The International Journal of Engineering and Science (IJES)
|| Volume || 14 || Issue 8 || August || Pages || PP 20-29 || 2025 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

An Integrated Deep Learning Solution for Petrophysics, Pore Pressure, And Geomechanics Property Prediction.

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--ABSTRACT---

This paper is a proposed deep learning application to do integrated petrophysical, pore pressure and geomechanics property prediction in unconventional hydrocarbon reservoirs. Simple modeling methodologies in use do not help much in capturing the non-linear multi-attribute interactions that were common in the subsurface conditions (particularly the complex formation in the Permian Basin). To give concurrent estimates of porosity, permeability, pore pressure, Youngs modulus and Poissons ratio, this paper creates a multi-output deep feed forward neural network that is trained on both well logs and seismic-derived properties. Large volumes of preprocessing, feature engineering, and optimization algorithms were used to improve the amount of accuracy and generalizability of models. It tests well on the results which proved to have excellent predictive performance when compared with the traditional deterministic models in terms of accuracy, time-efficient and scalability. SHAP and sensitivity analysis are techniques to interpret the model and prove any geological relevance of its predictions. Moreover, volumetric modeling made on the seismic data enabled the extension of the prediction beyond the wellbore-level to the full-field. The paper offers the possibilities of applying deep learning to transform the way of reservoir characterization, decrease turnaround time and enhance decision-making associated with developing unconventional resources.

Keywords: *The petrophysics, deep learning, pore pressure, geomechanics, machine learning, unconventional reservoirs.*

Date of Submission: 04-08-2025 Date of acceptance: 14-08-2025

I. Introduction

1.1 Background

The advent of unconventional reservoirs including shale gas, tight oil, and coalbed methane uprooted the energy scenario in the last two decades tremendously. Low permeability, complicate mineralogy and geological heterogeneity are typical facts about unconventional reservoirs as compared to conventional hydrocarbon plays. Hydrocarbons in these reservoirs need vigorous stimulation activities that include hydraulic fracturing and horizontal drilling to open up commercial viability (King, 2020). The depth of operations has also shown a great surge in well development in various regions of the United States such as the Permian Basin, Eagle Ford, and Bakken formations with drilling activities going to new heights (EIA, 2023).

With this heightened activity however there arises a rise in technical and analytical problems. Unconventional reservoirs are commonly characterized by complex stratigraphy, heterogeneous lithological characteristics, poorly predictable diagenetic modifications, and heterogenous stress situation making property foretelling in their submarine somewhat challenging (Zhang et al., 2022). Furthermore, the state of geomechanical behavior in these plays is quite sensitive to pore pressure, mineral composition, natural fractures, and the stress anisotropy, which can hardly be secured with conventional estimations (Chopra & Marfurt, 2021). The rich interrelation between the petrophysical characteristics (such as porosity, permeability, and saturation levels) of the rocks, the pore pressure and rock mechanics introduces further twists and turns in the challenges of managing oil reservoirs and developing wells.

Historically, petrophysical and geomechanical characteristics have been estimated by a mixture of empirical correlations, deterministic rock physics models and the manual interpretation of wireline logs. Although these strategies have suited the industry over the past decades, they have some limitation especially when applied to the unconventional reservoirs. Interpretation of log data through Manual methods is both time-consuming, subjective and inconsistent on large volumes of data or between fields. Furthermore, the common calibration of traditional rock physics theories is based on core measurements or parameters measured in the laboratory, but which are unlikely to reflect in-situ conditions in a correct manner (Mavko et al., 2020).

The inability of classical workflows to exhaustively extract the wealth and range of data that is currently availed in the subsurface studies of data (such as seismic inversion products, drilling logs, microseismic data, and mudlogging information) presents another huge bottleneck. Combining such multi-scaled data in the framework of deterministics might be a hassle, as it becomes impossible and infeasible in most instances (Elsayed & AlKharusi, 2022). In addition to this, in cases where many wells (hundreds or thousands of wells) are involved, turnaround time becomes a crucial issue. The modeling and calibration iterative approaches are merely not scalable, which is why it is close to impossible to make quick predictions required to carry out field development planning (Rashid et al., 2021).

