

## Article

# Porosity and Permeability Estimations from X-Ray Tomography Images and Data Using a Deep Learning Approach

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## Abstract

This work presents a novel deep learning workflow for estimating porosity and permeability from combined data, where numerical variables such as high-resolution bulk density (RHOB) and photoelectric factor (PEF) data are integrated with X-ray computed tomography (X-CT) image data, using a dual-energy X-CT approach (DECT). Convolutional neural networks (CNNs) were calibrated with routine core analysis (RCAL) laboratory measurements from one well from Sinú-San Jacinto Basin (Colombia). The CNN architecture combines two main branches: An image branch, in which a CNN extracts spatial features from normalized X-CT sections using  $3 \times 3$  convolution layers, ReLU activation, batch normalization, and maxPooling, and a numerical branch, which processes the input vectors corresponding to RHOB and PEF using fully connected dense layers and dropout regularization. Both branches are concatenated in a fusion layer, from which the model's final predictions are made. Results indicate a strong correlation between porosity, permeability, RHOB and PEF logs, and CT images. The porosity model achieved excellent predictive performance, with an  $R^2 = 0.996$ ,  $MAE = 3.96 \times 10^{-3}$ ,  $MSE = 3.82 \times 10^{-5}$ , and 0.064 maximum error. The permeability model also performed well, with a linear  $R^2 = 0.983$ , though metrics reflected the wide dynamic range of permeability. Consequently, artificial neural networks (ANNs) can accurately predict porosity and permeability at various depths where no corresponding laboratory data exists, demonstrating excellent predictive capabilities over several rock intervals, in a high vertical resolution because of X-CT data scale (0.625 mm).

**Keywords:** X-ray computed tomography (X-CT); artificial intelligence (AI); rock images; well logs; convolutional neural network (CNN)



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## 1. Introduction

X-ray computed tomography (X-CT) is a useful tool in rock characterization as it allows observation inside the rock and generates 3D digital versions of the drilling cores, even when they are still preserved (e.g., aluminum sleeves or others). Contrasting conventional techniques such as scanning electron microscopy (SEM) or mercury injection porosimetry, X-CT is a non-destructive technique that allows the observation of the internal heterogeneity of the rock at different scales and with high spatial resolution [1–3].

X-CT scanning is often included in the reservoir characterization workflow but, currently, it is not easy to integrate this information into petrophysical models. The present

workflow aims to estimate high-resolution data for porosity and permeability from X-CT images, such as bulk density (RHOB) and photoelectric factor (PEF) data calculated from X-CT measurements, using a dual-energy computed tomography (DECT) approach based on Compton scattering and the photoelectric effect [3,4].

X-CT is based on the differences in X-ray absorption between materials with different electronic densities, a principle known as differential attenuation. X-CT scanning divides the bodies into a coefficient matrix where each element is called a voxel (which is equivalent to a 3D pixel). A unique X-ray attenuation coefficient is estimated for each voxel using the Hounsfield scale, which means that voxel attenuations are given in X-CT numbers. Each voxel in the image corresponds to a specific attenuation coefficient; therefore, the grayscale values represent the differential interaction of X-rays with the medium (e.g., rock versus air). This principle enables internal contrast visualization and the estimation of physical parameters of interest, making X-CT a precise technique for the characterization of porous media [4].

Among these physical parameters, porosity and permeability play a central role in reservoir engineering. Porosity determines the storage capacity of fluids within the rock, influences hydrocarbon saturation, and constitutes a key parameter in static and dynamic reservoir simulation models. Accurate porosity estimation is essential for designing efficient development and production strategies [5]. Permeability, on the other hand, controls fluid flow capacity in porous media and depends on the geometry and connectivity of the pore space, in addition to its non-linear relationship with porosity [6,7].

Conventionally, porosity estimation can be from well logs as some of them directly relate to this property (density, neutron, sonic, etc.) [8]. On the other hand, permeability must be correlated with the estimated porosity using rock type definitions based on permeability–porosity relationships such as the Winland’s equation [9] or the flow zone indicator (FZI) [10].

Within this context, RHOB and PEF are commonly used petrophysical parameters. RHOB is widely applied to estimate porosity from well logs because it directly reflects the properties of the rock matrix and pore fluid content [11]. Meanwhile, the photoelectric factor is associated with the effective atomic number of the rock and is highly sensitive to mineralogical composition, making it an important parameter for differentiating lithologies and characterizing sedimentary facies [6]. Together, RHOB and PEF enable discrimination of facies and compositional variations that are essential for petrophysical interpretation [6,11]. The X-ray attenuation coefficients estimated by the X-CT scan are related to density and the atomic effective number factor (which is directly related to PEF). Because of this, RHOB and PEF numbers can be estimated from the X-CT images [3].

Mineralogy directly governs porosity and permeability; the presence of clay minerals, carbonate cementation, or vuggy porosity can significantly modify pore space connectivity. Therefore, integrating mineralogical information, either directly or inferred from CT-derived properties such as PEF, substantially enhances petrophysical interpretation [12].

A relevant advancement in X-CT-based characterization is the dual-energy approach, which employs scanning at two different energy levels. This methodology enables the separation of density-dependent contributions associated with bulk density (RHOB) from compositional effects linked to the effective atomic number, which is directly related to PEF [4,13].

Several studies have applied dual-energy computed tomography (DECT) scanning to characterize porosity and permeability in heterogeneous lithologies and to calibrate results against laboratory measurements. These works demonstrate the practical utility of DECT in computing porosity and permeability curves and in differentiating materials within core samples [14,15].

Several approaches have been developed to estimate porosity using X-CT-based measurements, primarily due to the direct relationship between attenuation responses, RHOB, and pore volume. One early methodological development introduced the use of dual-energy acquisition to calibrate attenuation coefficients against reference materials, enabling improved porosity estimation through contrast separation [16]. Subsequent work advanced this approach by conducting sequential X-CT scans before and after replacing the saturating fluid, which made it possible to infer porosity variations associated with fluid substitution and matrix contribution [17]. Another relevant contribution formalized X-CT-based porosity workflows for standard cylindrical plug-type core samples (1–1.5 in. diameter), demonstrating consistent applicability under both single- and dual-energy scanning modes [18]. In addition, other technical assessments have documented the broader role of X-CT in formation evaluation, including porosity estimation, material differentiation, and structural characterization of heterogeneous cores, showing different applications of X-CT in the petroleum industry [19].

Artificial intelligence (AI) techniques have been widely explored for predicting reservoir properties using geophysical and petrophysical data. Early applications employed artificial neural networks (ANNs) for lithological and flow unit discrimination in a highly heterogeneous reservoir, integrating geophysical logs (gamma ray, deep induction, and bulk density), as well as core description to improve zone identification [20]. AI-based inversion workflows have also been adopted for porosity estimation in reservoir models; for example, ANN inversion enabled reliable prediction of porosity in producing intervals of the Bermejo field, outperforming conventional interpretation approaches in operational settings [21]. Subsequent studies demonstrated that ANN-based non-linear mapping yields superior accuracy compared to regression-based approaches when predicting porosity directly from well logs in crystalline formations [22]. More recent implementations employed back-propagation neural networks using sonic, density, and resistivity responses as predictors and reported strong agreement between ANN-predicted porosity and laboratory-derived values, even outperforming estimates obtained from conventional neutron–density cross plots [23].

In parallel, recent advances in AI-driven quantitative methods, e.g., signal processing and feature fusion, have demonstrated the importance of combining multiscale and multidomain information to enhance predictive robustness of physical properties in complex geosystems. For example, feature-fusion-based learning strategies for automated micro-seismic signal interpretation, showing that integrating heterogeneous attributes improve both accuracy and generalization in noisy geological environments [24]. Related work further highlighted how energy dissipation characteristics extracted from combined physical and numerical representations can reveal key rock-mass behaviors under complex stress conditions, underscoring the value of hybrid data-driven frameworks in subsurface characterization [25].

Building on these developments, machine-learning-based methodologies have leveraged RHOB and PEF values derived directly from X-CT data; using routine core analysis as ground truth, ANNs were developed to generate continuous, high-resolution porosity profiles along full core sections [26], also integrating X-CT-derived data with numerical petrophysical data within a hybrid deep learning framework, enabling direct, high-resolution prediction of both porosity and permeability properties without explicit pore segmentation [27].

As evidenced from the reviewed literature, the incorporation of AI has significantly strengthened the use of X-CT for rock properties estimation. Convolutional neural networks (CNNs) have demonstrated outstanding performance in predicting permeability and porosity from 3D images of porous media. Physically informed models that integrate

direct numerical simulations (DNSs) with CNN architectures have achieved highly reliable permeability predictions, demonstrating that embedding pore-scale flow information improves generalization and accuracy [28].

Additionally, recent developments in deep learning have combined multiscale X-CT imaging with petrophysical measurements, enabling a more accurate representation of pore networks and connectivity patterns within heterogeneous rock systems [29]. These research advances highlight the relevance of incorporating physically based features, such as mineralogical and structural attributes, into CNN-driven workflows for enhanced petrophysical characterization.

The present study contributes to this research direction by integrating X-CT imaging, dual-energy parameters (RHOB and PEF), and laboratory measurements obtained from routine core analysis (RCAL) in a hybrid deep learning architectures for the high-resolution prediction of porosity and permeability. An innovative workflow is implemented in which CNN-based models trained with Boyle porosity and air permeability are subsequently applied to predict petrophysical properties in intervals lacking direct measurements, while preserving the native vertical resolution of 0.625 mm provided by X-CT scanning. This approach yields a robust methodology that not only enhances the prediction of petrophysical properties but also addresses key limitations identified in previous studies regarding resolution constraints, multisource data integration, and applicability in geologically complex intervals. The complete workflow is fully documented including acquisition, preprocessing, model architecture, training, and validation along with limitations and improvement opportunities (e.g., X-CT resolution and mineralogical influence).

