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ML Driven Integrated Approach For Perforation Interval Selection Based On Advanced Borehole Images AI Assisted Interpretation

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Abstract

Carbonate reservoirs are typically naturally fractured, resulting in a complex network of fluid movement that plays a crucial role in determining their production and recovery performance. However, due to the inherent complexity and heterogeneity of these reservoirs, evaluating their recovery potential is a highly challenging task. In this study, we propose an Al-assisted workflow that utilizes machine learning techniques to identify sweet spots in carbonate reservoirs.

A supervised Deep Learning model is utilized to segment relevant features, specifically fractures, in borehole images using pixel-wise identification. Subsequently, sinusoidal fitting algorithms are employed to determine the dip and strike of each feature. The obtained dip magnitude and azimuth direction of fracture planes are analyzed using supervised machine learning techniques to identify the orientation of the three principal stress axes that caused the fracturing. Based on borehole image interpretation, a feature map is generated and employed for porosity estimation and partitioning. The reservoir connectedness index is estimated based on porosity analysis and the feature map, which is utilized as input for image-based permeability estimation. Finally, an integrated approach combining advanced borehole image interpretation and stress analysis is used to identify sweet spots based on the reservoir's rock quality and geomechanical properties for perforation.

Quantitative information extracted from BHI was utilized to identify heterogeneous zones that showed higher secondary porosity and pore connectedness. This information proved to be valuable in identifying the most productive zones and in understanding the correlations between different carbonate porosity components and well productivity data. We observed an excellent correlation between production log profile and the connectedness log derived from the borehole image, indicating that the variation in production profile is likely triggered by the textural variation in the reservoir. The pore connectedness index serves as a significant and relevant qualitative measure to predict the producibility of the reservoir and can be used to optimize the completion of future wells.

To overcome limitations in characterizing carbonate reservoirs, machine learning techniques have been used. This involves annotating geologic features using a well database, with supervision from subject matter experts. The resulting machine learning model is tested on new wells and can identify pay zones, perforation intervals, and stress analysis, including minimum and maximum horizontal stresses. The models successfully detect fractures, breakouts, bedding planes, vugs, and slippage passages with pixel-level precision, reducing BHI analysis time. Machine learning is a promising development in reservoir characterization, improving the accuracy and efficiency of analyzing carbonate reservoirs.

BHI interpretation and preprocessing

One of the primary aspects involved in the characterization of reservoirs is the assessment of secondary porosity and its impact on the flow of reservoirs. The identification and quantification of the influence and proportion of secondary porosity in reservoir permeability are subject to limitations due to the available methods.

The most commonly employed technique for quantifying secondary porosity relies on borehole images, which necessitates manual interpretation and data identification. This process heavily relies on the expertise and time of subject matter experts. To address this challenge, one of the widely adopted approaches is the utilization of supervised computer vision algorithms, which fall under the domain of artificial intelligence. This subfield of AI aims to enhance the automated performance of visual tasks by gaining knowledge through experience.

Supervised computer vision algorithms accomplish this by optimizing the task function or model based on examples they have learned from the data during training. As a result, they can make informed decisions when presented with new data. However, when applied to borehole images, certain machine learning challenges need to be addressed. These challenges include the following:

- Detecting features in wells from different reservoirs using a model trained on wells from one reservoir can be highly challenging, as reservoirs may exhibit distinct geological characteristics. This algorithm addresses wells from various reservoirs, encompassing carbonates, shales, or any formation type with distinguishable heterogeneities in borehole images.
- The handling of parts of borehole images with missing data, depicted by vertically slanted white strips, poses considerable difficulty. Substituting these areas with inappropriate values could lead the machine to learn non-existent patterns within the remaining image, further complicating the analysis process. Therefore, we created a deep learning approach based on a Generative Adversarial Network (GAN) [1] architecture to automatically fill the gaps [2].

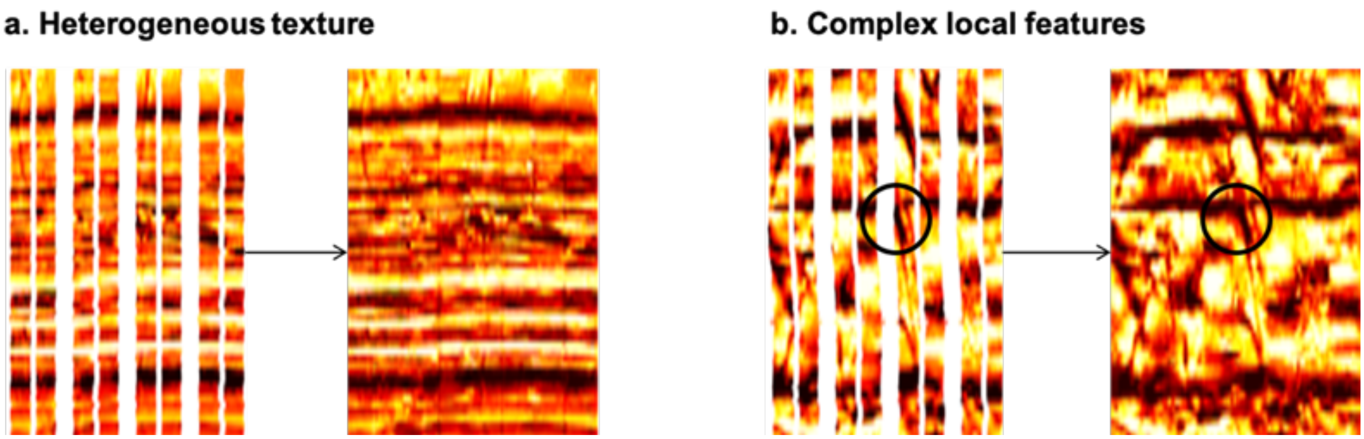

Figure 1. Examples of gap filling algorithm to a, highly heterogeneous image dominated by bedding planes and b, image with a relatively uniform matrix but a complex structure of intersecting features.