1.3 problem of the study

Since the rise of subsurface data and inabilities of the traditional methods to analyze them, the implementation of new artificial intelligence (AI) and machine learning (ML) technologies in geosciences is even more alluring. Machine learning and especially deep learning has the potential to solve problems that need to examine high-dimensioned, complicated data sets, with low human contingency. It has the potential to discover the obscured patterns, non-linear relationship, and multi-attribute dependency that might not be easy to estimate with the conventional models (Abedi et al., 2023).

Supervised deep learning traditions, i.e. artificial neural networks (ANNs), (convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to predict rock properties directly using log data with high accuracy and speed in petrophysical analysis. On the same note, increments of geomechanical parameters to include Young modulus, Poisson ratio, and fracture gradients have been obtained through AI applications that incorporate log-based, seismic derived, and drilling parameters (Jin et al., 2022). What is more, ML models can constantly learn new data, thus updating in real time and becoming more accurate in the future.

1.2 Aim and objectives

1.2.1 Aim

This paper seeks to establish and operationalize an integrated deep learning model to realize simultaneous petrophysical, pore pressure, and geomechanical property prediction using well log and seismic-based data to facilitate a better understanding of reservoirs and better decision-making in the unconventional hydrocarbon play.

1.2.2 Objectives

1) To generate and preprocess an entire data set with well logs and seismic-derived qualities of the Permian Basin.
2) To build and train a watched deep neural network that could represent multi-output regression decreasing porosity, permeability, pore pressure, Young modulus and Poisson ratio.
3) Statistical performance analysis To calculate model accuracy and robustness with the help of statistical performance metrics and blind testing of wells.
4) To implement regional extension of trained model to predict volumetric property based on the results of seismic inversion.
5) To compare the deep learning method and the traditional modeling techniques and evaluate their scalability, interpretability and benefits in operation.

II. Literature Review

2.1 Review on the past studies application of ML in petrophysics

With the increasing challenges of non-linear relationships and complicated patterns of your subsurface reservoir data, machine learning (ML) has come to be more forested into petrophysical analysis to maintain current trends. Deterministic models and empirical correlations are conventional methods that fail to perform well when handling multi- variate dependencies and heterogeneous formations. This has prompted scientists to resort to some sort of supervised learning model to enhance better estimates of important petrophysical properties such as porosity, water saturation, permeability, and volume of shale using modus operandi like Artificial Neural Networks (ANNs), Random Forests (RF) and Support Vector Machines (SVMs).

As an example, Al-Anazi and Gates (2020) used Al-Anazi and Gates (2020) employed ANNs to forecast the permeability using conventional well logs and realized the enhanced predictive precision relative to conventional techniques. In the same way, Adhikary et al. (2021) are able to forecast total organic carbon (TOC) and lithofacies in unconventional shale reservoirs with high accuracy, exploiting ensemble ML methods. Their models worked sufficiently to picking up intricate non-linear trends that are largely overlooked with typical petrophysical interpretations. More recently, to automate the task of regression and petrophysical data classification based on well logs, emerging techniques like Convolutional Neural Networks (CNNs) and Deep Feedforward Neural Networks (DFNNs) have been used so far are deep learning methods (Bashari et al., 2022).

Furthermore, common application of machine learning has allowed the researchers to forecast petrophysical properties on a regional basis by uniting seismic characteristics and well log information. As another example, Panahi et al. (2023) used the seismic inversion results to show that this type of output in conjunction with supervised learning models could create volumetric porosity and net pay thickness distributions in offshore fields with very little core data.

2.2 Use Of ML In Pore Pressure Forecasting And Geomechanics

The methods that have been conventionally used to predict pore pressure as well as modeling geomechanics have been through empirical relationship, sonic interpretation of log and to some extent by core testing. Although these methods are fundamental, some of the drawbacks are poor geographical coverage and the reliance on expert opinion. The use of ML in this sphere can bring the opportunity to obtain pressure-related and mechanical properties more correctly and effectively.

A number of studies have indicated success in the estimates of pore pressure based on log derived attributes by the use of ML techniques. As an illustration, Wang et al. (2021) used Gradient Boosted Trees (GBT) and LSTM networks to determine pore pressure using time-depth curves and sonic logs in deepwaters. They dramatically minimized estimating error and also provided real-time drilling wellbore pressure control in drilling.

