Rock Physics Driven Machine Learning for Quick & Improved Reservoir Characterization

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SUMMARY

Machine learning has been used in the petroleum industry for a long time, but its usage was limited due to hardware and data constraints. With the advancement in hardware capabilities in recent times, machine learning usage has expanded in various domains. Still, in many real situations, the inadequacy of well data required in seismic reservoir characterization poses a challenge to the use of recently developed deep machine learning methods, e.g., convolutional neural networks (CNN). Theory guided machine learning (TGML) generates a large amount of 1D synthetic data to capture the variability in the conditions of the reservoir using a rock physics model, conforming to the regional geology and depositional setup. The corresponding amplitude variation with offset (AVO) responses are used for training and validating a CNN network. The concept of transfer learning is used to validate the CNN training on real well properties before applying to the 3D seismic data for predicting several elastic and reservoir properties simultaneously.

Here, we present a case study on a West Tryal dataset from the Northern Carnarvon basin, Australia with limited well control in the survey area. A rock physics model is established on one of the wells and then geological knowledge about the area is used to simulate various scenarios of reservoir variation in subsurface to predict the elastic properties in 1D. Each set of reservoir and elastic properties can be regarded as a synthetic well. A real-world wavelet is used to compute the AVO responses for each synthetic well. With this, there are many synthetic wells and synthetic seismic data to be used in the deep neural network for machine learning. Trained and validated convolutional neural network is then transferred on the real dataset and later applied on the 3D seismic data to predict multiple reservoir properties, acoustic impedance, Vp/Vs, porosity, volume of clay and water saturation simultaneously.

A comparison is made between the acoustic and density prediction from seismic inversion, and one predicted from TGML and between porosity and water saturation predicted from a conventional workflow and the one predicted from TGML, showing the improvement in quality of prediction and value addition by removing workflow repetition.

Keywords: Machine learning, neural network, convolutional neural network, theory guided machine learning

INTRODUCTION

The integration of wells and seismic geophysical datasets to estimate reliable reservoir properties is one of the key challenges in exploration and development fields. Generally, a seismic inversion is performed to estimate elastic properties like acoustic impedance, shear impedance and density. To derive reservoir properties, these inverted elastic properties are later used in statistical relationships like multi linear regression or basic machine learning like probabilistic neural networks, etc. A multi linear or nonlinear relationship for each reservoir property using seismic amplitude and inverted elastic properties needs to be established, thereby training, and validating for each reservoir property separately. With the improvement in computational power in recent years, deep neural networks (Goodfellow et al., 2016) are used in the energy industry. But deep neural networks require a large amount of data for training, thereby limiting its usage. Downton et al. (2020) came up with a novel approach for data augmentation using a theory-based method. A rock physics model is used to simulate possible geological variations in the field. These hundreds of geological simulations are then used in the deep neural network, a convolutional neural network in this case, to estimate multiple reservoir properties simultaneously.

GEOLOGY OF THE AREA

We follow Meath and Bird (1976) to describe the geology of the area and history of discovery. The West Tryal Rocks gas field is located offshore at the western margin of the Barrow Sub-basin, in the Carnarvon Basin of Western Australia. It was discovered by West Australia Petroleum Pty Ltd in 1973 on a South Westerly extension of the Rankin Platform where, farther north, several major gas/condensate discoveries have been made by Burmah Oil Company of Australia Ltd since 1971.The productive structure at West Tryal Rocks lies at a depth of 3200 m in about 150 m of water column. It consists of an elongate north - trending uplifted block of Triassic and possibly Lower Jurassic reservoir rocks called the Mungaroo beds. The block is unconformably capped by the Lower Cretaceous Muderong Shale which also provides the lateral seal across the bounding faults. The reservoir section dips to the north more sharply than does the sealing unconformity so that progressively younger pre-Cretaceous sediments subcrop the unconformity in that direction.

The shales of Middle to Late Jurassic age in the Barrow Sub-basin to the East are believed to be the primary source of hydrocarbons, although the overlying Muderong Shale cannot be ruled out (Playford and Johnstone, 1959). The sands are mainly medium to very coarse grained and possess good porosity and permeability. Preliminary reserve estimates indicate that the field contains more than 28 x 10^9 m^3 of gas.