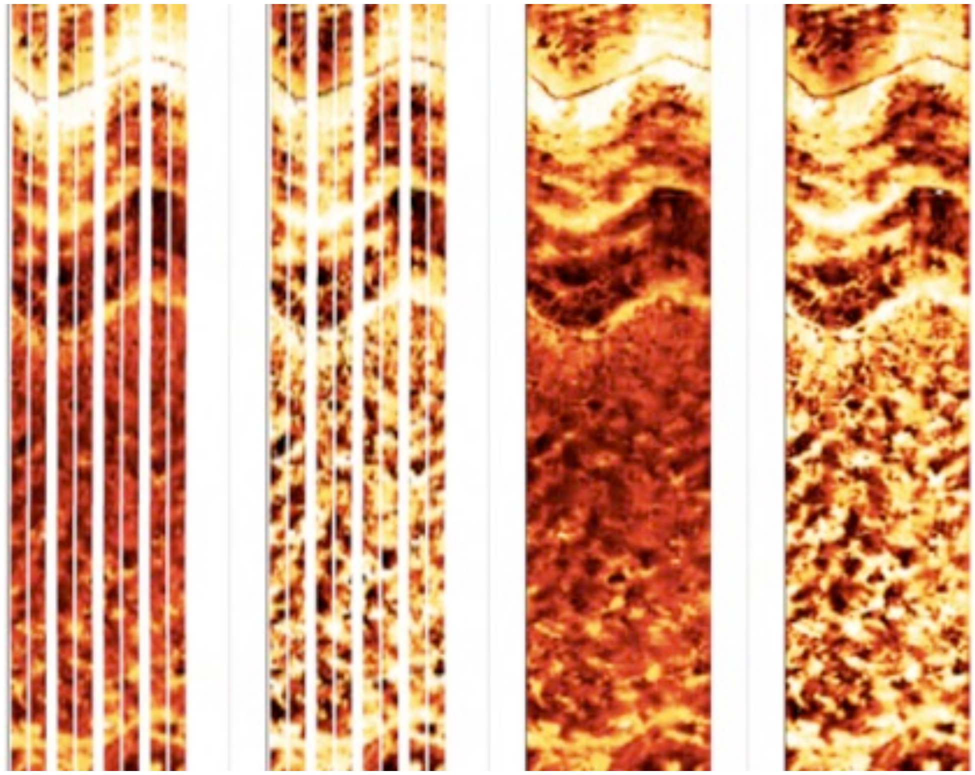

Figure 2. Gap filling example

- The labels provided by the geologists often do not have pixel wise precision, causing the machine to become confused while trying to learn inconsistent patterns. This limitation is mitigated using different data and label augmentation techniques. However, imprecise labeling makes it hard to have a robust performance measure.
- There may be only a few examples of certain features for training the model. This makes it difficult for the machine to detect these underrepresented features.

Semantic segmentation involves the application of algorithms to automatically classify image pixels into user-defined classes, facilitating subsequent analytics and data processing. We use a convolutional neural network (CNN) [3] to compute a probability map for pixels belonging to specific classes. In this application a class is defined as any of the heterogeneity in the borehole image, however this method is applicable to any type of heterogeneities in an image. During iterative training of the CNN module, a binary mask is employed as the ground truth for each image, where 0 corresponds to the background and 1 signifies pixels belonging to the specific class. The loss function penalizes discrepancies between the binary mask and the map generated by the CNN. After training, the CNN module provides the optimal probability for each pixel in the image.

To classify regions in the borehole image based on heterogeneities, a class-specific threshold is established. Pixels with values above the thresholds are assigned to the corresponding class, while those below the thresholds are assigned to the background. As a result, distinctive regions representing various heterogeneities in the borehole image are identified as shown in figure 3.

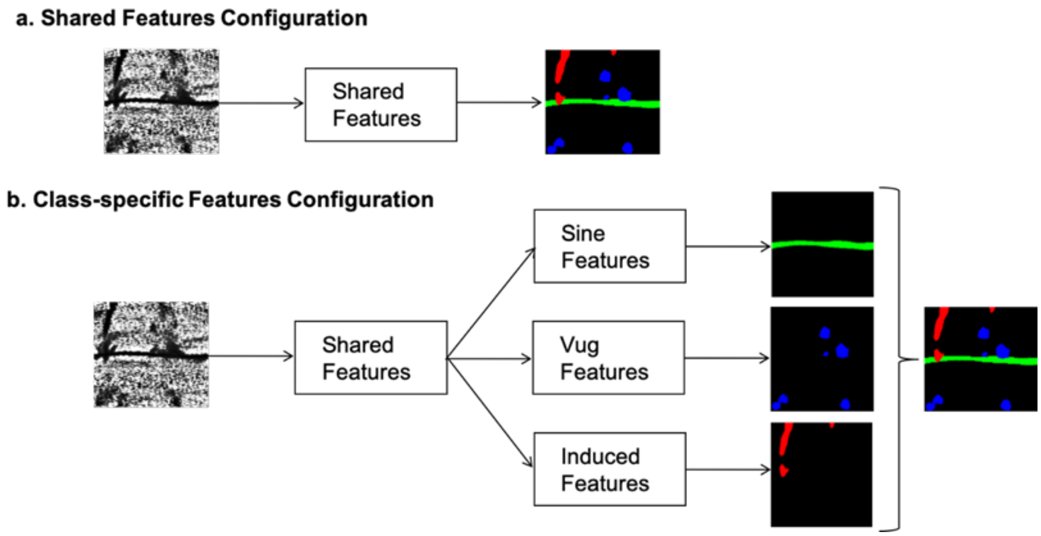

Figure 3. Description of the CNN Semantic Segmentation module in two different configurations: a, multi-task shared features configuration and b, single-task class specific configuration.