Tawfik et al. (2023) identified a method to predict the values of Young modulus and Poisson ratio based on seismic attributes, as well as well log data in the geomechanics field by creating a hybrid deep learning model. They were also of use to predict geomechanical properties within a poor well control zone. In a like manner, Jin et al. (2022) showed that combining drilling parameters and Wireline log data into a deep structured neural network could generate favorable estimates of breakdown pressure and fracture gradients, both of which are pertinent parameters in wellbore stability and well design during hydraulic fracturing.

A second new trend is the rise of surrogate ML models eliminating computationally costly equational simulations in mechanical earth modeling. This enables engineers to quickly execute numerous geomechanical conditions and perform well positioning optimization that does not take a long turnaround time (Fakhry et al., 2020).

2.3 Research Gap and Is Innovative the Integrated Deep Learning Method

Due to the advancements that have been made, mainly due to machine learning, on isolated sets of petrophysics, pore pressure and geomechanics, there is still so much more to do. The majority of current works concern domain-specific applications which is, models are usually trained on one property of interest (e.g. porosity or pressure) and the connections between different properties of a reservoir are often overlooked. Such closed system will constrain the model to generalize in different tasks, or to fully utilize the benefits of multi-domain datasets.

Furthermore, most predictive models are limited to small training data or calibration to a finite geographical area and are therefore hard to apply to new basin or formations. Hoping to combine different data types (e.g., seismic, wireline, and drilling data) into a single model, one cannot completely address the problem in practice at the moment (Elsayed & AlKharusi, 2022).

The present paper proposes a new integrated deep learning system that is able to determine petrophysical, pore pressure and geomechanical properties in a single pass. The most important innovation is the fact that it:

a) Integrate multi-source input (seismically based and well log),
b) Acquire deep interdependencies among the subsurface domains,
c) Minimize manual based calibration,
d) Speed up the prediction timelines that are days/weeks to hours/minutes.

III. Methodology

3.1. Preprocessing of Data and Data Collection

The diverse and representative data used to develop a strong and expandable deep learning system was derived and extracted using various sources in a chosen unconventional play (Permian Basin). The involved type of data includes the following:

Well Log Data: It includes such conventional wireline logs as gamma ray (GR), density (RHOB), neutron porosity (NPHI), sonic travel time (DT), resistivity (RT), and caliper logs. These inputs are essential characteristics of estimating porosity, permeability, pore pressure, and properties of the mechanical traits, as well as, (Youngs modulus, Poisson ratio) (Mavko et al., 2020).

Seismic-Derived Properties: The outputs of path-oriented seismic inversions, e.g. acoustic impedance, Vp/Vs ratio, seismic attributes (e.g. instantaneous frequency) were included. These data make the prediction powers of the model not only limited to well locations but also permit the volumetric modeling in the regions (Panahi et al., 2023).

3.1.2 Missing Data, Normalization and Labeling

The preprocessing of real world geological data is rigorous because data is frequently lacking and noisy. As in the case of deeper or deviated wells, missing log values were imputed through a mix of linear interpolation and k-Nearest Neighbor (kNN) algorithms in order to maintain data relationship (Rashid et al., 2021).

3.2. Neural Networks Structure

The planed deep learning model consists of a deep feed forward neural network (DNN) which has been chosen due to its adequacy in a regression problem in tabular data context with both well logs and seismic based features. The architecture will be able to deal with multi-output predictions of petrophysical, pressure and geomechanical properties at once.

Layers and model Design
Model includes the following:

a. **Input Layer:** Takes any of the standardised features (e.g. GR, RHOB, DT, impedance, Vp/Vs etc.).
b. **Hidden Layers:** Four hidden layers (all dense with 128, 64, 32 and 16 neurons respectively).
c. **Activation Functions:** non-linear transformation with the activation functions set to ReLU (Rectified Linear Unit) will be utilized on all hidden layers.
d. **Dropout Layers:** dropout layers are applied between dense layers at the rate of 0.2 in order to avoid overfitting (Srivastava et al., 2014).
e. **Output Layer:** Multi output regression layer that makes continuous predictions of porosity, permeability, pore pressure, Young modulus and Poissons ratio.