## 2. Theoretical Framework

The estimation of petrophysical properties such as RHOB and PEF is fundamental for reservoir characterization. Traditionally, RHOB and PEF are obtained from well logs or laboratory analysis of core samples. RCAL provides measurements such as porosity, permeability, and grain density under ambient conditions, serving as ground truth data for calibrating indirect measurements [5].

With the advent of advanced imaging technologies, X-CT has become a valuable non-destructive method for characterizing rock properties in 3D. X-CT scanning at dual energy levels allows differentiation of materials based on their attenuation coefficients, enabling indirect estimation of RHOB and PEF from X-CT numbers [30]. The DECT approach improves the accuracy of RHOB prediction by calibrating attenuation values using reference materials of known density and composition [4,13].

### 2.1. Physical Principles of X-Ray Attenuation and X-CT Fundamentals

X-CT relies on the differential attenuation of X-ray radiation when it passes through materials with distinct electron density and composition. When a monochromatic X-ray beam traverses a homogeneous medium, the transmitted photon flux decreases exponentially as a function of path length and attenuating properties of matter. The basis of X-ray measurements is the Beer–Lambert law [31], which describes the relationship between the reduction in X-ray intensity and the physical properties of the medium through which the beam propagates. The attenuation process is expressed as can be seen in the following Equation (1):

$$\frac{I_1}{I_0} = e^{-\mu l} \quad (1)$$

where:

$I_1$ : intensity of the X-ray upon arrival (after passing through the sample).

$I_0$ : intensity of the original in the source.

$\mu$ : linear attenuation coefficient of the material.

$l$ : length of the material that the ray passes through.

According to the above, the attenuation of X-rays is related (although not exclusively) to the properties of the material through which they pass; more specifically, this coefficient can be obtained by means of the expression shown in Equation (2):

$$\mu = \rho \left( a + \frac{Z_{eff}}{E^{3.6}} \right)^b \quad (2)$$

where:

$\rho$  total density of the material studied.

$Z_{eff}$ : effective atomic number of the material.

$E$ : output energy of the X-ray.

$a$  and  $b$ : coefficients that depend on multiple factors such as the energy of acquisition and the type of source used.

Equation (2) defines the linear attenuation coefficient of a material, whose relevance lies in the fact that it explicitly depends on both the bulk density ( $\rho$ ) and the effective atomic number ( $Z_{eff}$ ) of the rock. This formulation evidences a non-linear relationship between these two variables, since  $Z_{eff}$  appears divided by the photon energy term. Such a dependency enables the dual-energy (DE) approach, in which measurements of the attenuation coefficient at two distinct X-ray energies allow the independent estimation of density and effective atomic number. Moreover, Equation (2) highlights that the sensitivity of attenuation to  $Z_{eff}$  decreases as the X-ray energy increases, implying that high-energy beams tend to emphasize density effects, whereas lower-energy beams are more responsive to variations in  $Z_{eff}$ . This principle underpins DECT acquisition and its applicability for deriving physical properties from X-CT measurements.

## 2.2. Physical Meaning of RHOB and PEF and Their Estimation from X-CT Data

In petrophysics, RHOB and PEF are fundamental parameters for lithological discrimination and mineralogical interpretation. Bulk density represents the combined contribution of the mineral matrix and fluids within the pore space and therefore provides information related to porosity, mineral composition, and fluid type. In conventional well log acquisitions, RHOB is obtained from gamma ray attenuation measurements using formation density tools, which quantify electron density and convert it to apparent bulk density after environmental corrections.

PEF, in contrast, is directly related to the photoelectric absorption component of X-ray interaction, which strongly depends on the effective atomic number of the material. For a given rock, PEF can be approximated as a function of  $Z_{eff}$  according to empirical relations [32]. This sensitivity allows PEF to distinguish lithologies with similar densities but different mineralogical assemblages, for instance, separating quartz-rich sandstones (low  $Z_{eff}$ , low PEF) from carbonate or clay-rich rocks (high  $Z_{eff}$ , high PEF).

In DECT workflows, RHOB and PEF can be estimated by performing two scans at distinct energy spectra. The dual acquisition enables separation of attenuation components dominated by Compton scattering (mainly density dependent) and photoelectric absorption (atomic number dependent). Once calibrated using reference standards (phantoms), DECT intensity pairs ( $I_L$ ,  $I_H$ ) corresponding to low and high energy can be inverted to obtain spatial distributions of RHOB and PEF at voxel resolution. Thus, each X-CT voxel is mapped not only to an attenuation coefficient but also to calibrated petrophysical estimators, enabling mineralogical and lithological interpretation directly in the rock volume.

This capability is particularly relevant for core-based studies, where DECT enables continuous high-resolution profiles of density and atomic number contrasts, linking geological description, laboratory measurements, and predictive modeling of petrophysical properties.

### 2.3. Deep Learning (DL) and Petrophysical Property Estimation from Images

To enhance the interpretation of X-CT images, machine learning (ML) techniques, particularly CNNs, have been widely adopted. CNNs are well-suited for extracting spatial features from image data and have demonstrated excellent performance in tasks such as porosity prediction, segmentation of lithological units, and fracture identification [33]. By training CNN models on annotated X-CT image datasets with corresponding core measurements, it becomes possible to automatically predict RHOB and PEF distributions with high resolution and generalization ability.

Moreover, recent studies have shown that incorporating PEF into the prediction workflow improves accuracy in heterogeneous lithologies, as PEF reflects mineralogical composition rather than porosity directly [6]. The integration of X-CT imaging, RCAL data, and CNN-based ML algorithms creates a robust framework for high-resolution petrophysical property estimation, offering improved insight over traditional log-based approaches.

Although the effective atomic number ( $Z_{eff}$ ) and PEF are correlated, they differ conceptually:  $Z_{eff}$  represents the averaged elemental composition of the material, whereas PEF represents the energy-weighted photoelectric response. In practice, using both variables simultaneously can introduce redundancy; in this work,  $Z_{eff}$  is considered only as an auxiliary variable and used only when PEF is not available, acknowledging its partial dependence and correlation.

This hybrid methodology enables interpreters not only to estimate physical properties but also to visualize internal rock features in 3D without destroying the sample, providing context to measurements and allowing for quality control of regions with anomalies such as fractures or vugs.

## 3. Methodology

A dataset comprising 36 X-CT images of three-foot drilling core sections, from a well in Sinú-San Jacinto Basin, located in the northwestern corner of Colombia, which is a prolific area for oil and gas seeps among Colombian basins [34], along with their corresponding RHOB and PEF data, was used as input for training, testing, and validating our model. Both numerical and image input information had to undergo preprocessing to train a robust model.

The spatial resolution used in this study (0.625 mm slice thickness) corresponds to one of the highest resolutions achievable with modern medical X-CT scanners, which are the standard equipment used for imaging full drilling cores. This scale of X-CT imaging is appropriate for identifying changes in lithology, large-scale textural features, and structural heterogeneity such as fractures or bedding.

### 3.1. Preprocessing of Numerical Information

A total of 55 porosity and permeability data points were available from RCAL at specific locations along the core section. Given that the vertical resolution of the X-CT images corresponds to 0.625 mm ( $\approx 0.002$  ft), these 55 control points were insufficient to match the high-resolution sampling of the tomographic data.

To increase the representativeness of the dataset, a controlled numerical data augmentation procedure was implemented. Specifically, for each original RCAL value, 20 additional points were generated above and below the reference measurement by applying small

perturbations of  $\pm 1\%$ . This range is intentionally conservative and lies within the typical experimental uncertainty of routine porosity and permeability measurements. As a result, the augmented samples preserve the original data distribution and physical consistency, serving exclusively to increase sampling density relative to the X-CT resolution.

This adjustment increased the density of information, expanding the total number of data points from 55 to 2255. This procedure has proven useful in the contexts of digital rock physics and image analysis [28,29]. Table 1 summarizes the descriptive statistics of the augmented dataset.

**Table 1.** Numerical data frame for the neural network.

| Property | Density | PEF    | $Z_{eff}$ | Porosity | Permeability |
|----------|---------|--------|-----------|----------|--------------|
| Count    | 2255    | 2255   | 2255      | 2255     | 2255         |
| Mean     | 2.497   | 3.560  | 14.002    | 0.055    | 5.025        |
| Std      | 0.340   | 1.612  | 1.526     | 0.036    | 23.073       |
| Min      | 2.197   | 1.879  | 11.916    | 0.009    | 0.003        |
| 25%      | 2.413   | 2.519  | 12.925    | 0.028    | 0.017        |
| 50%      | 2.464   | 3.183  | 13.794    | 0.048    | 0.095        |
| 75%      | 2.501   | 3.943  | 14.638    | 0.076    | 0.651        |
| Max      | 5.168   | 10.264 | 19.095    | 0.146    | 145.174      |

The augmentation of the 55 laboratory measurements into 2255 data points was not intended to introduce new geological variability but rather to reconcile the mismatch between the spatial resolution of the X-CT images (0.625 mm per slice) and the physical volume represented by a conventional core plug (~2.5 cm length). Each laboratory measurement corresponds to a rock volume approximately 40 times larger than a single X-CT slice. Without expanding the measurement interval, each RCAL point would be associated with a single pixel row, which would artificially underrepresent the physical scale of the measurement and reduce the effectiveness of training the mixed-input model.