There are 5 sand packs M, N, O, QRS and T as per the geological model. The M sand is the major gas saturated pack and is encountered in 2 wells. Delineation of the hydrocarbon bearing M sand is the prime objective of this study.

A 3D seismic data set, Figure 1, is available in the area with a maximum angle of 38 degrees. Two wells are present in the area with basic petrophysical interpreted logs like porosity, water saturation and volume of clay along with elastic logs, well WTR_4A shown in Figure 2.

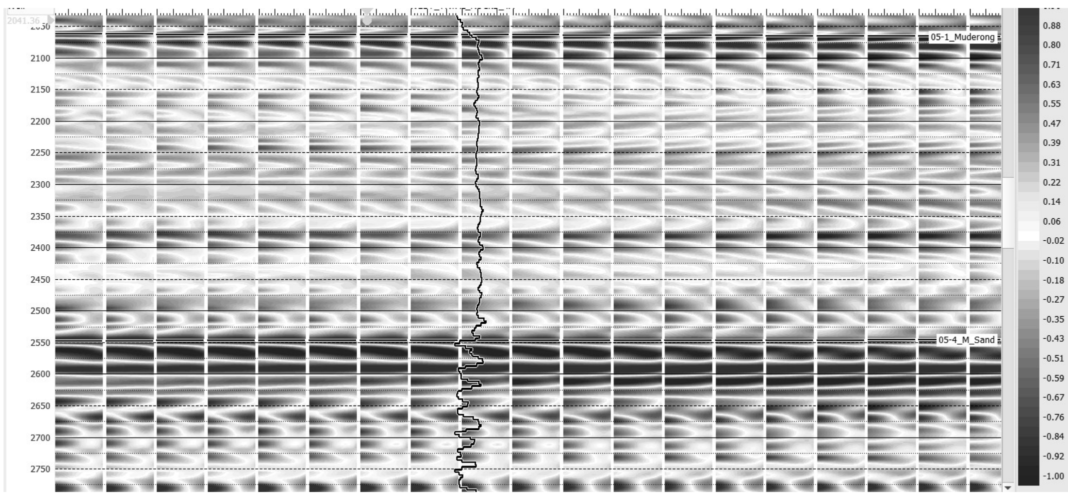

Figure 1. Seismic gather section along a line passing through a well.

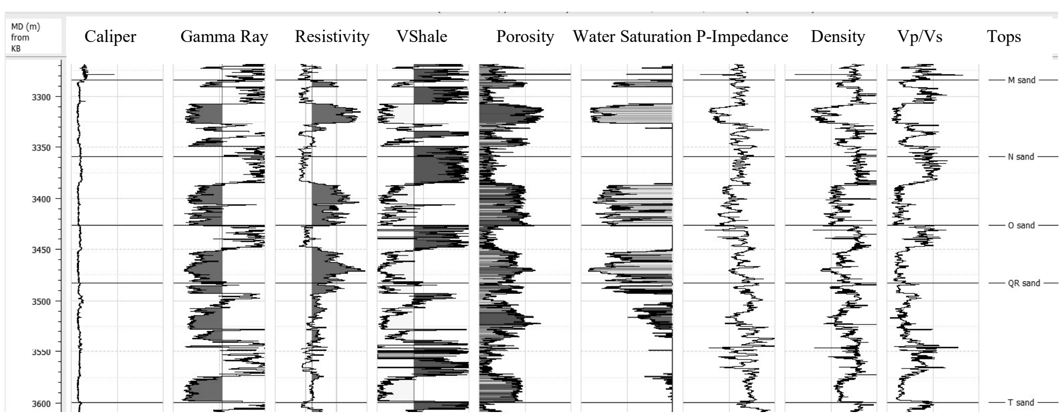

Figure 2. Measured and petrophysical logs available in WTR_4A.

