A Paradigm shift in Elastic and Petrophysical properties prediction using RPM guided Machine Learning: A case study to define new emerging and Promising Technology

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Abstract

In reservoir characterization studies, seismic inversion is carried out to generate elastic properties such as P-impedance, S-impedance, Vp/Vs ratio, and density. These properties, along with seismic-derived attributes, were used as inputs in linear regression or neural network methods to predict petrophysical properties such as porosity, volume of clay, and water saturation sequentially. Advanced machine learning techniques like Convolutional Neural Network (CNN) has been increasingly employed across various industries. However, CNN requires a large amount of sample data for efficient network training, which poses a significant challenge in exploration scenarios. This limitation is overcome by utilizing an Rock Physics Modeling (RPM) theory-guided approach, where geological variations are captured by simulating the thousands of synthetic wells under various scenarios, including changes in reservoir thickness, volume of clay, porosity, and water saturation.
The RPM theory-guided deep learning Convolutional Neural Network method is employed to simultaneously predict elastic and petrophysical properties from seismic and well data. In this approach, the authors utilized a newly developed HRS software's GeoAI Tool to predict elastic and petrophysical properties simultaneously.

Introduction

In a Hydrocarbon Exploration, seismic inversion studies have been carried out to generate elastic properties by using seismic and well data and those elastic properties were used to property model one petrophysical properties sequentially. Most of the exploration areas having limited well control, this imposes uncertainty in prediction of elastic and reservoir properties using theory-based approach and Machine learning methods. With the improvement in computational power in recent years, deep neural networks (Goodfellow et al., 2016) are used in the energy industry. Convolutional neural network (CNN) works through convolution and pooling based on Image classification and feature extraction method as shown in fig.1. But CNN requires 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 an RPM theory-based method. A rock physics model is used to simulate possible geological scenarios in the field. These thousands of geological scenarios are then used in the deep neural network, a convolutional neural network in this study, to estimate multiple reservoir properties simultaneously.

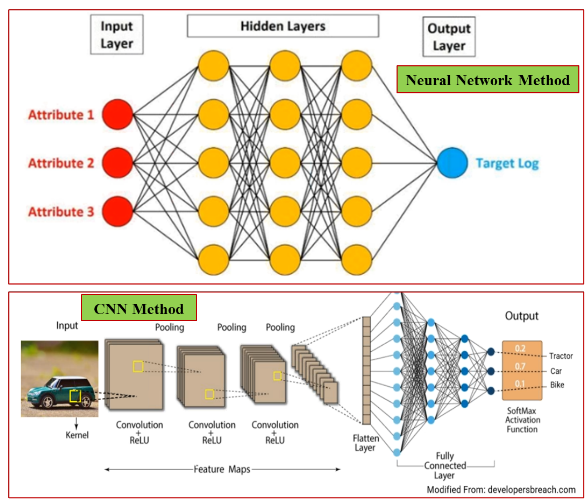

Fig 1: Schematic diagram of Neural network method and CNN method

Present study area, Agartala Dome which is located in Tripura Fold belt, A&AA Basin, India has gas bearing reservoir sands within Upper Bhuban and Middle Bhuban formations with varying thickness. In order to make the learning process of CNN more efficient, real and robust, transfer learning process is used before its application to real seismic gather data. In this case study using GeoAI tool predicted simultaneously multiple properties, P-Impedance, S-Impedance, Vp/Vs ratio, PHIE and Volume of clay. These CNN predicted results are compared with Pre-stack inversion results and Emerge Tool's Property modelled volumes, CNN results show better lateral continuity and higher resolution.

Geology of the Study area

Tectonically, the study area falls in the western part of Assam-Arakan foldbelt, India. The northward drift of the Indian plate and collision with Eurasian plate, initiated subduction. Continued northerly drifting resulted in the subduction along the Indo Burmese plate, which is the driving mechanism for the structuration of Tripura Fold belt.

The study area, Agartala Dome field is a concealed structure located in Tripura Fold belt; the structure is wide with a slight crestal shift towards south and was initially identified as a geomorphic high through photo-geological data (Fig.2). Till date, 62 wells including 36 exploratory and 26 development wells have been drilled and it has established multi-layered reservoir sands. Gas bearing pay sands are identified within Middle Bhuban and Upper Bhuban formations, Agartala dome field holds largest volume of gas reserves among other producing fields of Tripura Fold belt, A&AA Basin.