Borehole Image derived porosity

New approach for borehole derivied porosity was deleped inhouse in order to overcome limitation of existing techniques widely used in industry [7].

This innovative approach capitalizes on borehole images for multiple analyses, including structural dip assessment, fault and fracture identification, and determination of minimum and maximum horizontal stress orientation. However, its primary strength lies in quantifying the fraction of secondary porosity in heterogeneous or dual porosity carbonate formations.

We have devised a novel method that utilizes borehole electrical images to conduct porosity and image connectivity analysis, enabling valuable insights into permeability assessments in carbonate reservoirs. By implementing this technique, we can extract essential information regarding the spatial distribution of porosity and the extent of secondary porosity fraction.

To ensure the effectiveness of our approach, we make the assumption that the resistivity data obtained from the electrical images corresponds to measurements from the flushed zone of the borehole. These electrical images are further calibrated using external shallow resistivity and log porosity data. This calibration process results in the transformation of the electrical images into a comprehensive porosity image of the borehole, thereby enhancing the accuracy and reliability of subsequent porosity and permeability analyses.

The utilization of borehole electrical images in conjunction with our calibrated porosity data offers a powerful and sophisticated tool for characterizing carbonate reservoirs. By gaining detailed insights into the porosity distribution and the contribution of secondary porosity, we can better understand the flow behavior and permeability patterns within these complex geological formations, ultimately aiding in improved hydrocarbon exploration and recovery strategies. The following equation is used to get such transformation [8]:

$$\phi_i = \phi_{ext} (R_{ext} * C_i)^{1/m}$$

where φ_i is the derived porosity for each button of the image, φ_{ext} and R_{ext} are the porosity and the shallow resistivity respectively, from conventional logs, C_i is conductivity of each button from the image and m is Archie cementation exponent. The porosity image undergoes automated analysis in short intervals, typically around 1.2 inches, resulting in a continuous output of primary and secondary porosity components of the rocks. At specified sampling rates, porosity distribution histograms are generated. Homogeneous carbonate intervals exhibit narrow, unimodal distributions, whereas fractured, vuggy, or heterogeneous carbonates display bimodal porosity distributions.

To differentiate the contribution of secondary porosity from the matrix fraction, we apply a continuous cutoff to the porosity histograms. Points above the threshold are attributed to secondary porosity, while points below the threshold represent the matrix porosity.

While this technique has proven valuable and has been successfully adapted in numerous carbonate reservoirs globally, it does have certain limitations:

- The accuracy of the primary/secondary porosity distribution heavily depends on the chosen cutoff method to separate matrix porosity from secondary porosity. Manual intervention is often necessary to fine-tune processing parameters for different facies.
- The porosity partitioning approach simplifies the classification into only primary and secondary porosity categories. Under this classification, all contributions from various features like vugs, fractures, clays, and other conductive borehole elements, considered "false porosity" (e.g., induced fractures and borehole breakouts), are included in the secondary porosity. It does not allow for a separate identification of vuggy porosity and fracture porosity.

The identified limitations could have notable repercussions on the precision of porosity characterization, particularly when dealing with intricate carbonate reservoirs that exhibit diverse heterogeneities. Achieving accurate and meaningful outcomes in varying geological contexts necessitates meticulous consideration and calibration of the cutoff threshold.

Moreover, the current approach does not account for the geometrical properties of vuggy zones, preventing the distinction between isolated vugs and connected vugs. This limitation may lead to a lack of detailed resolution in characterizing these specific types of porosity features within the reservoir, potentially limiting the comprehensive understanding of fluid flow behavior and permeability patterns in the subsurface formations.

In our analysis, we work with a borehole static image in which pixel values are normalized to a range between 0 and 1, covering the entire well. This normalized image allows us to discern the contributions of both the matrix and heterogeneities to the total porosity.

Within this framework, we define primary porosity as the porosity associated with the matrix, while secondary porosity encompasses all regions of heterogeneity that we extract using the semantic segmentation module. To calculate the primary and secondary porosity for each row in the static image, we classify pixels as either "heterogeneity" if they belong to a heterogeneity region or "matrix" otherwise.

For each row in the static image, the primary porosity is computed by summing the pixel values that belong to the matrix and then normalizing the sum by the total number of pixels in that row. Similarly, the secondary porosity for the row is determined by summing the pixel values that belong to the heterogeneity regions and normalizing this sum by the total number of pixels in the row.

The results of our analysis yield a porosity versus depth plot, as shown on the right side of Figure 3. To enhance the visualization of the relative contributions of primary and secondary porosity, we stack the secondary porosity on top of the primary porosity. Given substantial porosity fluctuations between consecutive rows, we present the results using a moving average approach. In this specific application, we use a window span of 1 foot for the moving average. However, it is important to note that this window span can be adjusted as needed, depending on the length scale of heterogeneities observed in the borehole images. This allows us to better capture and understand the porosity variations along the borehole depth, providing valuable insights into the reservoir's porosity distribution and heterogeneity contribution.