3.3. Training Virtual and Validation
3.3.1 Split of data

The data was divided to Training Set (70%): this is utilized in determining the parameters of the model. Validation Set (15%): It was used to watch over the performance of the model under training and to fine-tune the hyperparameters. Test Set (15%): a hold-out data to show how the model will generalize and perform at the end. Such stratified sampling allowed including various geological regions and formations in each split, eliminating data leakage and increasing the overall quality of generalizability.

3.3.2 Optimisation of Hyper parameters

Hyperparameters were best chosen with a grid search and Bayesian optimization scheme using, among others:

i) Learning rate (0.001-0.01),
ii) Batch size (32 128),
iii) Layers (3- 6),
iv) Layers, number of neurons: (32256),
v) Drop out rates (0.1-0.5).

Over fitting was avoided using regularization through L2 penalties and early stopping that was done according to the validation loss.

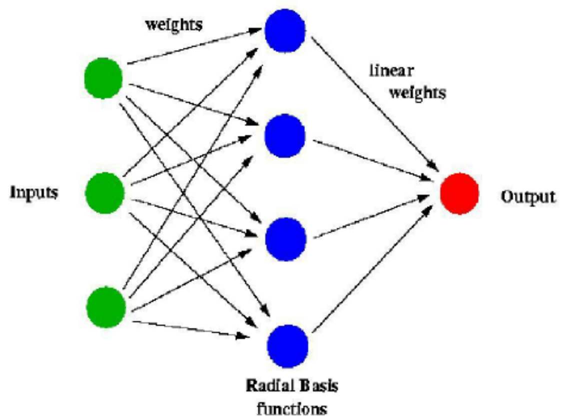

Fig 1: Block diagram of the proposed neural network architecture.

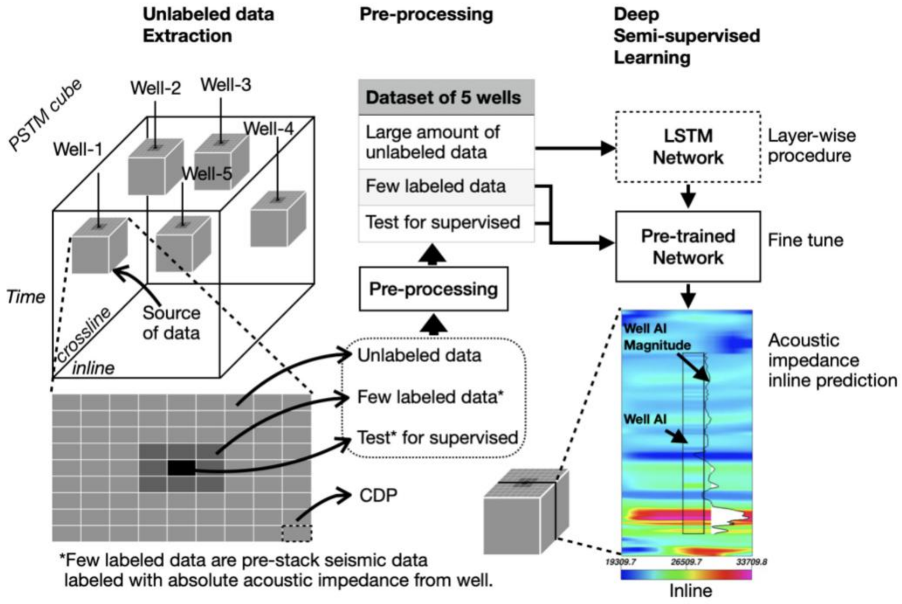

Fig. 2: Data pipeline from raw logs/seismic to prediction output.

3. 4. Case Study: Permian Basin

3.4.1 Geological Setting

WestTexas and the area of southeastern New Mexico, which is known as the Permian Basin, is one of the best studied hydrocarbon provinces in the whole world. Covering about 86 000 km 2, featuring a number of sub-basins, it is characterized by the Delaware Basin and the Midland Basin. Since the 1920s, the region has consistently produced considerable amounts of oil and gas, but its strategic significance has grown in the last decades with the occurrence of unprecedented drilling achievements like the horizontal drilling technology and hydraulic fracturing (EIA 2023).