DATA AUGMENTAION USING ROCK PHYSICS MODELING

As a large amount of data is required to train a deep neural network, with only 2 wells in the study area, data augmentation is required to use deep neural network. An unconsolidated (soft) sandstone (Dvorkin and Nur, 1996) model that was further extended to stiffer sandstones by Allo (2019) through the matrix stiffness index (MSI) is established using one of the wells, WTR_4A (Saputra et al., 2022). Layer statistics and vertical variability are estimated on the well logs. The rock physics model and data statistics are used together to generate geological scenarios in the field. Porosity, water saturation, volume of clay and thickness of M sand variations are used to capture the geological variability in the area, thereby generating 225 synthetic wells. The sonic, shear sonic and density curves in synthetic wells are used to convolve with real seismic wavelet to generate synthetic AVO signatures using the Zoeppritz equation (Zoeppritz, 1919) for each well. This generates a large number of synthetic wells and synthetic seismic data, thereby allowing us to use a deep neural network for training and validation purposes.

CONVOLUTIONAL NEURAL NETWORK

A convolutional neural network (CNN) is used here to simultaneously estimate multiple elastic and reservoir properties. CNN is generally used in image classification (LeCun et al., 1998) in various industries and requires a large amount of data for training. Theory guided data augmentation fulfills the basic requirement of a large dataset, thereby allowing CNN to be used in subsurface property prediction in this case. CNN is composed of 2 steps, convolution, and pooling, as shown in the schematic diagram Figure 3.

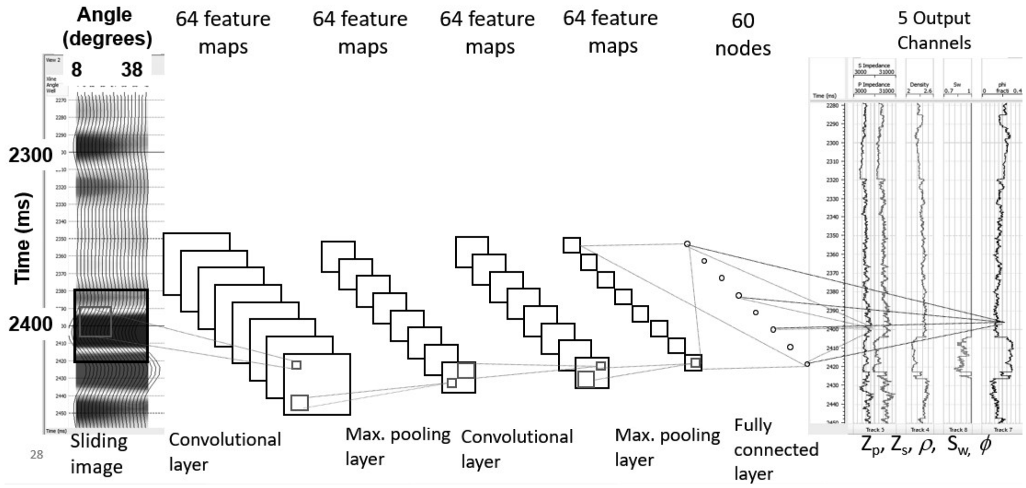

Figure 3. Schematic diagram of convolutional neural network.

The input for the CNN is 30x80 image size where 30 is the number of angle traces present in the seismic and 80 is the size of the rolling time window. As we have a large number of synthetic wells for training, we have a choice to use a deep neural network, 250 hidden layers in this case. The training and validation curve, usually called L curve is used to optimize the number of epochs used in the CNN.100 epochs are tested with 30% data used for validation. A 3x3 filter size is used with 2 convolutional layers. The output of the second maximum pooling layer is flattened and used as input into a fully connected network. The CNN is first trained and validated on synthetic wells and synthetic seismic data. Once the CNN is trained with the synthetic data, seismic and model scalars are estimated using the real-world seismic wavelet. These scalars are used again at the synthetic well, thereby improving the match between well and CNN predicted properties. So far, synthetic data has been used for training and validation purposes in CNN, whereas we would like to incorporate real seismic data as well within the training. Hence a transfer learning is used in the process. After training the CNN on the synthetic data, the convolutional layers are frozen, then a subset of the real well and seismic data are used to update the weights of the fully connected part of the network. Transfer learning helps in incorporating real data and thereby improving the match between predicted and well properties, shown in Figure 4. Transfer learning helps in accounting for the difference between real and synthetic data.