The  $\pm 1\%$  perturbation does not alter geologic meaning; instead, it creates a narrow numerical envelope that allows the model to generalize within the spatial extent of the plug interval. Although such augmentation may produce optimistic metrics during the training phase, it does not affect the validation or testing performance, which are computed using un-augmented and randomly held-out portions of the dataset. Thus, the  $R^2$ , mean squared error (MSE), and mean absolute error (MAE) values reported for validation and testing constitute the true indicators of model performance.

From this data frame, the input data for the model will consist of RHOB, PEF or  $Z_{eff}$  (optionally, the model does not use both PEF and  $Z_{eff}$  simultaneously as  $Z_{eff}$  has no impact due to its dependence on PEF). In DECT, PEF is physically dependent on the effective atomic number ( $Z_{eff}$ ), following the well-known  $PEF \propto Z_{eff}^{3.6}$  relationship [32].

Once the desired information has been selected, a recommended practice is to standardize the data. This is a common requirement for machine learning models. The purpose of standardization is to transform the data so that its distribution has a mean value of 0 and a standard deviation of 1. This ensures that all numerical input parameters carry equal weight during the training process. The standardized value of the dataset  $x$  can be calculated using Equation (3):

$$z = \frac{x - \mu}{s} \quad (3)$$

where:

$z$ : the standardized value.

$x$ : the original value of the metric.

$\mu$ : the mean of the variable.

s: the standard deviation of the dataset.

Standardization is required to ensure that the variables contribute equally to the training process, preventing numerical bias toward features with larger magnitudes. Additionally, scaling the input space improves the stability of gradient-based optimization, accelerates model convergence, and enhances the generalization capability of the network. The output of this standardization procedure is presented in Table 2.

**Table 2.** Preprocessed numerical information, to be used for model training, testing, and validation.

| Property | Density                | PEF                    | $Z_{eff}$               |
|----------|------------------------|------------------------|-------------------------|
| Count    | 2255                   | 2255                   | 2255                    |
| Mean     | $2.52 \times 10^{-17}$ | $4.29 \times 10^{-16}$ | $-1.17 \times 10^{-15}$ |
| Std      | $1.00 \times 10^0$     | $1.00 \times 10^0$     | $1.00 \times 10^0$      |
| Min      | −0.884                 | −1.04                  | −1.37                   |
| 25%      | −0.248                 | −0.646                 | −0.706                  |
| 50%      | −0.0988                | −0.234                 | −0.136                  |
| 75%      | 0.0109                 | 0.237                  | 0.417                   |
| Max      | 7.85                   | 4.16                   | 3.34                    |

Figure 1 summarizes the complete preprocessing workflow applied to X-CT images and numerical data prior to model training. The pipeline includes image quality control, grayscale normalization, z-score standardization, resizing, and tensor construction, followed by numerical data preprocessing and synchronization with RCAL measurements. This workflow ensures consistent spatial alignment, numerical stability, and reproducibility of the proposed hybrid deep learning approach.

### 3.2. Image Acquisition

Medical DECT was utilized to obtain images for both detailed geological characterization and quantitative assessment of RHOB and PEF. Each rock sample was scanned sequentially at two distinct energy levels (one low,  $\leq 100$  kV, and one high,  $>100$  kV), ensuring consistent sample positioning across scans to facilitate dual-energy analysis and maximize the separation of photoelectric and Compton-dominant regimes. Alongside the core samples, three cylindrical reference phantoms, quartz, Teflon, and distilled water contained within PVC tubes with known density and PEF values, were placed longitudinally to calibrate the measurements.

All core sections were scanned from top to bottom at 3-foot intervals (approximately 0.91 m) to ensure accurate depth tracking throughout the processing workflow, achieving a vertical resolution of 0.625 mm per image. The scan field diameter was set to 24 cm, yielding an in-plane spatial resolution of about 460 microns and allowing simultaneous inclusion of both the core and reference phantoms in every image. This configuration enabled accurate and reproducible estimation of rock properties using DECT methodology, thereby validating the robustness of the analytical approach.

To ensure transparency and reproducibility, the complete acquisition parameters of the DECT dataset used in this study are summarized in Table 3. These metadata describe the experimental conditions applied during scanning, including tube voltage, current, slice thickness, and the spatial resolution of the reconstructed images. These settings provide the maximum practical resolution for whole-core scanning in medical X-CT systems while maintaining sufficient photon flux for stable dual-energy inversion.

|                                               |                                           |                                                                                                                                                                                                                                                  |
|-----------------------------------------------|-------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <b>Flowchart:<br/>Image<br/>preprocessing</b> | <b>1. X-CT Data Acquisition</b>           | Medical DECT scanning of whole core<br>Fixed vertical resolution: <b>0.625 mm</b><br>Consistent top to bottom orientation for all samples                                                                                                        |
|                                               | <b>2. Image Quality Control</b>           | Visual inspection of raw X-CT slices<br>Removal of corrupted or low-quality slices<br>Verification of depth consistency between slices                                                                                                           |
|                                               | <b>3. Grayscale Normalization</b>         | Conversion of raw X-CT values to standardized grayscale range<br>Intensity normalization to reduce scanner-dependent variability<br>Ensures consistency across slices and datasets                                                               |
|                                               | <b>4. Image Standardization</b>           | Z-score standardization of pixel intensities: $z = \frac{x-\mu}{\sigma}$<br>Centers data around zero mean and unit variance<br>Improves numerical stability during CNN training                                                                  |
|                                               | <b>5. Image Resizing and Cropping</b>     | Cropping to region of interest (core interior only)<br>Resizing to fixed input dimensions required by CNN<br>Preserves vertical textural continuity of the core fabric                                                                           |
|                                               | <b>6. Image Tensor Construction</b>       | Stacking of preprocessed 2D slices<br>Conversion to model-ready image tensors<br>Alignment of image depth with numerical data                                                                                                                    |
|                                               | <b>7. Numerical Data Preprocessing</b>    | Input variables: RHOB, PEF or $Z_{eff}$ (only one of these two is available)<br>Z-score standardization applied to all numerical features<br>Ensures comparable scaling with image-derived features                                              |
|                                               | <b>8. RCAL Data Integration</b>           | Laboratory porosity and permeability measurements (55 control points)<br>Controlled numerical data augmentation ( $\pm 1\%$ )<br>Expansion to 2255 training-aligned data points<br>Assignment of RCAL properties to corresponding X-CT intervals |
|                                               | <b>9. Multimodal Data Synchronization</b> | One to one matching of: X-CT image slice<br>Numerical inputs (RHOB, PEF or $Z_{eff}$ )<br>Target labels (porosity, permeability)<br>Final dataset prepared for CNN training and validation                                                       |
|                                               | <b>10. Model Input</b>                    | Image tensors $\rightarrow$ CNN image branch<br>Numerical features $\rightarrow$ fully connected branch<br>Fusion through concatenation layer                                                                                                    |

**Figure 1.** Schematic workflow of the proposed methodology, illustrating the sequential processing stages from X-CT acquisition and preprocessing to hybrid CNN–numerical data fusion and Data Integration for petrophysical property prediction.

**Table 3.** DECT acquisition parameters for the 36-image dataset. The X-CT scanner used is a General Electric Optima CT660 medical device (GE Healthcare, Tokyo, Japan).

| Parameter                       | Value                                             | Description                                                    |
|---------------------------------|---------------------------------------------------|----------------------------------------------------------------|
| Tube voltage (High-energy scan) | 140 kV                                            | Standard for maximizing Z-contrast in DECT.                    |
| Tube voltage (Low-energy scan)  | 100 kV                                            | Used to enhance attenuation separation between materials.      |
| Tube current                    | 50 mA for high energy and<br>60 mA for low energy | Fixed for all scans to ensure consistent exposure.             |
| Slice thickness                 | 0.625 mm                                          | Maximum resolution achievable with the medical X-CT equipment. |
| In-plane XY resolution          | 0.46 mm (460 $\mu$ m)                             | Derived from 24 cm FOV/512 detector matrix.                    |
| Scan field of view (FOV)        | 24 cm                                             | Allows simultaneous inclusion of core and phantoms.            |
| Reconstruction matrix           | 512 $\times$ 512                                  | Standard clinical reconstruction grid.                         |
| Pixel spacing                   | 0.468 $\times$ 0.468 mm                           | Consistent with XY resolution.                                 |
| Reconstruction kernel           | Standard (soft tissue)                            | Used to avoid artificial edge enhancement.                     |
| Number of slices per interval   | Variable (top-to-bottom)                          | Corresponds to $\sim 1$ slice every 0.625 mm.                  |

### 3.3. Preprocessing of X-CT Images

For the estimation of RHOB and PEF in the rock it is necessary to perform dual-energy scanning, using a high energy level (above 100 kV) and a low energy level (at or below 100 kV). Both scans employed materials with known properties (phantoms). This approach allowed the identification, in each image slice, of the relationship between X-ray attenuation (X-CT numbers) at both energy levels and the known RHOB and PEF values. Subsequently, the results were calibrated using rock samples with known properties, and necessary adjustments were made to the calculated properties to ensure the accuracy of the estimated values.

It is important to highlight that this estimation is conducted by extracting X-CT numbers from specific areas within the rock images, known as regions of interest (ROIs), thereby avoiding measurements from sections that could bias the calculation, such as fractures or void spaces.

Not all log sets contain porosity and permeability data. Therefore, it is necessary to segment the images into intervals where porosity and permeability information is available. Since the amount of tomography data (RHOB and PEF) corresponds to the vertical pixel dimension of the core images, this segmentation can be directly performed by selecting the pixels containing porosity and permeability information. This process results in segmented images, as illustrated in Figure 2, for each interval.