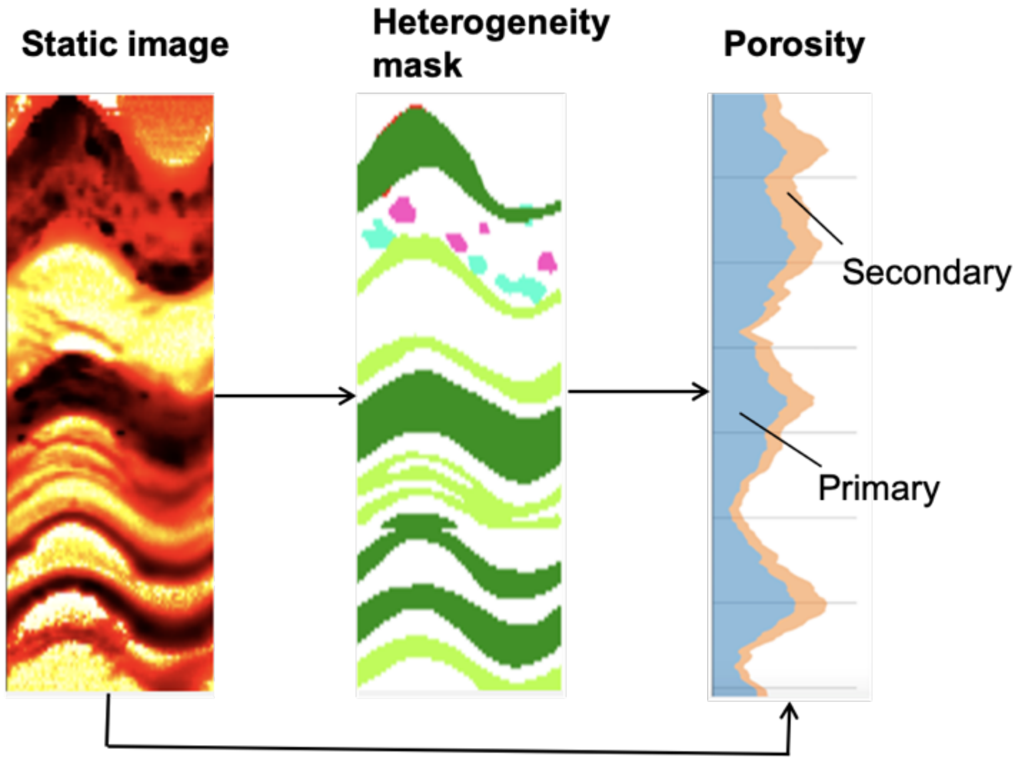

Figure 4. Primary and secondary porosity calculation from the static image and the heterogeneity mask computed though semantic segmentation

Permeability estimation from borehole images

We have developed an innovative algorithm that predicts the permeability of a formation at a specific depth based on borehole images (BHI) [9]. This algorithm employs the Finite Element Method (FEM) to solve the diffusion equation on the matrix derived from the static BHI. The matrix is obtained by automatically detecting and removing natural and induced features through segmentation and inpainting techniques. The algorithm has demonstrated its ability to automatically identify pay zones and even detect additional perforation zones.

While the algorithm shows great promise and potential business value, it consists of several complex steps, which result in slow computational performance. On a local PC, it can take up to 15 minutes to calculate permeability for a single well. This becomes problematic when considering the possibility of multiple users accessing the application simultaneously. Slow processing times can lead to app crashes and may result in the loss of end-users, as modern users expect fast and responsive applications.

To address this issue, we proposed optimizing the computational time by approximating the permeability prediction function with a neural network. In an initial attempt, we utilized a lightweight Convolutional Neural Network (CNN) model to learn only the final step of the workflow, i.e., permeability prediction from the inpainted matrix image. This yielded promising results and accelerated the overall workflow by a factor of 20.

Encouraged by these results, we decided to explore this approach further. We recognized that even the steps preceding the permeability prediction were computationally intensive, necessitating optimization to achieve significantly reduced computational time for the entire workflow.

After multiple experiments, we ended up with a lightweight CNN model that we called DiffusionNet that was able to behave exactly as the the complex permeability algorithm in AI-BHI, but at a x70 speed-up. Simply said, DiffusionNet aims to get the permeability much faster than previous algorithm (speed-up x70), aiming us to claim real-time processing. DiffusionNet was also independent of any other module (e.g., segmentation, inpainting, etc.) and would thus avoid propagation of errors from those previous steps. Last but not least, DiffusionNet, can improves over time with more training-data (through continual learning) and thus converge to perfection (give exactly same output as FEM on the matrix)

In AI-BHI an algorithm based on physical model already exists. This physical model is based on the well known Darcy’s law applied on the borehole image to estimate the formation permeability at every depth. This method solves the following equation system, the conservation of mass and the Darcy's equation based on borehole images in order to identify the vertical, horizontal and the average permeability. The combination of the last mentioned two equations make the problem equivalent to solve the following, so-called diffusion equation: $\nabla\left(\frac{K}{\mu}\nabla P\right) = 0$ where K is the permeability at each point (x, y) and P represents the pore pressure. The output of the model is the equivalent vertical and horizontal normalised permeabilities. The pore pressure is estimated based on finite element method (FEM) considering multiple rectangular spaces ($\Delta x \times \Delta y$). This last spaces simply correspond to patches obtained from the division of the borehole image of the whole well into small rectangular patches (16 rows, 160 columns).