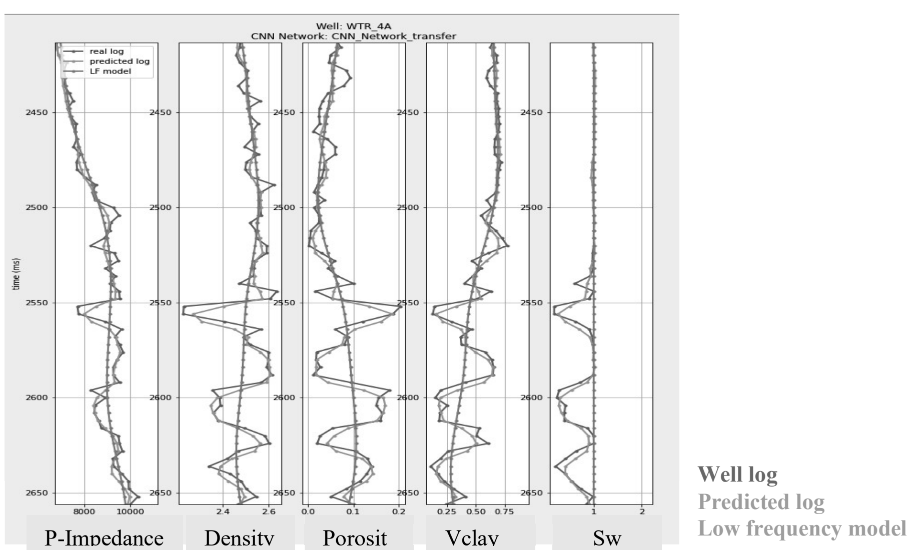

Figure 4. Elastic and reservoir properties prediction using CNN at well WTR_4A, after transfer learning.

Here, acoustic impedance, density, porosity, water saturation and volume of clay are predicted simultaneously using CNN. Elastic properties, acoustic impedance and density are compared with the traditional simultaneous inversion. It is observed that acoustic impedance from CNN is stable with better continuity and noise free compared to seismic inversion process shown in Figure 5.

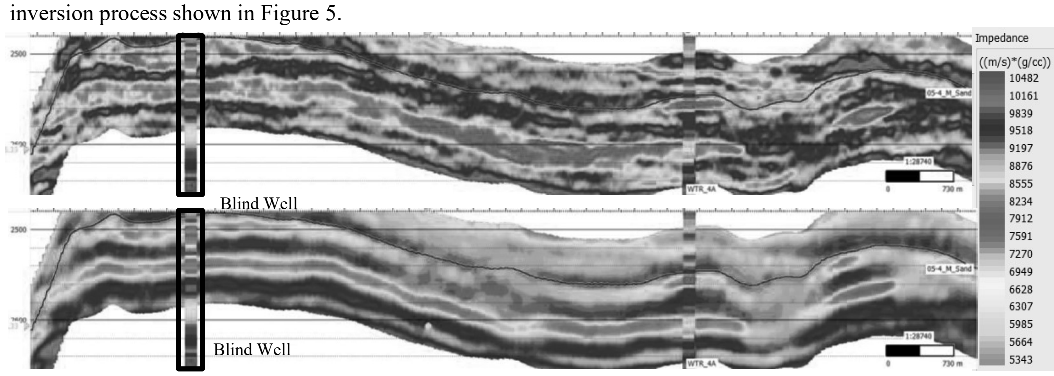

Figure 5. Comparison of acoustic impedance prediction from simultaneous seismic inversion (upper section) and acoustic impedance prediction from CNN (lower section), along an arbitrary line passing through two wells.

Also, there is an improvement in density estimation using CNN, as observed in Figure 6. In general, for inversion of good quality density higher angles greater than 45 degrees are required. Here in this case, the seismic data angle range is limited to 38 degrees, thereby predicting a noisy density property. The CNN density prediction is better in terms of event continuity, stability, and resolution. The M, N, O sands predicted from the CNN has better continuity and better correlation at the blind well compared to the density predicted from inversion.