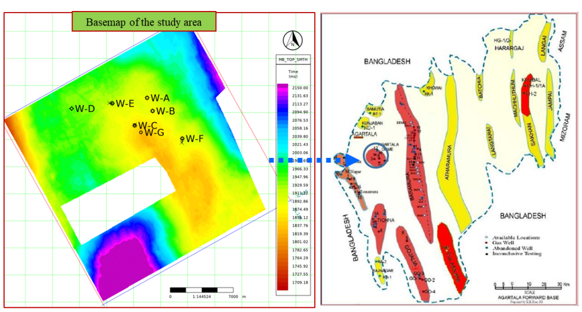

Fig 2: Basemap of the study area, Agartala Dome field

Data Inputs:

The conditioned Seismic angle gather ranges 5 to 33 deg were used in the current GeoAI study, seismic events are flat up to 33 deg with in ZOI and having frequency range at -12dB is 8 to 38 Hz. The extracted real angle dependent multi well single wavelet is used for the generation of synthetic AVO gathers from simulated pseudo elastic logs by using WellGen (Fig.3).

One representative well W-A, where RPM model is established and having processed logs (PHIE, PHIT, VCL & Sw) is used for generating synthetic catalogue of Pseudo elastic and petrophysical log curves, which is able to capture the geologic variations with in the study area.

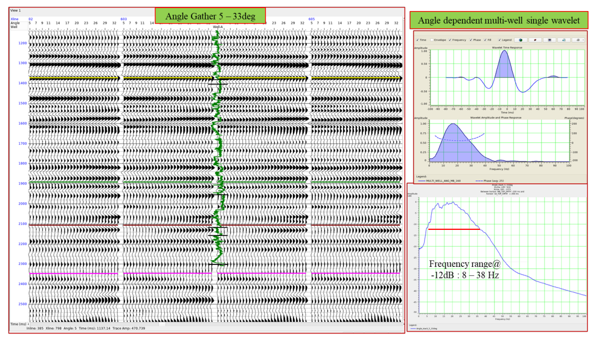

Fig 3: Angle gather 5 to 33 deg and Angle dependent multi well single wavelet used in current GeoAI study.

Crossplot analysis using P-Impedance vs Vp/Vs ratio shows Gas bearing reservoir sands of Middle Bhuban formations to be moderate P-impedance and low Vp/Vs as shown in Fig. 4. Low Frequency model using real well's elastic logs and petrophysical processed logs with high cut filter 10 Hz prepared and exported to use in CNN training to predict multiple elastic and Rock properties.

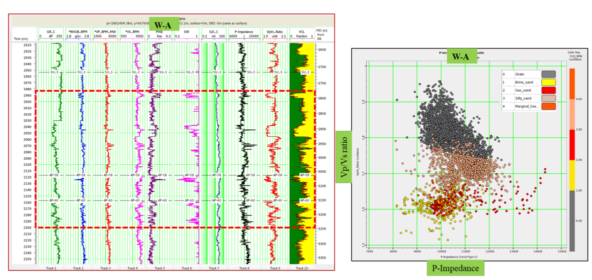

Fig 4: Crossplot analysis for the well W-A, Gas bearing sand reservoir facies are discriminated by Moderate P-Impedance and Low Vp/Vs ratio.

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Methodology: -

The HRS software's GeoAI Tool is a novel methodology for seismic reservoir characterization with limited well control, RPM theory guided deep machine learning CNN method is used to predict multiple reservoir properties simultaneously. Mainly It comprises of two processes WellGen and CNN, WellGen generates a catalog of synthetic wells and AVO gather data and the other process Convolutional Network (CNN) is trained on the synthetic AVO gathers and synthetic well data, predicts multiple reservoir properties simultaneously through image classification and feature extraction method.

RPM guided synthetic data generation for Training deep machine learning using WellGen

In this study authors used one RPM well, W-A, which is having multiple layers of reservoir sands with variable thickness. An unconsolidated sandstone RPM model (Dvorkin and Nur, 1996) that is further extended by Allo (2019) to include stiffer sandstones through the matrix stiffness index (MSI) is established using well W-A (Saputra et al., 2022). Well curves per layer statistics, vertical variability and rock physics model are used together to generate possible geological scenarios for porosity, water saturation, volume of clay and sand thickness is shown in Fig.5. This generated thousands of synthetic wells with the corresponding elastic and petrophysical responses.