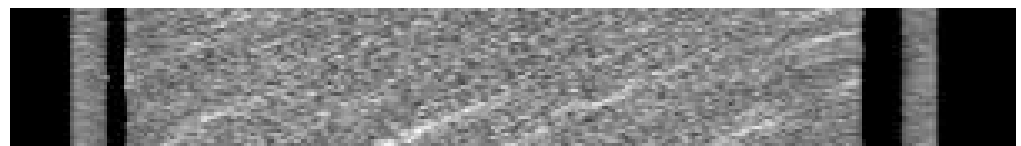


**Figure 2.** Grayscale section of an X-CT image used for neural network training, showing the segmentation applied to the intervals with RCAL data.

To streamline the model input process, the second step in image preprocessing involves converting the images to grayscale. Grayscale images have a single-color channel with a 256-level scale, which allows the attenuation intensity of X-rays to be represented in each voxel.

The original X-CT images utilize the Hounsfield scale, which spans from −1000 (representing air) to 3000 or higher for denser materials such as rocks. Converting to grayscale preserves relative attenuation information, facilitating normalization and subsequent training of CNNs.

Furthermore, standardization of the image data is necessary. Since an image is essentially a tensor comprising height, width, and pixel density per color channel (forming a matrix), it is common practice to scale its data to values between 0 and 1. Given that the maximum pixel value an image can be 255, the standardization process involves dividing the image tensor by 255, which transforms the data into a range between 0 and 1, according to Equation (4):

$$I_{norm} = \frac{I_{pixel}}{255} \quad (4)$$

where:

$I_{norm}$ : normalized pixel value,

$I_{pixel}$ : original pixel value (0–255).

Figure 3 provides an illustrative example. Each image in the dataset has dimensions of 41 pixels in height and 301 pixels in width, resulting in 55 image sections and a total pixel density of 2255 for training purposes.

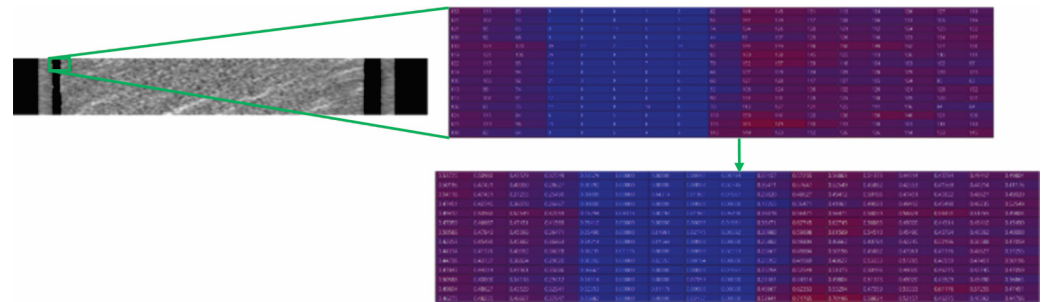


**Figure 3.** Example of pixel density standardization in X-CT images, showing the transformation of original values (Hounsfield Units (HU) to grayscale) to normalized values in the range [0,1]. Arrow indicate the sequential preprocessing steps applied to the image data.

### 3.4. Design and Parameters of the Deep Learning Model

In machine and deep learning contexts, input data can be categorized into three main types of information:

- Numeric or continuous data, such as geophysical well logs.
- Categorical data, including binary variables (e.g., Yes/No) or class-based descriptors such as lithofacies or rock type.
- Image-based data, which includes static images, three-dimensional volumetric datasets such as X-CT acquisitions, and even sequential information such as video.

In this study, a mixed-data problem is addressed, where numerical variables such as RHOB and PEF are integrated with X-CT-derived image data. This configuration requires a deep learning architecture capable of jointly processing heterogeneous data types and extracting meaningful representational relationships between them. The model must simultaneously learn spatial features from image tensors and non-linear correlations within numerical inputs, ensuring that both sources of information contribute to the prediction of petrophysical properties.

The proposed model is implemented in Python 3.7.12, using a set of well-established machine learning libraries to ensure reproducibility, which provides tools for building and training CNN and hybrid architectures. The computational environment consisted of:

- TensorFlow 2.4.1 and Keras 2.4.3 (version 2.x, Google Brain Team, Google LLC, Mountain View, CA, USA) for model construction, training, and optimization.
- NumPy 1.19.5 for numerical operations.
- Pandas 1.1.5 for dataset structuring and preprocessing.

The deep learning model is constructed using primarily the Tensorflow–Keras suite provided by Google. This suite offers comprehensive functionality for deep learning tasks, enabling the creation of multiple models and their concatenation into a single model. In summary, the designed architecture combines two main branches:

1. An image branch, in which a CNN extracts spatial features from normalized X-CT sections using  $3 \times 3$  convolution layers, ReLU activation, batch normalization, and maxPooling.
2. A numerical branch, which processes the input vectors corresponding to RHOB and PEF using fully connected dense layers and dropout regularization.

Both branches are concatenated in a fusion layer, from which the model's final predictions, porosity and permeability, as applicable, are derived. This scheme allows for the simultaneous use of textural information from images and the quantitative precision of numerical data, improving the model's predictive capacity compared to using each data type in isolation. The architecture of the proposed model is depicted in Figure 4.

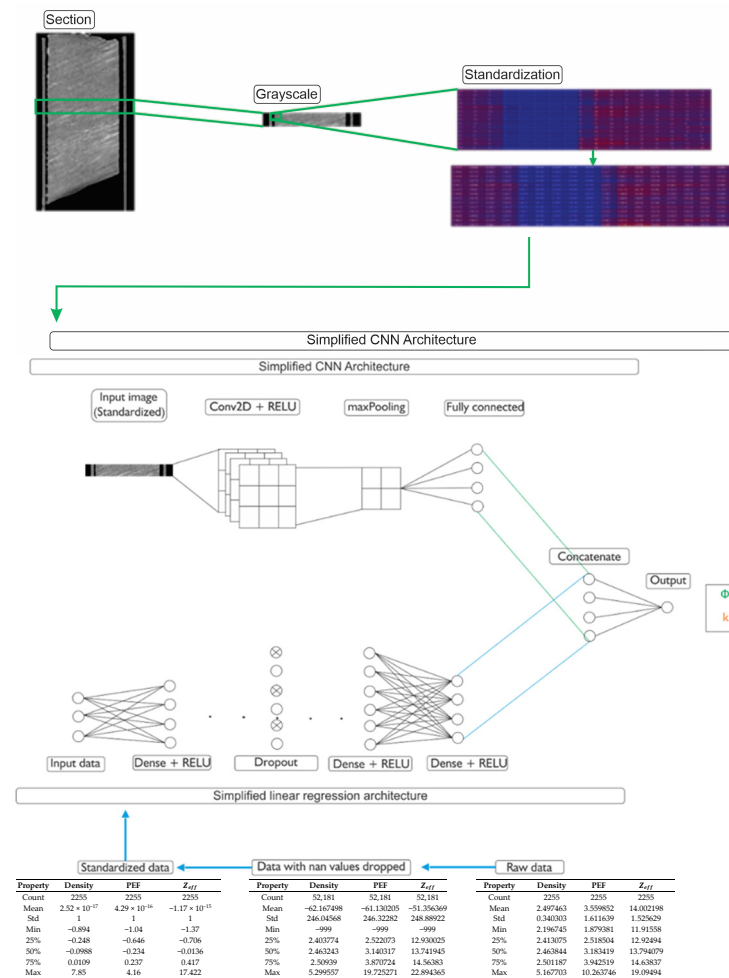


**Figure 4.** Schematic of the proposed architecture of the deep learning model, showing the combination of the image branch (CNN) and the numerical branch (dense layers) in a fusion layer for the prediction of petrophysical properties.

The image processing branch employs CNNs, widely used in image processing due to their ability to recognize spatial and textural patterns. First, each X-CT image section is processed pixel by pixel through a set of convolutional filters, consisting of three 2D convolutional layers with 16, 32, and 64 filters, respectively. A kernel size of  $3 \times 3$  with “same” padding and ReLU activation is used in all convolutional layers. The progressive increase in filter count follows standard deep learning practice, enhancing the model’s ability to capture increasingly complex spatial patterns.

Each filter (or convolutional neuron) acts as a weight matrix that is moved across the image, generating a new feature map. This results in filtered representations that capture relevant properties such as pixel density variations, edges, and internal rock textures. Next, each convolutional layer is followed by batch normalization to stabilize learning and, subsequently, the image undergoes maxPooling, which partitions the image into sections and selects the maximum pixel density value within each region (e.g., using an ordered pair with a pool size of (1,2)) to reduce horizontal resolution while preserving vertical structural details relevant to core fabrics. This process helps extract the most prominent features while mitigating the risk of overfitting the model to the training data.

The combination of convolution and maxPooling forms the fundamental building block of CNNs, enabling the hierarchical extraction of visual features. In subsequent stages, these feature maps are flattened and sent to the fusion layer, where they are integrated with the model’s numerical data.

A schematic representation of the initial structure of the image branch is illustrated in Figure 5, which shows a first two-dimensional convolutional layer (Conv2D) with 16 filters, followed by a maxPooling layer with a window size of (1,2). The convolutional filters extract relevant visual features from the X-CT images, while maxPooling reduces dimensionality and concentrates the information on the most representative features. This combination forms the basis of image processing in the convolutional neural network (CNN).