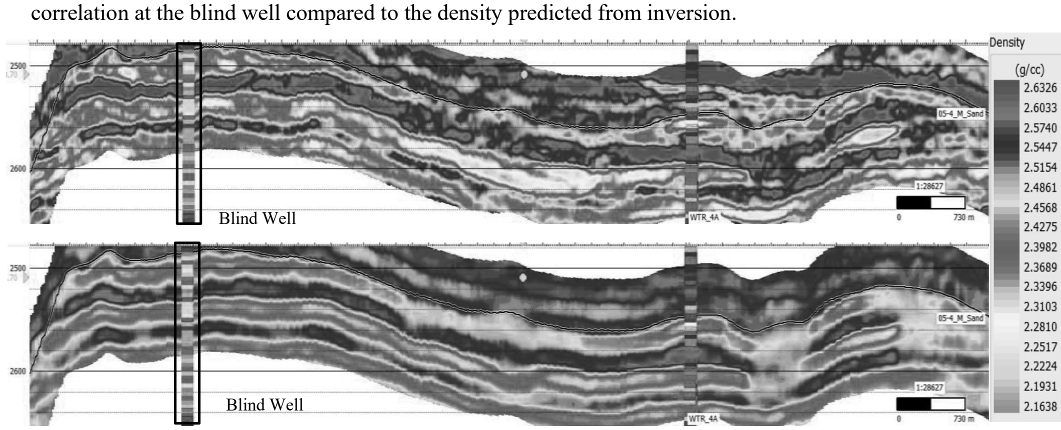

Figure 6. Comparison of density prediction from simultaneous seismic inversion (upper section) and density prediction from CNN (lower section), along an arbitrary line passing through two wells.

Further comparison is made in Figure 7, in terms of maps generated for the M sand capturing arithmetic mean of the samples from M sand horizon to 30ms below from both the methods.

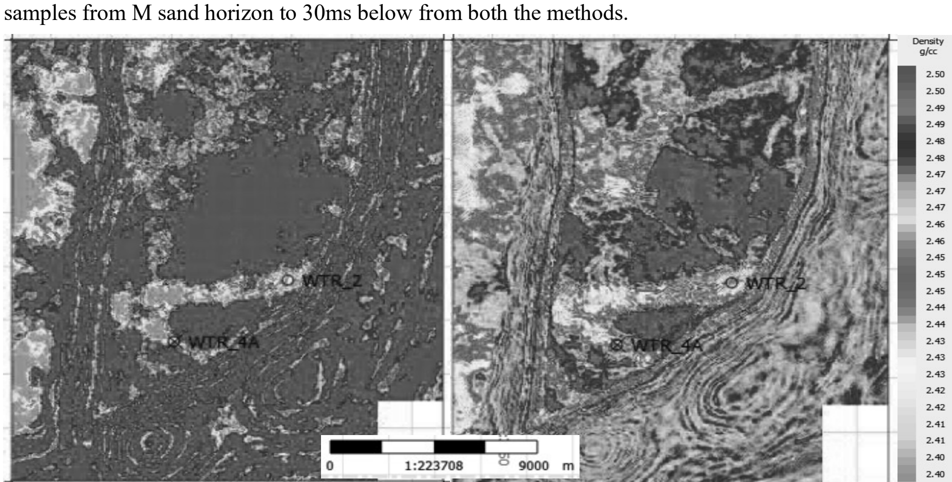

Figure 7. Density for M Sand, using seismic inversion(left) and using CNN (right).

A further comparison is made for reservoir properties, porosity, and water saturation with traditional methods. A multi linear regression (Hampson et al., 2001) is used with seismic amplitude and elastic properties derived from seismic inversion. Multi linear regression is trained using well WTR_4A and applied on volume around M sand, each for porosity and water saturation. A comparison is made for porosity (Figure 6) and water saturation (Figure 7) along the same section as shown in Figure 3.

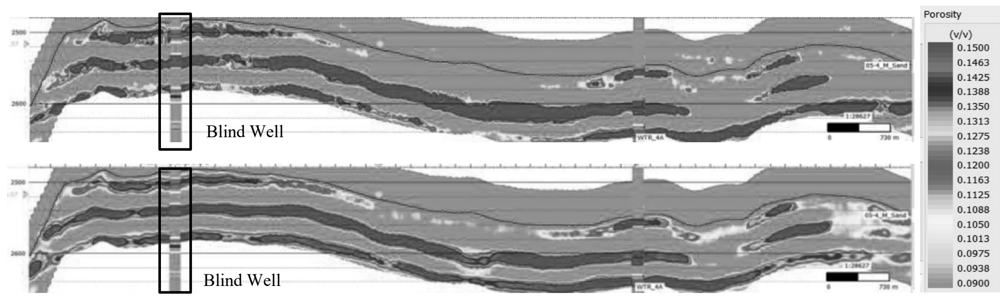

Figure 6. Comparison of porosity prediction from multi linear regression (upper section) and porosity prediction from CNN (lower section), along an arbitrary line passing through two wells.