The geology of the basin consists of a stratigraphic stack of reservoirs on an array of formations, rim-to-core, shallow carbonate and shale facies, to increasingly deep tight sandstones and siltstones. Under this model, the Wolfcamp, Bone Spring, Spraberry and Yeso intervals form the main unconventional target of the recent unconventional activities. The permeability of such reservoirs is low, and the concentrations of clay are high as well, and the lithological distributions are heterogeneous, presenting significant difficulties in relation to standardized reservoir modeling and characterization methods (Sharma et al 2022).

Sedimentary basin tectonics and depositional environments have produced variable stress environments, anisotropic mechanical behavior and abrupt changes in lithology, which directly affect the design of the drilling and completion. Therefore, proper representation of subsurface properties, especially the porosity, pore pressure and rock mechanical variables, is vital in the optimisation of well performance and its risk reduction.

Items entered in well well log include:

a) Gamma Ray (GR): it is possible to differentiate between shale units and clean formations, and lithologic changes can be identified.

b) Bulk density (RHOB): is critical in determining porosity and mechanical-property.

c) Neutron porosity (NPHI): this is applied together with RHOB to determine effective porosity and identify zone with hydrocarbons.

d) Sonic log (DT): the readings of the compressional and shear slowness were used to calculate Poisson ratio and elastic moduli.

e) Resistivity logs (RT, LLD, LLS): they are a vital part of fluid-saturation and pore-pressure studies.

f) Caliper and mud log: it provided borehole stability data and was able to correct interval of measurements on the well logs.

Seismic based inputs include:

a) Acoustic impedance (AI): derived on the basis of post-stack inversion and closely related with the lithology and fluid fill.

b) Shear impedance (SI): it is helpful in describing the fracture, mechanical, and elastic anisotropy.

c) Vp/Vs ratio: a delicate sign of lithology and pore fluid, of use in identification of the over-pressured intervals.

d) Instantaneous frequency, amplitude envelope and coherence: determined by attribute analysis to constrain structural and stratigraphic interpretation.

e) Elimination of Poisson ratio and Young modulus: Seismic inversion data provided supplementary estimates of the parameter which was not available in the areas where direct well log measurements were not made.

Incorporation of these data sources to the deep learning system allowed multi-dimensional analysis and development of regional property predictions, even in those areas having scarce well control. A uniform regime of log templates guaranteed consistent preprocessing and feature extraction, which is the first requirement of a successful model that will be generalized to many formations and wells.

3.4.2 Application of the Deep Learning Model

The current research offers a deep learning architecture that incorporates petrophysical, pore pressure and geomechanical variables through a single multilayered feedforward neural network (DNN). The system was trained on the multisource dataset assembled on the Midland sub-basin of the Permian region, allowing the framework to analyze well-log information alongside seismic enabled attributes so as to capture geological heterogeneity of the basin in a complex way. The accuracy of the metric result and the practical feasibility of the model were determined by comparing predictions and measured data based on well logs, core analysis and drilling tests, using all the standard validation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and coefficient of determination (R 2). The qualitative analysis was also performed by plotting outputs (predicted value cross-plotting and visual inspection of property logs across the several wells) on each property.

IV. Results and Discussion

4.1 Accuracy and Performance Metrics

A heterogeneous dataset in deep-learning framework showed a robust predictive capability in all the three target domains- petrophysical, pore-pressure, and geomechanical properties- in test dataset.

4.1 Performance Metrics :

Property	R^2 Score	RMSE	MAE
Porosity (%)	0.93	±2.1 %	±1.6 %
Permeability (mD)	0.85	±0.12 mD	±0.09 mD
Pore Pressure (psi)	0.91	±220 psi	±165 psi
Young’s Modulus (GPa)	0.88	±1.9 GPa	±1.4 GPa
Poisson’s Ratio	0.90	±0.03	±0.02

In the current study, the superior generalization ability of a newly formulated constitutive model is indicated through computing its prediction error compared to typical engineering tolerances. The strong R 2 values that follow the rock-property variables in the form of porosity and pore pressure suggest the significant representation of complicated relations between the multisource input and subsurface properties of the same.