It is worth mentioning that this last assumes to have a matrix image as input which is not the case of BHIs. Indeed, BHIs not only represent the formation in its background (called matrix), but also some natural or induced during drilling geological features like bedding-planes, fractures, vugs, breakouts, etc. So, in order to feed a matrix to the FEM, an innovative workflow has been proposed. This workflow consist in four main steps: (i) segmentation where natural and induced features are automatically extracted from the image; (ii) features removal where all features are removed from the static image; (iii) inpainting where the imputed zones of the static image are filled with surrounding pixels an inpainting algorithm; permeability where the Darcy's law is then applied on the matrix and the feature image in order to compute the matrix permeability and the features permeability, respectively.

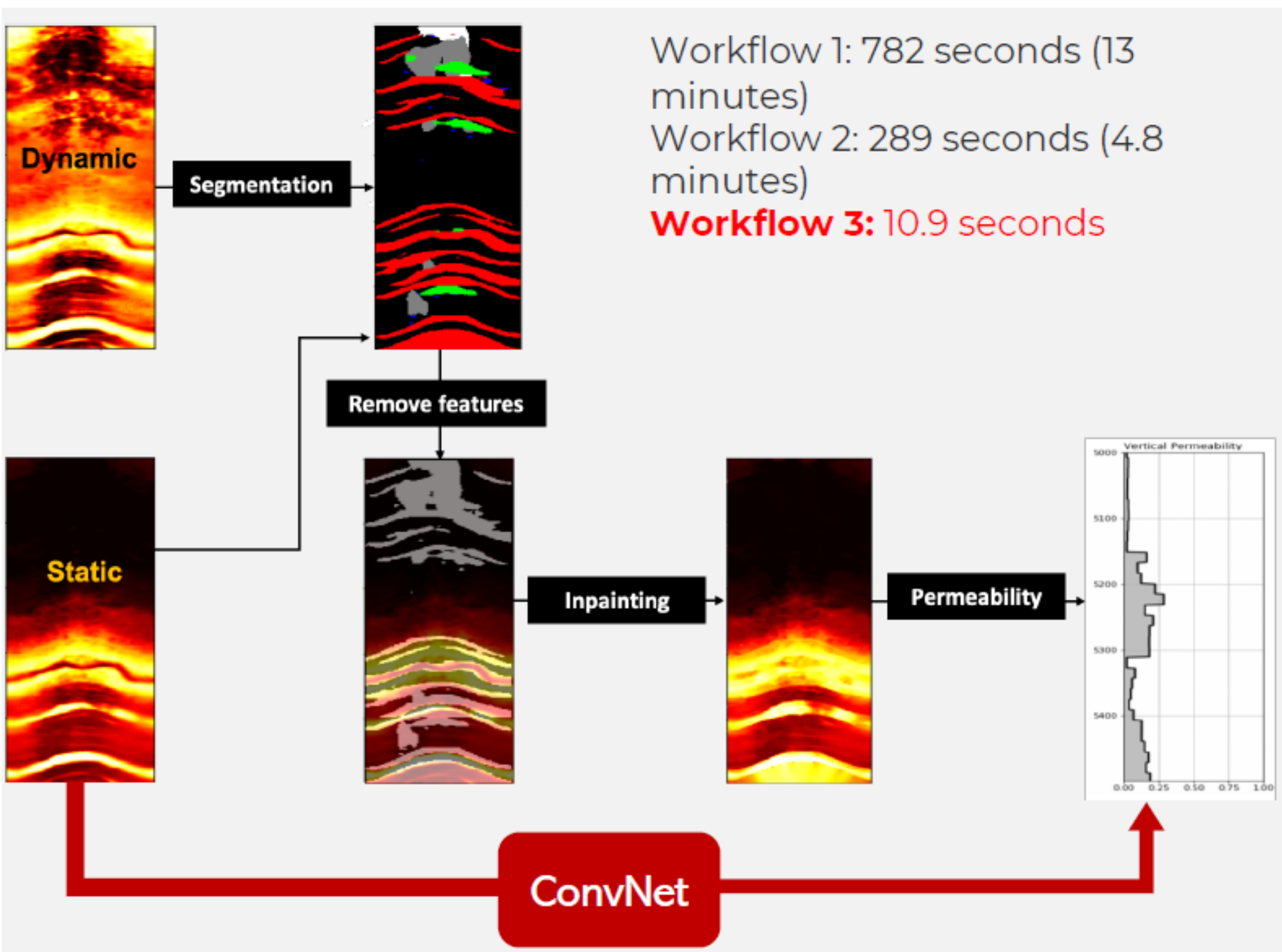

Figure 5. Permeability prediction using ConvNet

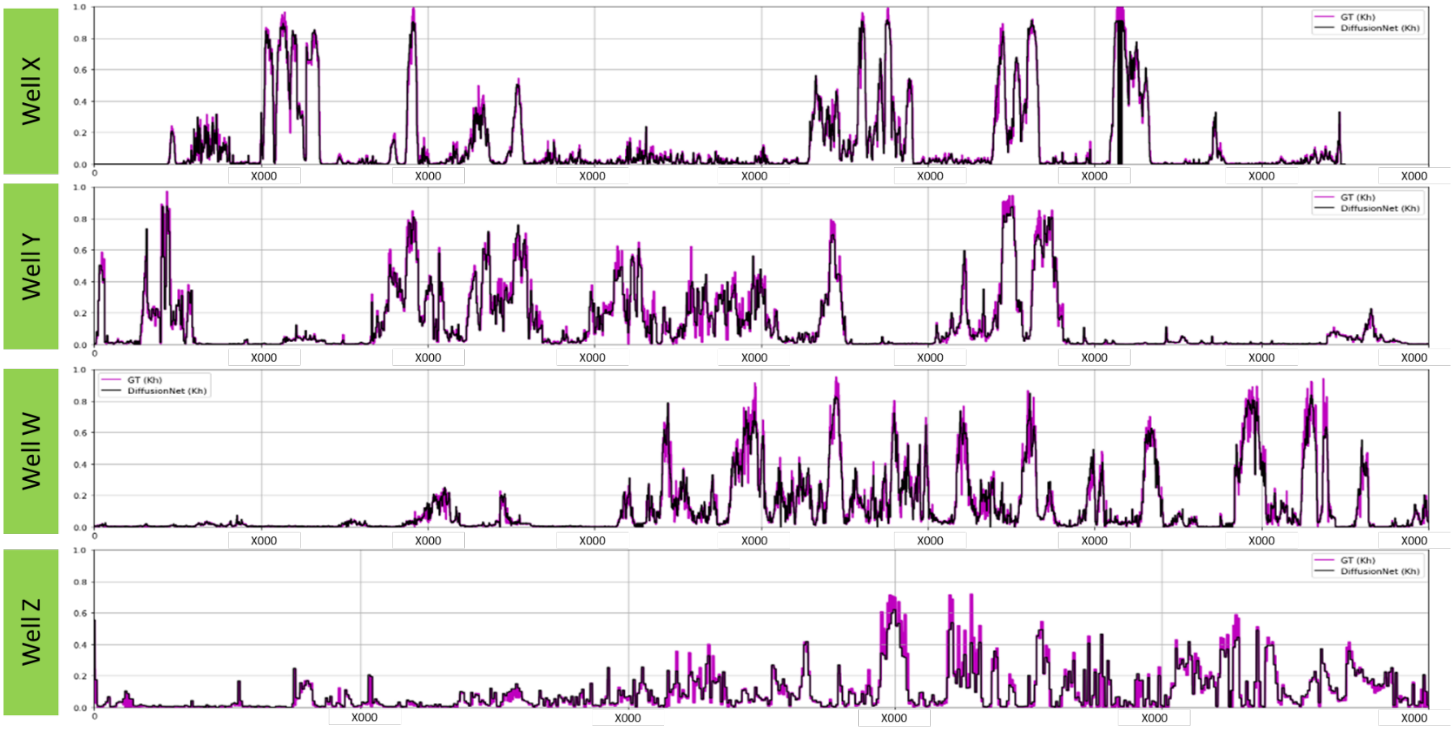

Figure 5. Permeability derived from borehole images

Case Studies

By implementing machine learning, we have successfully addressed the limitations and uncertainties in characterizing carbonate reservoirs. This approach utilizes a database of numerous wells to train the machine learning model, which annotates and identifies geological features, effectively mitigating the aforementioned limitations and uncertainties.

The technique's outputs, including image total porosity, primary porosity, and secondary porosity curves, can be incorporated into an empirical equation to enhance permeability calculations, but this requires core calibration. This technique proves particularly useful in cases where the porosity system is primarily influenced by a single secondary porosity type, such as vuggy porosity or fracture porosity, characterized by low clay content and minimal borehole artifacts. However, it is essential to carefully select appropriate parameters and cut-offs to achieve accurate results.