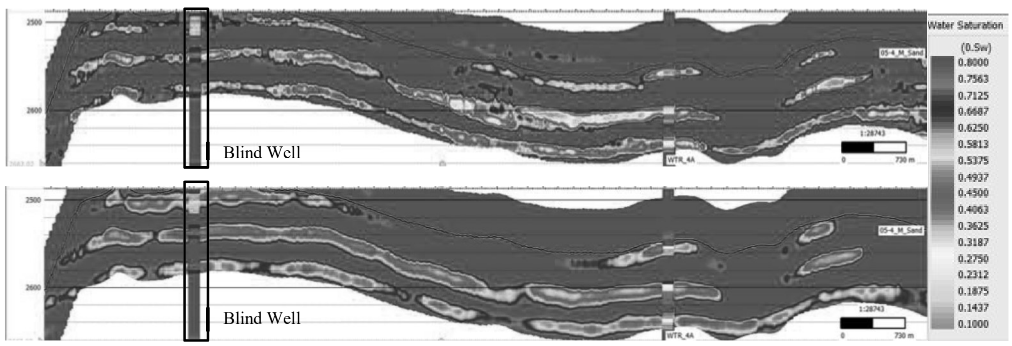

Figure 7. Comparison of water saturation prediction from multi linear regression (upper section) and water saturation prediction from CNN (lower section), along an arbitrary line passing through two wells.

It is observed that both porosity and water saturation prediction using CNN is better compared to the traditional method in terms of sand continuity and better correlation at the blind well. Further maps for the M sand distribution, taking samples from M sand horizon to 30ms below are generated for porosity (maximum attribute) and water saturation (arithmetic mean attribute) predicted from traditional multi linear regression and CNN are shown in Figure 8 and 9.

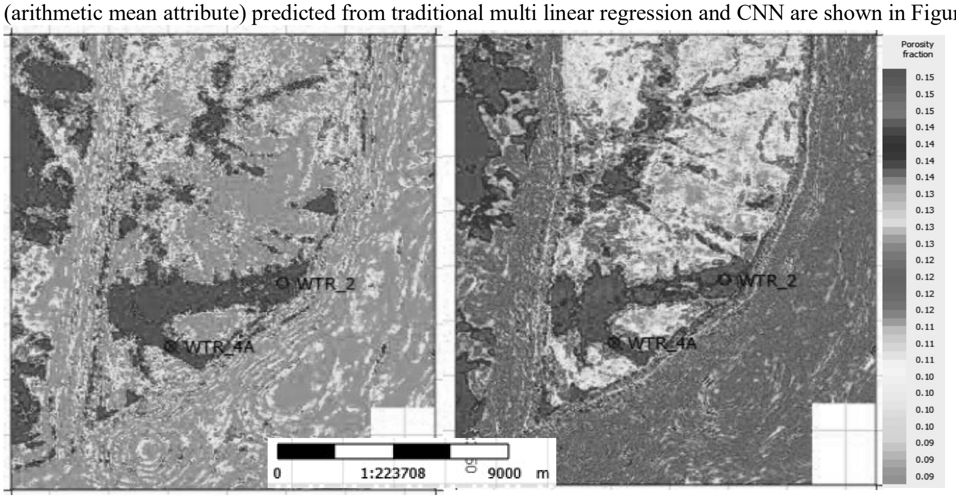

Figure 8. Porosity for M Sand, using traditional multi linear regression(left) and using CNN (right).