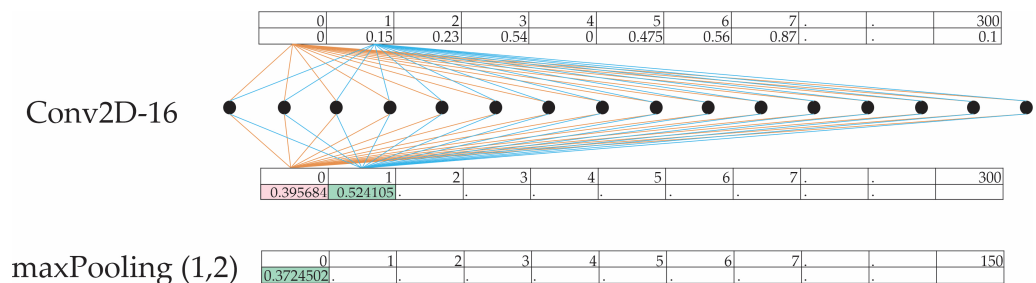


**Figure 5.** Initial architecture of the image branch of the deep learning model. The application of a convolutional layer (Conv2D with 16 filters) and a maxPooling layer ( $1 \times 2$  window) is illustrated, which allows the extraction and condensation of characteristic features from computed tomography (X-CT) images.

On the numerical input side (lower model in Figure 4), the architecture is simplified. The numerical input branch consists of a linear configuration with a fully connected network with four dense layers (32, 64, 128, and 256 neurons) using ReLU activation. The final feature maps are flattened into a 1D vector. Based on initial experiments, a dropout rate of 0.2 was added to mitigate potential overfitting. This decision is based on the observation that initial models did not exhibit overfitting when trained on the available data. Furthermore, the models are successfully validated on both the test and validation datasets.

Following the individual processing of the image and numerical inputs, both branches are merged through a concatenation layer and subsequently processed by a dense layer of 4 neurons, ensuring balanced contribution of image-based and numerical features. This specific value is selected to ensure consistency between the two branches of the model. In this final stage of the architecture, the feature representations produced independently by the two branches, the CNN image processing branch and the numerical multilayer perceptron (MLP) branch, are merged into a single predictive model. Each branch outputs a 4-dimensional latent vector, and these two vectors are concatenated to form an 8-dimensional joint representation. This fused vector is then passed through a fully connected layer with four neurons and ReLU activation, which enables the model to learn non-linear interactions between the spatial features extracted from the X-CT images and the numerical descriptors (RHOB and PEF).

Finally, the output of this layer is fed into a single-neuron dense layer with linear activation, generating the final prediction of ( $\varphi$ ) or permeability ( $k$ ), which outputs a scalar value corresponding to the estimated property. In this study,  $\varphi$  and  $k$  are predicted using two independent but structurally identical models. Both models share the same hybrid architecture composed of a CNN branch for X-CT images and a numerical MLP branch for RHOB, PEF and optionally  $Z_{eff}$  (for intervals where only one of these two logs is available), but they are trained separately using different target variables. For porosity prediction, the model is trained using laboratory Boyle-porosity measurements as target labels, while permeability predictions are trained using air-permeability values from RCAL. In both cases, the model optimizes the MSE between predicted and measured values, allowing  $\varphi$  and  $k$  to be obtained directly from the output of the final dense neuron layer. The initial

learning rate was set to  $1 \times 10^{-3}$ , identified as the best compromise between stability and convergence speed after preliminary tuning experiments employing a logarithmic sweep between  $1 \times 10^{-4}$  and  $1 \times 10^{-2}$ . All operations follow a strictly sequential structure, without parallel paths, skip connections, or residual links, ensuring a fully reproducible and well-defined data flow throughout the entire model.

This hybrid design (CNN for images + MLP for numerical data) combines the advantages of both approaches:

- CNNs capture complex spatial patterns from X-CT images.
- Dense layers accurately process physical variables.
- Fusion improves predictive capabilities compared to using independent inputs.

Figure 6 presents a schematic overview of the proposed hybrid deep learning architecture used in this study. The model is designed to jointly exploit spatial information from X-CT images and complementary numerical petrophysical data derived from dual-energy calibration. To this end, two parallel branches are implemented: a convolutional neural network (CNN) branch that processes X-CT image slices to extract hierarchical textural features, and a fully connected branch that handles standardized numerical inputs (RHOB, PEF, and  $Z_{eff}$  when applicable). The outputs of both branches are fused through a concatenation layer and subsequently mapped to porosity and permeability predictions via independent regression heads, enabling a consistent and reproducible framework for high-resolution petrophysical property estimation.

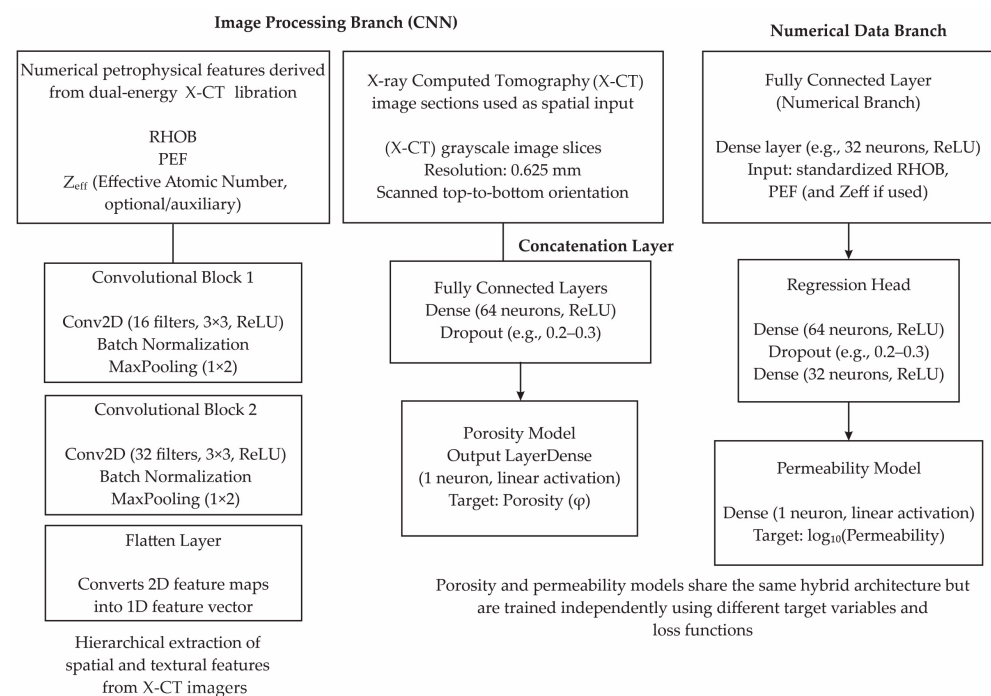


**Figure 6.** Hybrid deep learning architecture integrating X-CT image branch and numerical petrophysical data branch.

Once the model is designed, the parameters for the training and study of the model's metrics are established, as shown in Table 4, where the architecture is described, and Table 5, where the parameters and performance evaluation for validation (MSE) and testing (MSE, MAE and  $R^2$ ) are shown.

**Table 4.** Architecture of the proposed hybrid model, composed of an image branch (CNN) and a numerical branch (dense layers), which are concatenated to predict porosity or permeability.

| Image CNN Model        |                     |                                                  | Linear Regression Model                     |           |                                                   |
|------------------------|---------------------|--------------------------------------------------|---------------------------------------------|-----------|---------------------------------------------------|
| Layers                 | Operation           | Comment                                          | Layers                                      | Operation | Comment                                           |
| 3                      | 2D Convolution      | Kernel size = (3,3),                             | 4                                           | Dense     | Neurons = 32, 64, 128, 256, activation = “ReLU”   |
|                        |                     | Stride = (1,1),                                  |                                             |           |                                                   |
|                        |                     | Padding = “same”,                                |                                             |           |                                                   |
|                        |                     | Filters = 16, 32, 64,                            |                                             |           |                                                   |
|                        |                     | Activation = “ReLU”                              | 1                                           | Dropout   | Rate = 0.2, preventing overfitting                |
|                        | Batch Normalization |                                                  |                                             |           |                                                   |
|                        | maxPooling 2D       | Pool size = (1,2)                                |                                             |           |                                                   |
| 1                      | Dropout             | Rate = 0.2, preventing overfitting               | 5                                           | Dense     | Neurons = 128, 64, 32, 16, 4, activation = “ReLU” |
|                        | Flatten             | Flatten 2D Tensor from last layer into 1D tensor |                                             |           |                                                   |
| 4                      | Dense               | Neurons = 1024, 512, 256, 4                      |                                             |           |                                                   |
| Concatenate the models |                     |                                                  |                                             |           |                                                   |
| Layers                 | Operations          |                                                  | Comment                                     |           |                                                   |
| 1                      | Concatenate         |                                                  | Concatenate the model                       |           |                                                   |
| 1                      | Dense               |                                                  | Neurons = 4, Activation = “ReLU”            |           |                                                   |
| 1                      | Dense               |                                                  | 1 output (the physical property prediction) |           |                                                   |

**Table 5.** Parameters used for training and validation of the hybrid deep learning model.

| Parameter                      | Value                        |
|--------------------------------|------------------------------|
| Maximum number of epochs       | 300                          |
| Validation portion             | 20%                          |
| Test portion                   | 20%                          |
| Performance metrics validation | MSE                          |
| Performance metrics test       | R <sup>2</sup> , MSE and MAE |
| Number of batches              | 8                            |
| Optimizer                      | Adam (lr = 0.001)            |
| Loss function                  | Mean squared error (MSE)     |

In summary, the proposed hybrid CNN architecture design processes X-CT images of size  $512 \times 512 \times 1$  through three convolutional blocks (16, 32, and 64 filters), each followed by batch normalization and maxPooling ( $1 \times 2$ ). After feature extraction, the image branch is flattened into a feature vector of 2,097,152 elements, which is concatenated with a numerical branch composed of three standardized petrophysical inputs (RHOB, PEF or optionally  $Z_{eff}$ ) processed by a dense layer of 16 neurons. The fused representation is passed through a fully connected layer of 64 neurons and a final regression output layer. The complete model contains approximately  $1.34 \times 10^8$  trainable parameters, with the majority associated with the dense fusion layer.

