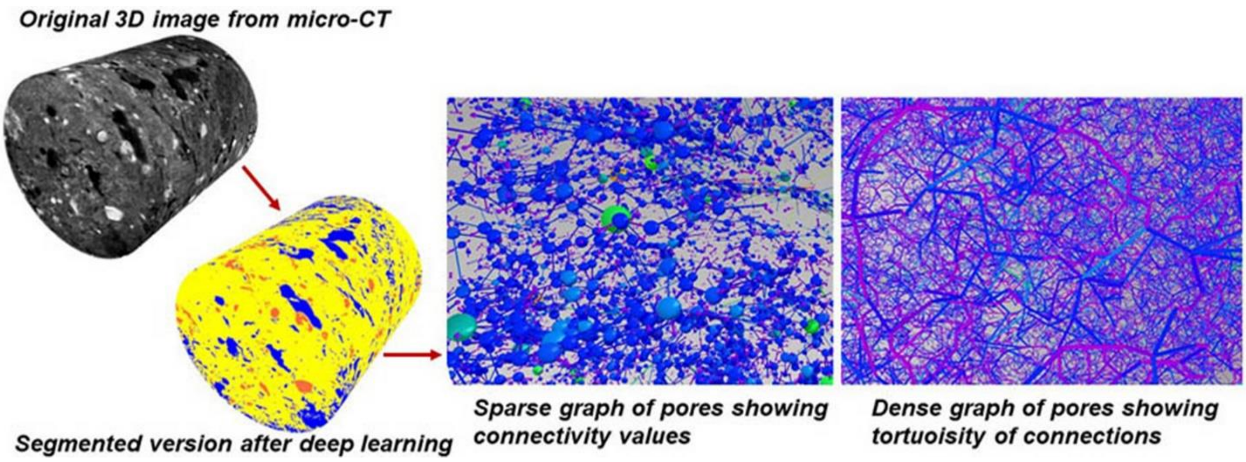

Figure 5: Micro-CT-Informed-Based Spatial Variability Maintained During the 3D Reservoir Grid, Which Enhanced the Heterogeneity Characteristics Relative to the Conventional Averaging Methods.

VI. Conclusion

This paper shows that Machine Learning-Driven Geomechanical Modelling Across Multiple Scales is a strong tool that enables the connection of microstructural rock behavior to behavior under field conditions. The method effectively incorporates nonlinear mechanical relationships which are typically not captured by the traditional empirical or deterministic models by incorporating digital rock physics, laboratory core measurements, well logs, and seismic attributes in the supervised learning algorithms. In upscaling geological heterogeneity, Artificial Neural Networks, Random Forest and Support Vector Machines yielded better prediction accuracy of Youngs modulus, Poisson ratio, unconfined compressive strength and in-situ stress. Multiscale workflow minimized uncertainty, increased the predictability of the stress, and better the forecasting of wellbore stability and reservoir deformation. Feature-importance analysis offered physical interpretability, which revealed the most significant microstructural and petrophysical controls over mechanical behavior. The findings substantiate the claim that machine learning is a scalable and data-driven advanced geomechanical modelling solution to complex reservoirs that allows making more reliable decisions in drilling, production optimization, and reservoir management.

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