In this study authors simulated 2250 synthetic wells with corresponding elastic and petrophysical log curves. A real seismic wavelet, extracted from Angle stack 5 to 33 deg is used to generate synthetic AVO signatures using Zoeppritz equation (Zoeppritz, 1919) from each synthetic wells. This simulated synthetic wells and synthetic seismic data as shown in Fig.5 and Fig.6 are used in the deep neural network CNN for training and validation purposes.

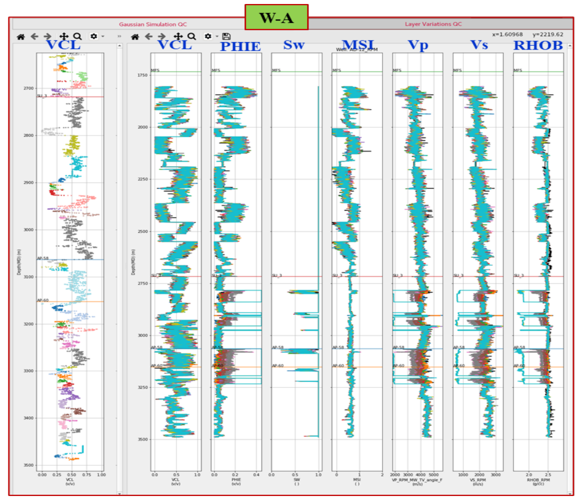

Fig 5: WellGen simulated synthetic logs with different scenarios are shown.

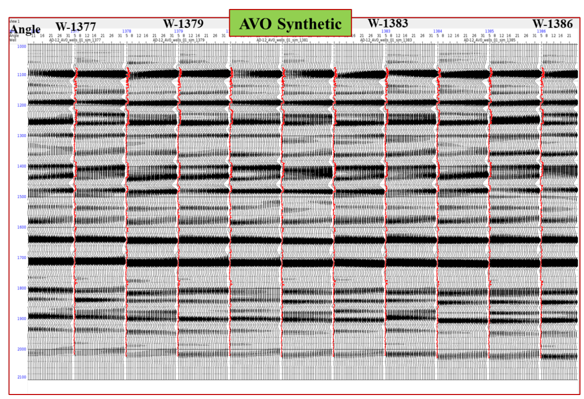

Fig 6: Synthetic seismic gather showing multiple scenarios with in zone of Interest, only few cases are shown in figure.

Convolutional Neural network (CNN)

CNN is used to predict multiple elastic and rock properties simultaneously. It is generally used in image classification (LeCun etal., 1998) in various industries and requires a large amount of labelled data for training. RPM theory guided approach helps data augmentation and creates large labelled data set for training and validation of CNN network (Downton et al. (2020).

CNN works through convolution and pooling. The present study used, input for the CNN image size is

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29 x 58, where 29 is the number of angle traces present in seismic pre-stack gather and 58 is the size of the rolling time window. In this case study, two convolutional layers are used each followed by maximum pooling layer. Each convolutional layer consists of 64 kernels of size 3x3 followed by a rectified linear unit (ReLu) activation function. The output of second maximum pooling layer is flattened and input into a fully connected network with one hidden layer with 60 nodes are shown in Fig.7.

The training and validation curves, usually called a L curve is used to optimize the number of epochs, in this study authors used 25 number of epochs and 60 hidden nodes. The 25 epochs are tested with 30% data used for validation.

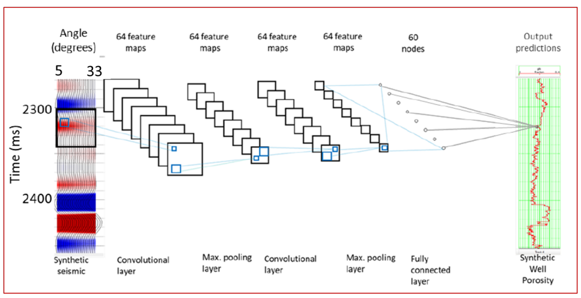

Fig 7: Schematic diagram of Convolutional neural network used in GeoAI.