### 3.5. Model Training, Validation, and Retraining Procedure

The initial dataset was divided into 1353 entries for training, 451 for validation, and 451 for testing. To reduce overfitting and ensure consistent model performance, the dataset was randomly shuffled prior to splitting. This procedure prevents sequential bias imposed by depth-ordered X-CT measurements, thereby improving generalization during validation and testing.

Given the moderate complexity of the proposed architecture and the relatively limited size of the training dataset, a batch size of 8 samples was selected. This configuration provides a balance between computational efficiency and gradient stability, reducing variance during back-propagation and preventing excessively noisy parameter updates. A total of 150 training epochs was adopted after observing diminishing returns in the validation loss curves and clear indications of early convergence.

The models were trained using the MSE as the loss function, selected due to its suitability for continuous regression tasks and its sensitivity to large deviations, which is critical for permeability predictions. Optimization was performed with the Adam optimizer, given its adaptive learning rate capabilities and robust convergence behavior. To mitigate overfitting, regularization strategies included early stopping with a patience window of 20 epochs and a minimum loss improvement threshold of  $1 \times 10^{-4}$ , as well as batch normalization layers after each convolutional block, which stabilize training by reducing internal covariate shift. These combined measures ensured reproducible convergence and enhanced generalization across training, validation, and test partitions.

A retraining stage was subsequently performed by incorporating an additional dataset acquired from the same well. This extended dataset consisted of 1057 training records, 353 validation records, and 353 test records, yielding a total of 1763 entries. The preprocessing workflow, comprising grayscale normalization of images and statistical standardization of numerical predictors, remained unchanged to ensure full methodological consistency between both training stages. The additional dataset included 53 new porosity measurements and complementary permeability information, increasing the physical coverage of the core interval and strengthening the representativeness of the learning sample.

A summary of descriptive statistics for the extended dataset used in the retraining stage is presented in Table 6.

**Table 6.** Descriptive statistics of the second dataset used for model retraining.

| Property | Density | PEF   | $Z_{eff}$ | Porosity | Permeability |
|----------|---------|-------|-----------|----------|--------------|
| Count    | 1763    | 1763  | 1763      | 1763     | 1763         |
| Mean     | 2.269   | 2.338 | 12.567    | 0.221    | 2678.960     |
| Std      | 0.161   | 0.741 | 0.922     | 0.081    | 4418.568     |
| Min      | 1.986   | 1.735 | 11.655    | 0.075    | 0.025        |
| 25%      | 2.141   | 1.921 | 11.989    | 0.162    | 8.646        |
| 50%      | 2.234   | 2.028 | 12.170    | 0.250    | 214.408      |
| 75%      | 2.392   | 2.595 | 13.033    | 0.292    | 3333.349     |
| Max      | 2.988   | 7.378 | 17.422    | 0.366    | 18,157.47    |

Both the new information and its corresponding images underwent identical pre-processing steps. This ensured consistency in the treatment of data across all aspects of the model.

The results obtained from the original models and the retrained models (porosity:  $R^2$  0.996, permeability:  $R^2$  0.983) are highly consistent in the predictions. Consequently, the analysis focuses on the fully retrained model, which incorporates additional data and benefits from the refined training process, which reinforces the validity of the results.

4. Results

This section presents the outcomes derived from implementing the hybrid deep learning model designed to estimate porosity and permeability from X-CT images and associated numerical data (RHOB and PEF). Model performance is assessed using standard quantitative metrics, including the coefficient of determination ( $R^2$ ), MSE, and MAE, which collectively provide insight into the predictive accuracy and robustness of the trained models.

The results are structured into two subsections. Section 4.1 focuses on the porosity prediction model, while Section 4.2 presents the performance of the permeability prediction model. For each case, self-contained figures are provided to directly compare laboratory-measured values with model predictions across the depth interval. In addition, the maximum observed errors are highlighted to illustrate local deviations within the predictions.

Finally, the reliability of the estimated curves is analyzed in the context of reservoir characterization, emphasizing the applicability of high-resolution predictions derived from X-CT-based measurements for extending conventional core analysis data across intervals lacking direct measurements.

4.1. Porosity Prediction Model

The performance of the porosity model is depicted in Figure 7. The results of the validation phase show an outstanding fit between the measured values and the values predicted by the neural network. The regression slope and the coefficient of determination ( $R^2$ ) approach 1, reaching a value of 0.996.

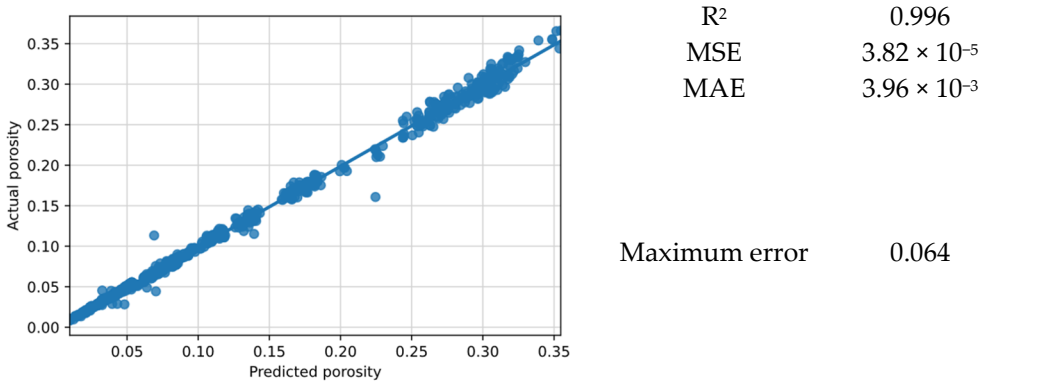


**Figure 7.** Comparison between measured and predicted porosity values using the deep learning model. An almost perfect fit is observed ( $R^2 = 0.996$ ), with low dispersion around the 1:1 line, indicating that the convolutional neural network accurately captures the variability of porosity from the images and computed tomography data.

Additionally, MSE is extremely low, at  $3.82 \times 10^{-5}$ , indicating that the model’s predictions align closely with the actual values. MAE is also impressively low, at  $3.96 \times 10^{-3}$ . The maximum error observed in the sample was 0.064, further confirming the robustness of the model.

4.2. Permeability Model

The performance of the permeability model is presented in Figure 8. The results obtained during the validation process are favorable, with the prediction slope and the R-squared coefficient approaching 1, specifically with a value of 0.983. However, it is important to note that, due to the logarithmic nature of the sample, both the mean square error and the mean absolute error exhibit relatively higher values. Additionally, the maximum error observed within the dataset is worth mentioning.

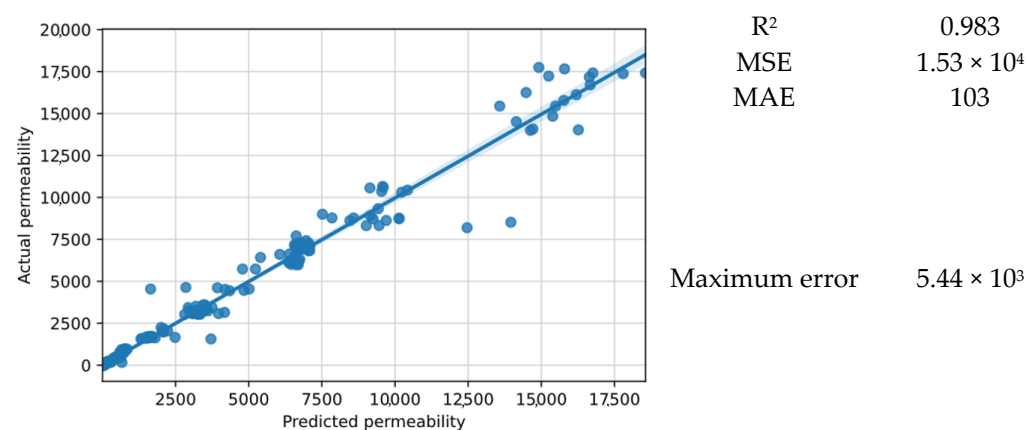


**Figure 8.** Comparison between measured and predicted permeability values using the deep learning model. The relationship shows a high coefficient of determination ( $R^2 = 0.983$ ), demonstrating the robustness of the model in predicting permeability from images and computed tomography data.

For permeability, model performance is additionally evaluated in  $\log_{10}$  space to account for the multiorder-of-magnitude variability of this property (Figure 9). The model achieves an  $R^2$  of 0.896, with a mean absolute error (MAE) of 0.077 in  $\log_{10}(k)$ , corresponding to an average relative error of approximately 19%. The mean squared error (MSE) is  $2.05 \times 10^{-2}$ , indicating limited dispersion around the 1:1 line. The maximum observed error (0.799 log units) remains below one order of magnitude, which is considered acceptable for reservoir engineering and flow characterization purposes.