For more complex scenarios, where the porosity system involves multiple types of vugs, fractures, solution-enhanced beds, etc., a more comprehensive technique is necessary. This comprehensive approach should encompass geological interpretations, rock texture analysis, and consideration of the geometrical variations of heterogeneities in the formation to achieve a detailed pore system characterization. The analysis of textural and porosity characteristics reveals a diverse array of heterogeneities, manifested as conductive and resistive (dense) regions across the entire interval. The conductive heterogeneities originate from porous areas, such as patches of intergranular and intercrystalline porosity, as well as moldic, vuggy porosity, and natural open fractures, exhibiting varying sizes, shapes, and conductivity levels. On the other hand, resistive heterogeneities stem from densely cemented areas with lower or zero porosity.

Utilizing quantitative data extracted from the borehole images, we successfully identified multiple heterogeneous zones associated with higher secondary porosity and increased connectedness. This quantitative information, coupled with the assessment of different pore types and the pore connectedness index, proves highly valuable for identifying the most productive zones and understanding the correlations between various carbonate porosity components and well productivity data. This streamlined process allows us to identify pay zones and select the optimal perforation intervals within a remarkably short timeframe of less than one hour per well.

Surprisingly, good production contributions have been observed from intervals where standard logs indicate low porosity, while zones with higher porosity may yield either major or minor contributions to well production.

However, we found an excellent correlation between the production log profile and the connectedness log derived from the borehole image. This suggests that the variation in production profile is strongly influenced by the textural variation in the reservoir. Zones dominated by connected, vuggy porosity tend to yield higher production rates, while zones dominated by fracture-connected porosity exhibit lower rates. Additionally, zones dominated by isolated vuggy porosity and matrix porosity demonstrate little to no contribution to production.

The pore connectedness index serves as a crucial qualitative measure, enabling the prediction of producibility and offering valuable insights for optimizing completion strategies in future wells.