In this current study, CNN is first trained and validated using synthetic wells and synthetic seismic data for five targets (P-Imp, S-Imp, PHIE, Vclay and Sw). 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 in CNN not included real data, through transfer learning gives the ability to use real data and which improves the match between predicted and well properties as shown in fig.8. After training the CNN on synthetic data, convolutional layers are frozen, then a subset of real well and real seismic data are used to update the weights of fully connected part of the network. The CNN operator created through transfer learning for 5 targets applied on real seismic gather and incorporated trend from exported Low frequency model of P-Imp, S-Imp, PHIE, Vcl & SW. Through this simplified machine learning approach, CNN predicted multiple elastic (P-Imp, S-Imp & Vp/Vs) and rock properties (VCL, PHIE & Sw) simultaneously.

Comparison of CNN Results with Conventional methods

In this study, CNN estimated multiple elastic and rock properties simultaneously are compared with deterministic Pre-stack Inversion results and HRS Emerge Tool's property modelled VCL and PHIE results. The RC line passing through wells are shown in Fig.9, depicts that CNN derived Vp/Vs shows better background match with wells and good lateral continuity with increased resolution, as shown in yellow box.

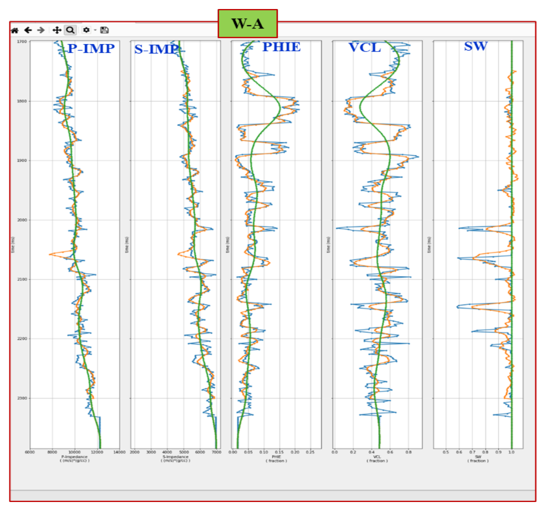

Fig 8: Elastic and Reservoir properties predicted using CNN at well W-A after Transfer Learning.

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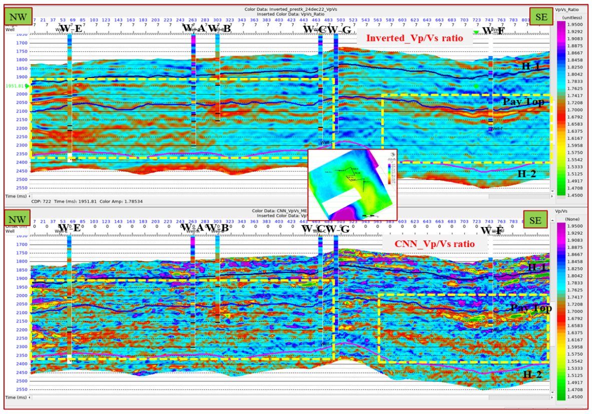

Fig 9: Arbitrary section comparing the Pre-stack Inversion result Vp/Vs with CNN estimated Vp/VS.

The arbitrary section from Probabilistic Neural Network modelled PHIE and VCL from Inverted results and seismic attributes are compared with CNN estimated PHIE and VCL volumes. It is shown in Fig.10 and Fig11. CNN results are having better background match with wells and improved lateral continuity and frequency content as compared to PNN results.

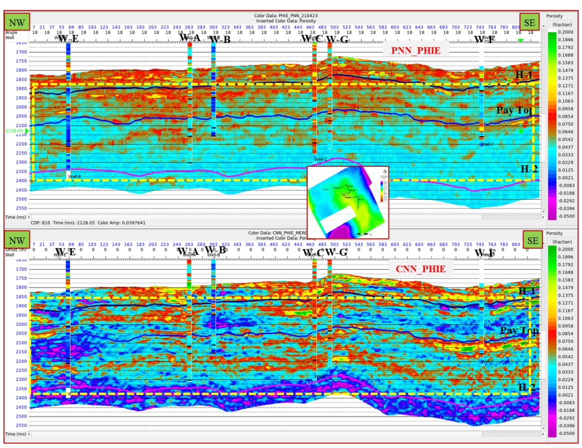

Fig 10: Arbitrary section comparing the Emerge Tool's PNN modelled PHIE with CNN estimated PHIE. CNN results are having better background match with wells and Improved frequency content and lateral continuity as shown in yellow box.