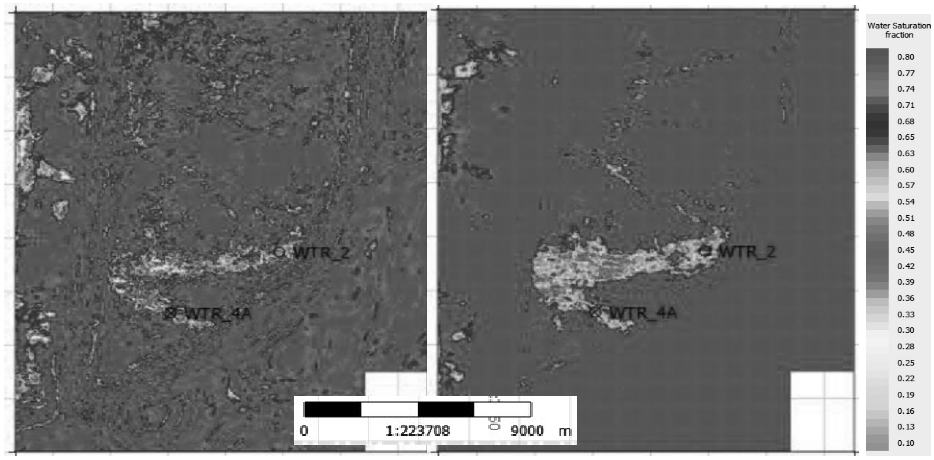

Figure 9. Water saturation for M Sand, using traditional multi linear regression(left) and using CNN (right).

For more quantitative comparison of properties predicted from multi linear regression and CNN, traces of density, porosity and water saturation are extracted at well location and compared with filtered well log properties, with a high cut filter of 80/90 Hz at WTR_4A used in training and WTR_2, blind well. A 1D comparison of predicted properties is shown in Figure 10 for the training well (left) and the blind well (right).

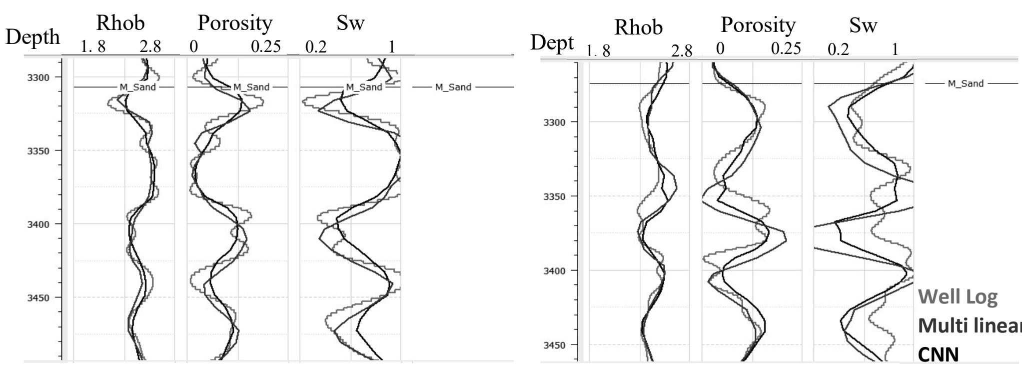

Figure 10. 1D comparison of predicted properties for well used in training (left) and blind well (right).

Correlation between predicted properties and filtered well logs is shown in Table 1 and 2.

Training Well	Density	Porosity	Water Saturation
Multi Linear Regression	82%	77%	84%
Convolutional Neural Network	85%	85%	86%

Table 1. Correlation between filtered well logs and predicted properties for well used in training.

Blind Well	Density	Porosity	Water Saturation
Multi Linear Regression	59%	43%	37%
Convolutional Neural Network	63%	72%	58%

Table 2. Correlation between filtered well logs and predicted properties for the blind well.

CONCLUSIONS

It is observed that rock physics guided machine learning using a convolutional neural network is an effective way to predict elastic and reservoir properties simultaneously. Rock physics helps in overcoming the data limitation for using deep neural networks in property prediction. Using a robust rock physics model, many synthetic wells and corresponding AVO responses are generated to be used for training a deep neural network in this case. The convolutional neural network predicts elastic and reservoir properties simultaneously, thereby reducing the turnaround time for a project. CNN predicted properties exhibit better spatial continuity and better correlation with well properties at blind well compared to prediction from traditional methods.

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