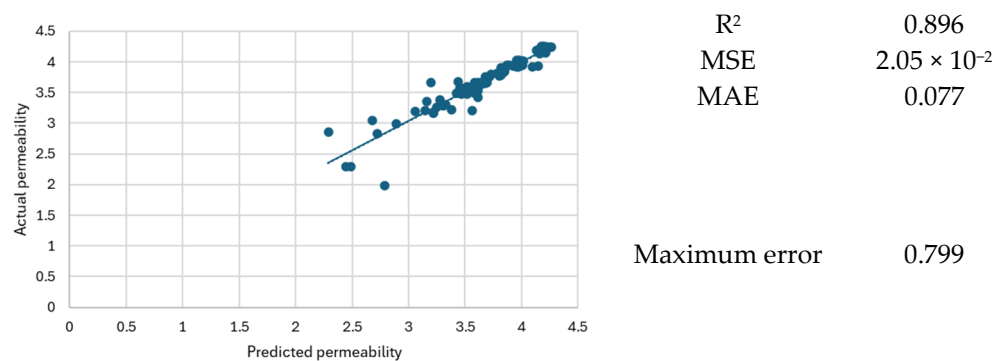


**Figure 9.** Comparison between measured and predicted permeability values in logarithmic scale. The relationship shows a high coefficient of determination ( $R^2 = 0.896$ ) with low dispersion on the logarithmic scale. Performance metrics ( $R^2 = 0.896$ ,  $MSE = 2.05 \times 10^{-2}$ ,  $MAE = 0.077$ ) indicate good agreement between predicted and measured values, with an average relative error of approximately 19%. The maximum observed error remains below one order of magnitude, which is acceptable for reservoir engineering applications.

4.3. Predictions

Once the porosity and permeability models were trained and validated, they were applied to generate continuous predictions along the entire length of the drilling core. These predicted profiles were subsequently plotted to facilitate visual interpretation and comparison with the measured laboratory data. To assess the agreement between the model outputs and the experimental values, the original porosity and permeability measurements are displayed as red reference points superimposed on the predicted curves.

The results obtained from the first dataset are presented in Figure 10, while the results from the second dataset are shown in Figure 11. These figures provide a visual representation of the predicted values alongside the original data points for a comprehensive analysis.

Figures 10 and 11 illustrate examples of porosity and permeability predictions at 1-foot intervals, linking these estimates with tomographic imaging data.

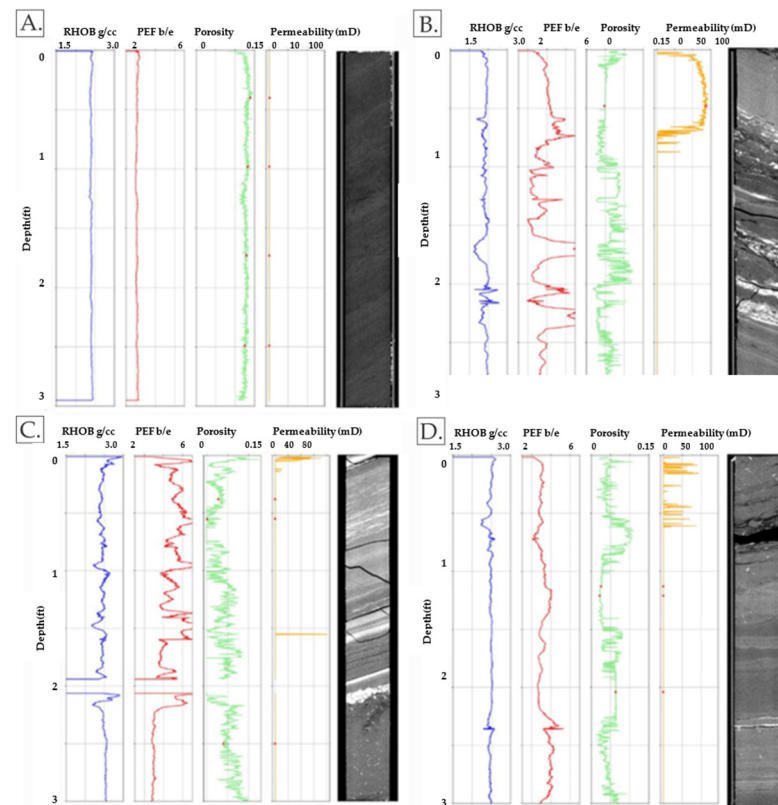


**Figure 10.** Predictions of porosity and permeability for different core sections (A–D) from the first dataset. Red dots represent laboratory measurements (RCAL), while curves correspond to deep learning model predictions from X-CT images.

In the comparative analysis between the data estimated by neural networks and laboratory measurements, a high degree of accuracy is evident in the prediction of petrophysical parameters. This fit is particularly apparent in the correlation of porosity and permeability curves, where the lithological variations identified by magnetic resonance tomography (0.75 feet in the superior section of Figure 10B,C) coincide with significant changes in the trends of these curves. Similarly, in Figure 10A, a homogeneous result was expected, with minimal variations in the porosity and permeability profiles, represented as a continuous and uniform vertical line.

The results obtained using the hybrid deep learning models demonstrate a high level of accuracy in predicting petrophysical properties from X-ray computed tomography images and derived parameters (RHOB and PEF). For porosity, the model achieved a coefficient of determination ( $R^2$ ) of 0.996, with extremely low MSE ( $3.82 \times 10^{-5}$ ) and MAE ( $3.96 \times 10^{-3}$ ) values, indicating an almost perfect agreement between the predicted values and laboratory measurements.

In the case of permeability, the model yielded an  $R^2$  of 0.983. Although the corresponding MSE and MAE values are comparatively higher due to the logarithmic nature of permeability, the predictions still exhibit a strong consistency with experimental data.

Depth-based predictions generated along the core sections (Figures 10 and 11) reveal excellent agreement between estimated and measured values, capturing both homogeneous intervals and lithological variations. These results confirm the capability of the proposed workflow to extrapolate reliable petrophysical profiles into intervals where experimental data are unavailable.

Overall, the findings validate the integration of DECT measurements with convolutional neural networks as a robust methodological framework for reservoir characterization and high-resolution petrophysical property estimation.

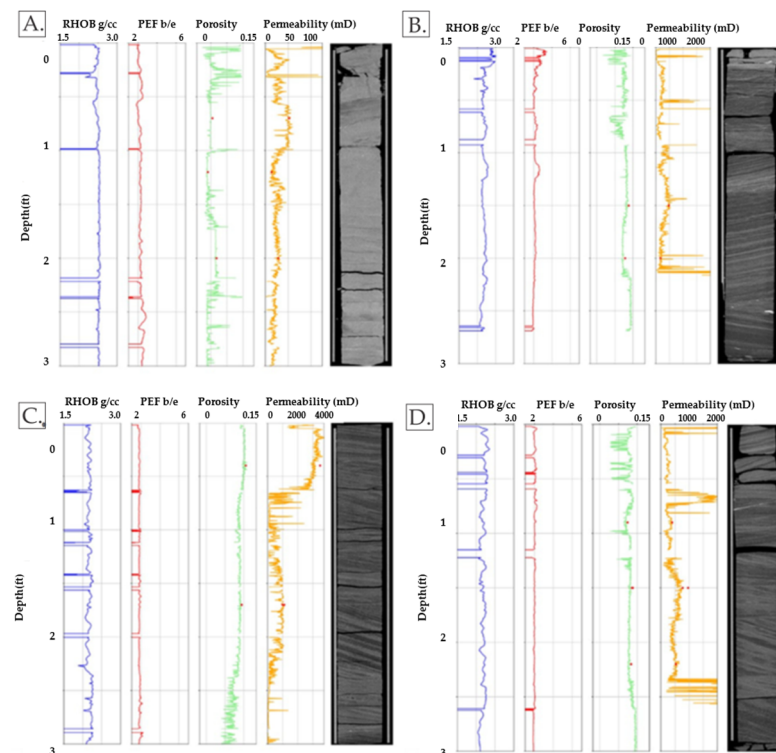


**Figure 11.** Porosity and permeability predictions obtained from the model retrained with the second dataset for different core sections (A–D). The consistency between the predictions and the measured values is evident, as is the model’s ability to capture lithological variations throughout the core.

## 5. Discussion

This section analyzes the results obtained from the proposed hybrid deep learning model, integrating X-CT imagery with derived petrophysical data. The discussion is structured around five key components. First, the results are interpreted from the perspective of model performance, reservoir characterization, and the continuity and reliability of the predicted petrophysical profiles. Second, the applicability of the DECT approach is examined, with emphasis on resolution scaling and its operational constraints when applied to full-core datasets. Third, the results are compared with previous studies and conventional methodologies, highlighting improvements, limitations, and differences in modeling strategies, particularly regarding model generalization. Fourth, special emphasis is placed on the primary limitation of the approach, namely, the restricted size and representativeness of the input dataset, which directly influences the achievable predictive variability. Finally, geological and physical applicability constraints are evaluated, including lithological variability, permeability ranges, and imaging resolution requirements. Collectively, these elements contextualize the findings, enabling a rigorous assessment of the applicability, robustness, and practical relevance of the proposed workflow in realistic industry environments.

### 5.1. Model Performance and Generalization

The developed model represents an attempt to utilize deep learning and artificial intelligence techniques, demonstrating a high predictive capacity in estimating porosity ( $R^2 = 0.996$ ) and permeability ( $R^2 = 0.983$ ) from grayscale X-CT images, as well as RHOB

and PEF derived from X-CT data. Furthermore, training and cross-validation show that the model maintains consistency and robustness even when incorporating new datasets.