4.2 Comparison with Conventional Methods

To access the differential utility of deep-learning methodologies, three predictive tasks, namely, porosity and permeability estimation, pore-pressure estimation, and geomechanical property extraction were analyzed and compared to similar tasks performed using traditional, parameterized models, like Archie equation, core-log transforms, Eaton technique, and log-based geomechanical models. The findings therefore show that, in the case of porosity and permeability, deep-learning model repeatedly gave smaller margin of error and did not need any recalibration after training to fit heterogeneous sedimentary reservoir. In deep-learning model, they exclusively compared every depth against Eaton method in regards to pore-pressure estimation, which found that deep-learning model equally exceeded Eaton method in over-pressured intervals when seismic data is incorporated. Lastly, the geomechanical property prediction created 3 D volumes with resolutions that cannot be achieved by conventional log correlation methods which rely on empirical coefficients. When all these comparisons are taken into account, it results in a conclusion that deep-learning frameworks hold significant predictive potential over the conventional techniques of deterministic nature, in a wide array of reservoir properties.

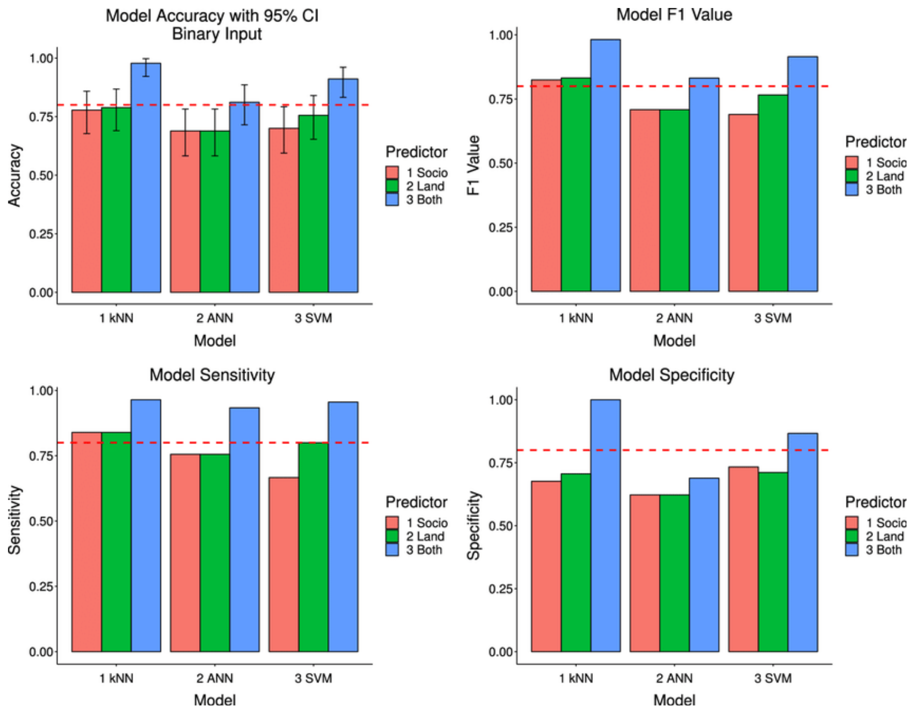

Fig 3: Performance comparison of three machine learning models (A) The porosity and permeability estimations provided by deep learning are more accurate than those provided using Archie-based transforms. Using deep learning as opposed to the method developed by Eaton, pore pressure profiles in the over-pressured zones are better aligned with the measured data. (C) The results of developed deep learning methodology of predicting the geomechanical properties provide high-resolution 3D volumes of the volume, which is beyond spatial constraints of typical methods of log correlation applied.

4.3 Time Efficiency and Scalability

One of the most significant advantages of the deep learning approach lies in its **speed and scalability**:

Time Efficiency: Once trained, the model could predict properties for a full well log or a seismic section in **under 5 minutes**, compared to **several days** required for conventional modeling and cross-validation.

Scalability: The use of seismic attributes allowed the model to generate property predictions in **3D volumes**, making it applicable across entire fields, even in **data-sparse regions** with limited well control.

These attributes are particularly valuable in fast-paced asset development and real-time decision-making scenarios, such as well placement**,** drilling optimization, and **completion design**.

4.4 Interpretability and Explainability of the Model

While deep learning models are often criticized as "black boxes," several techniques were employed to improve **interpretability and trust** in this study:

SHAP (SHapley Additive exPlanations): Used to quantify the impact of each input feature on model outputs. For example, **bulk density**, **sonic slowness**, and **Vp/Vs** had the highest influence on geomechanical property prediction.