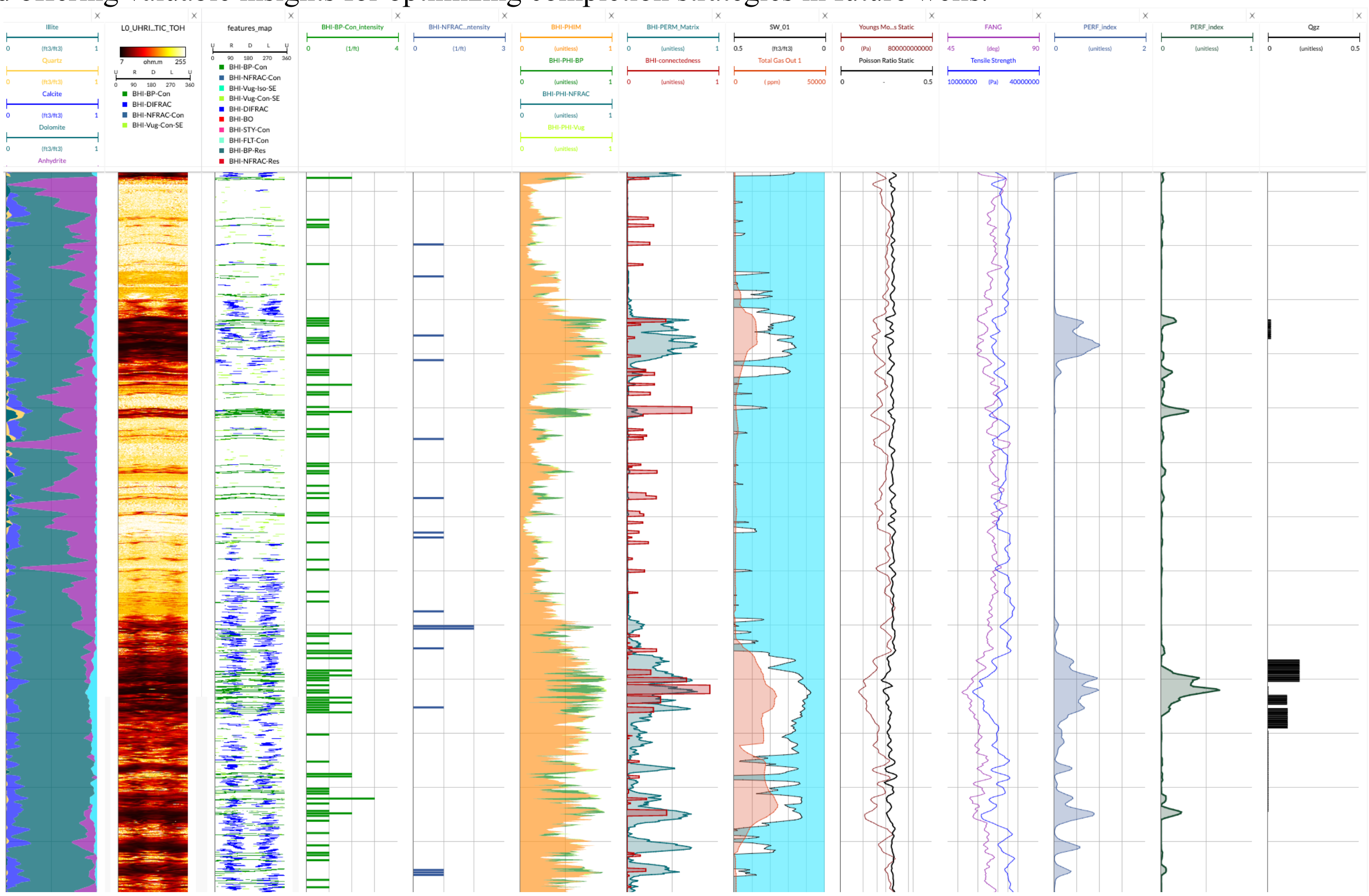

Figure 9. Example of estimated reservoir perforation index identification.