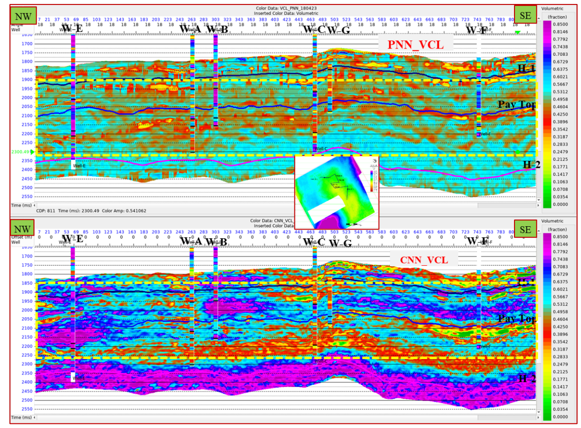

Fig 11: Arbitrary section comparing the emerge Tool's PNN modelled VCL section with CNN estimated VCL section. CNN results are having better background match with wells and Improved frequency content as shown in yellow box.

The horizon slices were extracted from the inverted P-Imp, Vp/Vs and CNN estimated Vp/Vs, PHIE and VCL volumes along the Pay top horizon with window 30ms down are shown in Fig.12 to Fig.14. The CNN extracted Horizon slices shows that better discrimination with improved resolution of Gas bearing reservoir facies at the well locations W-A, W-B &W-F, highlighted in yellow box.

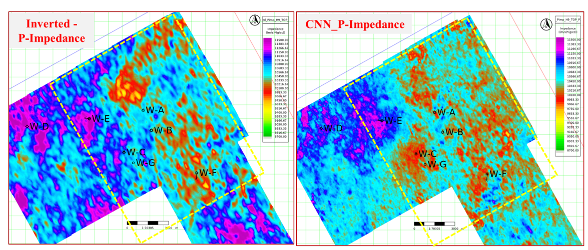

Fig 12: Horizon slices of Inverted P-Imp and CNN estimated P-Imp extracted along Pay Top with window 30ms down, CNN result shows better discrimination and validating with well locations W-A, W-F and W-G.

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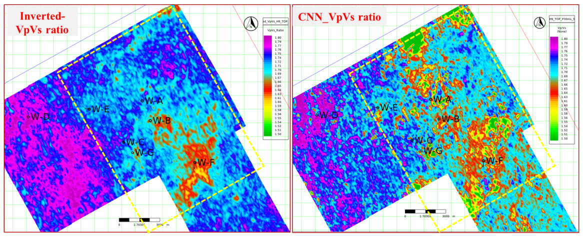

Fig 13: Horizon slices extracted from Inverted Vp/vs and CNN estimated Vp/Vs along Pay sand Top with window 30ms down, CNN result shows better discrimination and validating with Gas bearing wells W-A, WB and W-F.

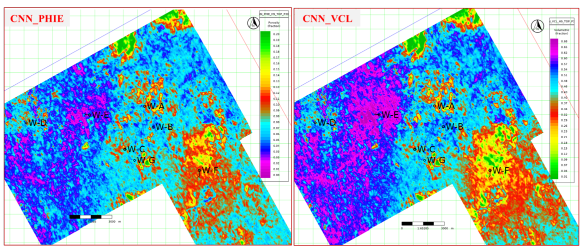

Fig 14: Horizon slices extracted from CNN predicted PHIE and VCL along Pay sand Top with window 30ms down shows the reservoir facies discrimination in better way and validating with drilled wells.

Conclusions

GeoAI is a novel methodology for Reservoir characterization with limited well control. Rock Physics theory and statistical simulations were used to model various geological scenarios using the single well W-A, in the current study. Deep neural network CNN has been used for training and validation with large number of simulated scenarios in the form of synthetic labelled data. RPM guided deep Machine learning CNN has been used to predict multiple elastic and rock properties simultaneously. The CNN estimated results are having better resolution and lateral continuity as compared with other conventional methods. In Hydrocarbon Exploration, this approach makes a paradigm shift in Reservoir characterization and helps in de-risking the prospect Identification.

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