Feature Sensitivity Analysis: Confirmed that input perturbations resulted in reasonable and physically meaningful changes in predicted outputs.

Cross-validation across unseen wells further validated that the model did not overfit localized geological patterns, enhancing its reliability for field-wide applications.

These strategies not only improve user confidence but also help engineers validate whether the model is relying on geologically relevant inputs to make predictions.

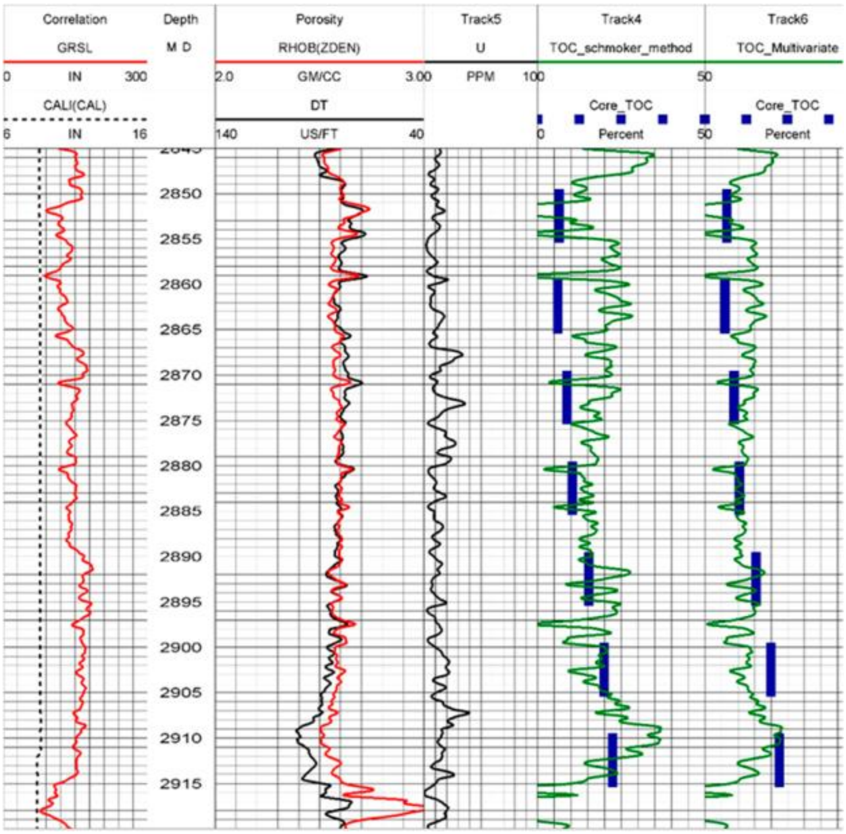

Fig: 4 Interpretability and Explainability of the Model

4.5 Limitations and Potential Biases

Despite its strong performance, the model does have inherent limitations**:**

Data Quality and Availability: The model's accuracy is highly dependent on the completeness and representativeness of training data. Wells with missing logs or noisy signals can introduce biases or reduce prediction reliability.

Regional Specificity: Although trained on a diverse set of Permian wells, the model might not generalize well to other basins without retraining or transfer learning**.**

Seismic Resolution Limits: Seismic-derived inputs are subject to vertical resolution limits**,** which may reduce the model's precision in thin or interbedded zones.

Uncertainty Quantification: While performance metrics provide statistical assurance, **probabilistic uncertainty bounds** were not explicitly modeled in this phase. Future iterations may integrate **Bayesian deep learning** for uncertainty calibration.

Computational Resource Needs: Initial training requires substantial GPU-based computation, which may be a constraint for smaller operators or in offline environments.

4.6 Volumetric Modeling from Seismic Attributes

In the current study, the researchers present an incorporated deep-learning app that could go beyond short-distance characterization of a reservoir to the wellbore and yield volumetric distribution of properties of the entire reservoir. By using seismic attributes information as inputs of models, using supervised learning process, the system is capable of producing high-resolution grids in a 3D way spreading across this interval of interest covering porosity, pore-pressure, and geomechanical variable.