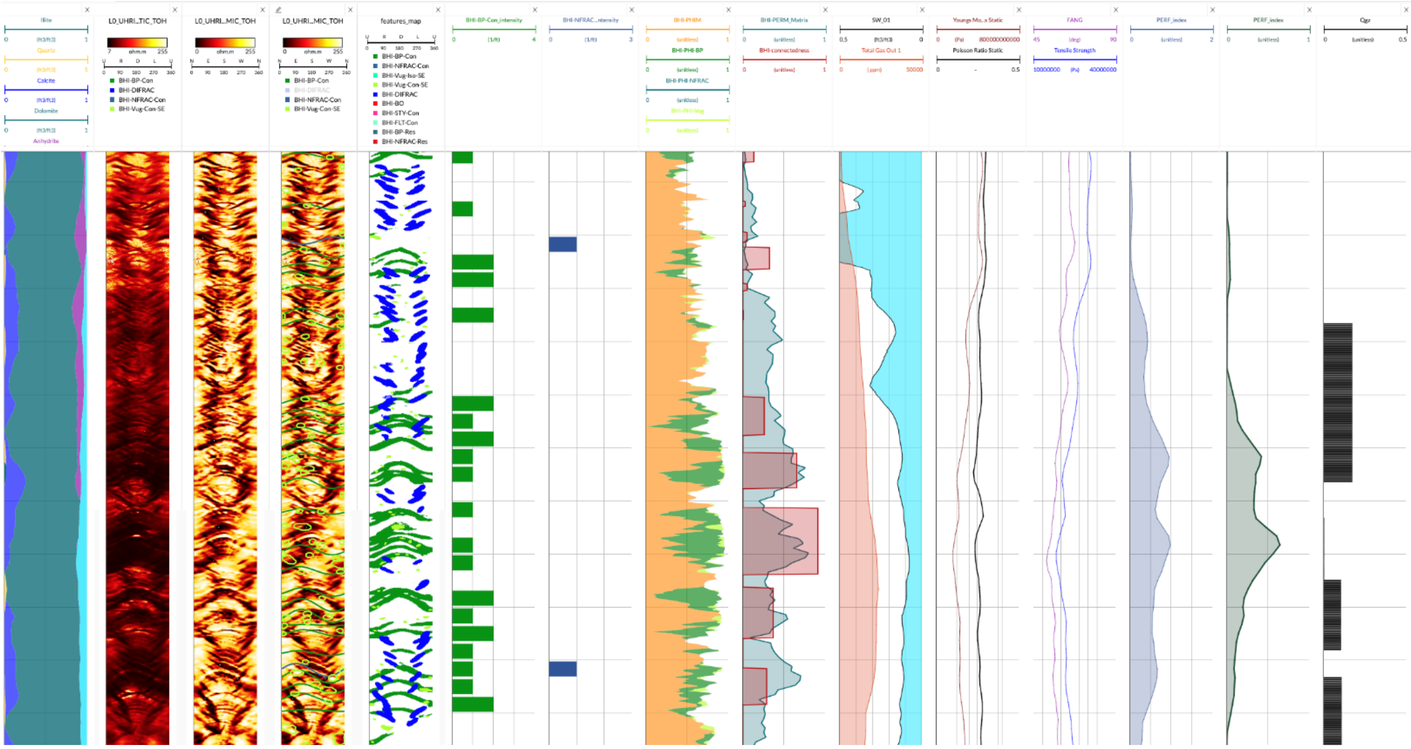

Figure 10. Example of estimated reservoir perforation index identification (closer lop).

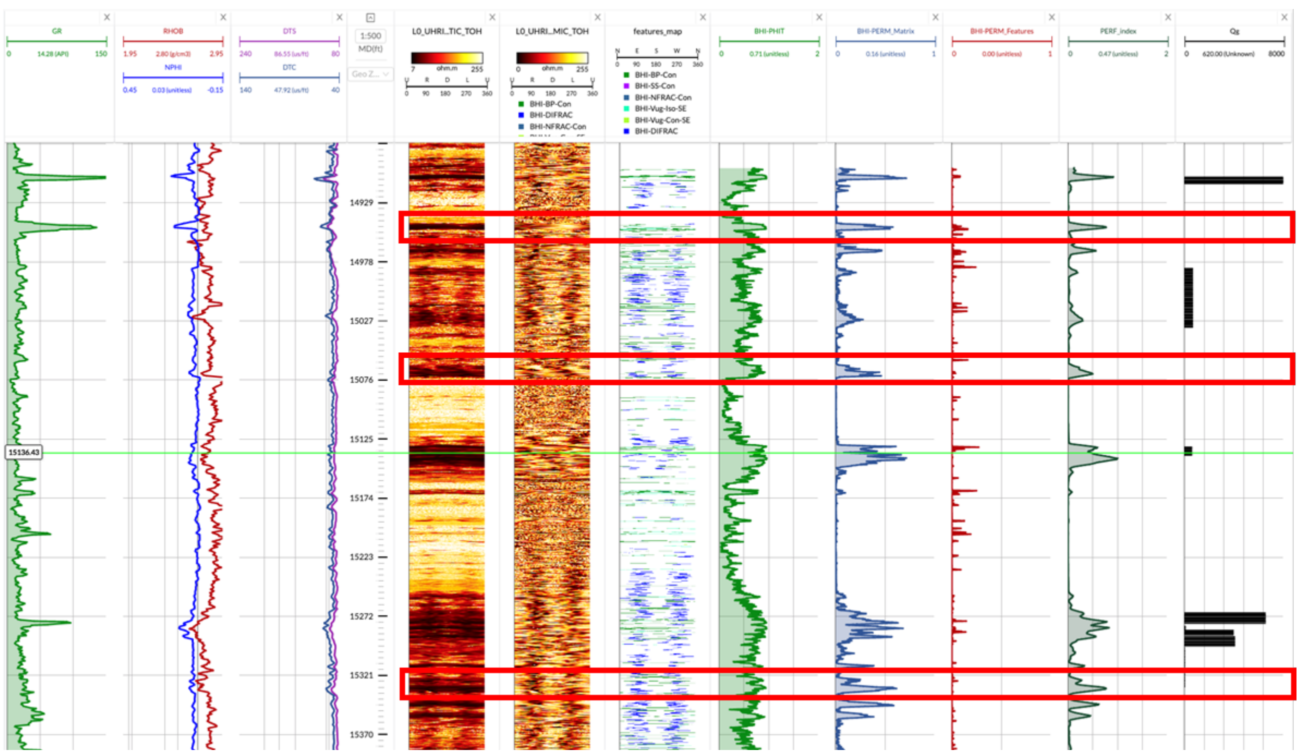

Figure 11. Example of estimated reservoir perforation index and link with PLT with missed intervals

Conclusions

To overcome limitations in characterizing carbonate reservoirs, machine learning techniques have been used. This involves annotating geologic features using a well database, with supervision from subject matter experts. The resulting machine learning model is tested on new wells and can identify pay zones, perforation intervals, and stress analysis, including minimum and maximum horizontal stresses. The models successfully detect fractures, breakouts, bedding planes, vugs, and slippage passages with pixel-level precision, reducing BHI analysis time. Machine learning is a promising development in reservoir characterization, improving the accuracy and efficiency of analyzing carbonate reservoirs.

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