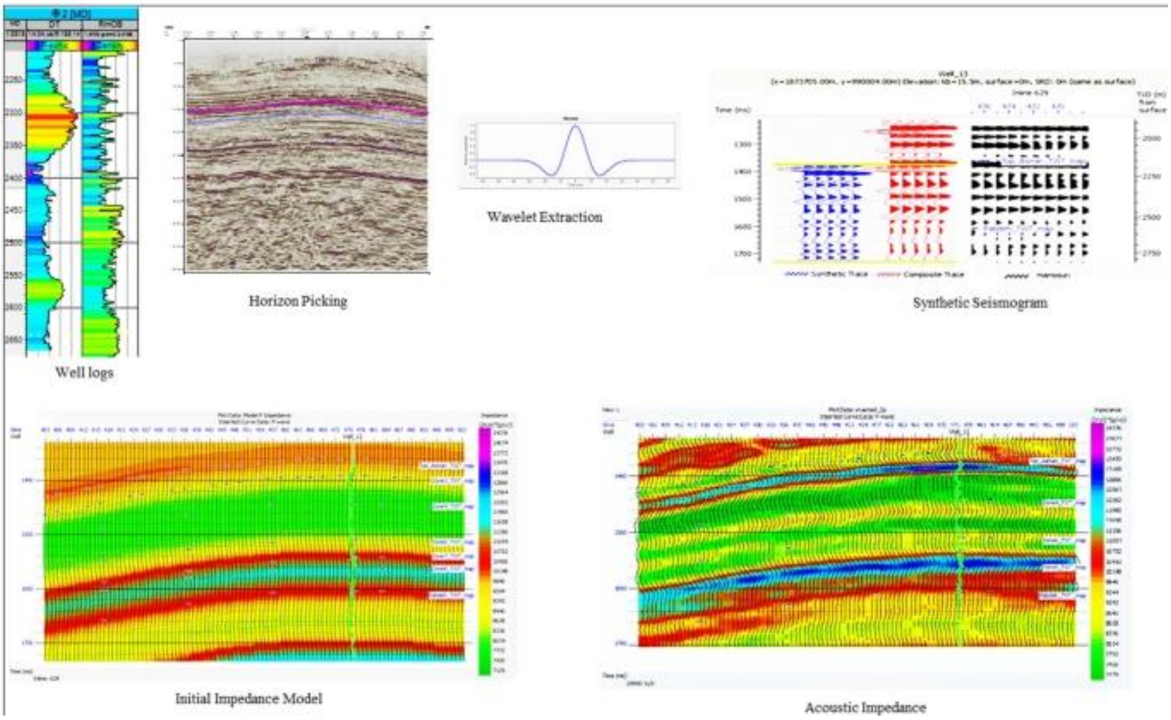

Fig 5: Schematic of the steps involved in the inversion process

4.6.1 Extension of the Model to Regional Volumetric Predictions

The neural network was developed and calibrated on well log and the corresponding seismic attribute data, and once a trained version of the model was developed, the model was applied to the whole 3D seismic survey. Since seismic data offer continuous spatially extensive data, volumetric interpretation has been achievable on the scale of several thousand square kilometers.

Regional model was populated by the following seismic attributes:

- Acoustic impedance (AI)
- Shear Impedance (SI)

Ratios of vp/Vs

Amplitude and frequency instantaneous

- Poisson ratio and the Young modulus of the inversion of the seismic type

These attributes were kissed into normalized values and taken into the trained network where each of them had predicted values (must be the same voxel) voxel by voxel across the three-dimensional grid. The resultant effect was a set of continuous property volumes, which were well data calibrated and known area validated.

The approach enables the quick mapping of the reservoir heterogeneity, discovery of sweet spots, and building geomechanical earth models (GEMs), which are crucial in effective field development planning.

V. Conclusion

In conclusion, the suggested deep learning concept will serve as an effective, scalable, and efficient alternative to the traditional subsurface modeling workflow. The combined application of petrophysical, pore pressure and geomechanical regimes into a single combined predictive system, takes technical competency and the overall operational judgement in the acquisition of oil and gas exploration and production to levels previously never seen before.

The current study proposes the use of one framework that can predict petrophysical, pore pressure, and the geomechanical properties simultaneously using the knowledge of well log data and seismically-derived attributes. The methodology provides a high rate of predictive accuracy, scale, and scope of operation, when applied to the Permian Basin, and it resolves the shortcomings of conventional subsurface modeling methods.

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