The combination of CNNs and regression estimation has yielded promising results, faithfully reproducing the trends measured in the laboratory (RCAL), which can be further enhanced by incorporating additional core information and optimizing training parameters. High-resolution petrophysical data can be used to extend laboratory measurements or to apply predictive models to wells without core samples but with available logs such as RHOB and PEF. Neural networks trained with high-resolution data improve the quality of the training and, consequently, the accuracy of predictions in nearby wells lacking tomography data, making this workflow advantageous for enhancing petrophysical evaluations [35].

The model training process involves utilizing the machine learning platform TensorFlow. Thanks to the GPU acceleration on the computer, each epoch takes approximately 1 min, resulting in a total training time of approximately 3 and a half hours for each model. Subsequently, estimating the scores of the testing set instances from the testing portion requires approximately 1 min to complete.

Evaluating permeability prediction errors in linear and  $\log_{10}$  scales provides a more meaningful engineering interpretation than only linear-scale metrics, as reservoir flow behavior is primarily controlled by relative permeability contrasts rather than absolute values. The low MAE observed in log scale demonstrates that the proposed model captures permeability variations with sufficient accuracy for practical reservoir characterization and modeling workflows.

Furthermore, if the lithology of the rock is known, the model's performance can be enhanced by introducing additional categorical variables, such as rock type, into the training process. This incorporation of relevant geological information can contribute to the model's accuracy and overall predictive capability.

In addition, the architectural choices, such as the number of filters, dense layer sizes, and dropout configuration, were selected based on empirical testing and standard CNN design guidelines to balance model complexity and generalization capacity. Specifying these parameters, along with software versioning, improves transparency and enables more robust comparison with future studies seeking to replicate or extend the proposed workflow.

## 5.2. Application Scale and Resolution DECT Approach

DECT provides measurements of RHOB, PEF, and  $Z_{eff}$ , which are sensitive to mineral composition. However, quantitative mineralogical estimation requires micro-tomography-scale resolution and controlled calibration standards, especially in heterogeneous siliciclastic and carbonate systems. Given the clinical-scale resolution used in this study ( $\approx 0.625$  mm in slice thickness), DECT does not allow a reliable mineralogical inversion suitable for petrophysical modeling. Therefore, mineralogical parameters were not incorporated into the model, although future work may benefit from integrating independent mineralogical data (e.g., X-ray diffraction (XRD)) to evaluate its influence on porosity and permeability prediction models.

Although it is true that this resolution does not allow direct imaging of pore throats or micro-scale features that control permeability, such capabilities are restricted to micro-computed tomography (micro-CT). Micro-CT achieves micrometric resolutions but only for very small sample volumes, making it operationally unfeasible to scan meter-scale core sections. Moreover, permeability estimation from micro-CT relies on pore-scale simulations such as DNS, which constitutes a fundamentally different methodological framework.

The objective of this study is not to directly resolve pore-scale geometry but rather to correlate macroscopic X-CT textures and dual-energy attenuation information (RHOB and PEF), calibrated with laboratory measurements (RCAL) using deep learning architecture.

This approach allows the model to extract structural and textural patterns at the centimeter scale that are statistically associated with porosity and permeability, even if submicron pore features cannot be explicitly imaged.

### 5.3. Comparison with Previous Studies, Limitations and Perspectives: Input Dataset Limitation

The application of X-CT to core characterization has been widely reported as a non-destructive approach for estimating key petrophysical properties such as porosity and density [1,30]. When integrated with modern artificial intelligence techniques, X-CT enables high-resolution prediction of rock properties and enhances conventional reservoir evaluation workflows through additional, spatially continuous measurements.

Within this context, previous research provides valuable reference frameworks for benchmarking methodological improvements. For instance, the development of PoreFlow-Net, a 3D CNN architecture, has demonstrated that flow parameters can be predicted directly from micro-CT volumes with notable accuracy, highlighting the potential of deep learning to infer transport properties from pore-scale imagery [36]. Furthermore, CNN frameworks incorporating physical constraints have been shown to significantly improve permeability estimation in heterogeneous lithologies [29], while physics-guided CNN models trained with DNS-derived permeability labels have sustained strong predictive performance even in complex porous structures [28]. Complementarily, studies making use of DECT for laboratory-scale core characterization have validated workflows for estimating RHOB and PEF from voxel-based attenuation values, supporting the calibration strategy adopted in the present study [14,15].

Collectively, these works reinforce that the combined use of deep learning, high-resolution X-CT datasets, and training strategies grounded in physical principles represents the current forefront of digital rock characterization. The reliability of such models depends strongly on imaging resolution and on the fidelity of the reference measurements used as labels during training.

Most importantly, the present study shows that simultaneously integrating RHOB and PEF derived from X-CT leads to improved predictive accuracy in heterogeneous rock intervals, outperforming approaches based solely on density or direct porosity estimates. This result highlights the practical usefulness of DECT-driven attributes for fine-scale petrophysical characterization and supports their application in workflows focused on extending laboratory measurements over entire core sections or reservoir intervals.

Despite the promising results, several limitations were identified. First, the training process relied primarily on data from a single well, which restricts spatial generalization and limits the applicability of the model to other geological contexts. All training, validation, and testing subsets were generated from the same well because no additional DECT scanned core or RCAL datasets were available from other wells in the field. Consequently, the present study does not include blind well validation. This limitation is acknowledged, and the workflow is designed as a single-well feasibility study intended to evaluate whether high-resolution X-CT-derived features can be used to predict porosity and permeability through a mixed-input deep learning framework.

Second, permeability predictions are subject to greater uncertainty due to their logarithmic nature and their non-linear relationship with porosity and textural attributes. Third, model performance intrinsically depends on the quality of X-CT acquisition and on the reliability of reference laboratory measurements obtained through RCAL, making the workflow sensitive to acquisition noise and measurement heterogeneity.

Future work should address these limitations by: (i) expanding the dataset to include samples from multiple wells and lithological settings to increase model robustness, (ii) incorporating categorical geological descriptors such as rock type or facies to en-

hance predictive performance, and (iii) benchmarking results against traditional flow-based permeability estimation models to formally validate applicability in operational reservoir studies.

In summary, the results obtained demonstrate that the integration of DECT, routine core analysis, and deep learning offers a robust framework for high-resolution estimation of petrophysical properties. Although limitations related to dataset size and representativeness remain, the methodology shows considerable potential to complement conventional well logs' petrophysical assessment and to extend characterization into intervals lacking direct core measurements. These findings provide support for the conclusions of this study and help delineate future research directions in the field of AI-assisted petrophysical modeling.

#### 5.4. Geological and Physical Constraints: Model Applicability

The applicability of the proposed deep learning model is constrained by the characteristics of the data used for training. First, the X-CT acquisition parameters must match the resolution employed in this study (0.625 mm slice spacing), as the model is calibrated to the image texture and attenuation variability associated with this voxel size. Second, the model is applicable only within the permeability range represented in the training dataset. Based on RCAL data, the training samples span approximately from 0.003 mD to 145.174 mD, and predictions outside this interval should be interpreted with caution.

Regarding lithology, the model was trained on core material composed predominantly of clay-rich sandstones with varying amounts of carbonate cement, as reflected by the observed PEF values (1.88–10.26). Consequently, the workflow is currently applicable to similar siliciclastic lithologies exhibiting moderate compositional heterogeneity. Application to other lithologies would require retraining with representative datasets, as their X-CT textural and mineralogical responses could differ significantly. These applicability boundaries have been added to ensure that the predictive framework is used within geologically and physically consistent conditions.

## 6. Conclusions

A hybrid predictive model utilizing a combination of CNNs and linear regression, implemented in a concatenated architecture, is proposed for the estimation of two petrophysical properties: porosity and permeability in a microscopic scale (0.625 mm). The model considers grayscale X-CT images and dual-energy-derived logs: RHOB and PEF, as input features, calibrated with laboratory measurements (RCAL). By leveraging this approach, a set of porosity and permeability logs were generated by applying the trained models to predict the values of these properties.

The performance of both the porosity and permeability models is highly satisfactory: porosity predictions achieve a coefficient of determination of 0.996,  $MAE = 3.96 \times 10^{-3}$ ,  $MSE = 3.82 \times 10^{-5}$ , and 0.064 maximum error, while the permeability model attains an  $R^2$  of 0.983. The reported performance metrics should be interpreted within the limits of single-well training data. Although higher uncertainty is observed for extremely high permeability values consistent with the logarithmic nature and variability of this property, the overall results demonstrate the robustness and reliability of the workflow.

The methodology enables the generation of high-resolution synthetic porosity and permeability logs, which can complement laboratory measurements and be extended to wells lacking core data, provided RHOB and PEF logs are available. The model also captures variations associated with mineralogy, stratigraphic architecture, and depositional environment, successfully reproducing alternating intervals of contrasting reservoir quality. This workflow provides a feasible approach for extending laboratory measurements and

enabling high-resolution petrophysical characterization in wells with X-CT data but limited core analysis.

The petrophysical properties of a rock are strongly controlled by its mineralogical composition, stratigraphic context, and depositional environment. This control results in alternating sequences of rocks with contrasting petrophysical characteristics, ranging from rocks with excellent reservoir potential to those of poor reservoir quality. The model captures these variations, reproducing alternating sequences of intervals with high and low reservoir potential.

Looking to pathways forward, expanding the training dataset to include multiple wells and diverse lithologies is recommended to enhance the model's spatial generalization capacity. Additionally, incorporating categorical geological variables such as facies or rock type, optimizing permeability modeling through log-space training, and exploring physics-informed approaches may further strengthen predictive performance and broaden applicability in reservoir characterization and simulation workflows.

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## Abbreviations

The following abbreviations are used in this manuscript:

|             |                                                    |
|-------------|----------------------------------------------------|
| UIS         | Universidad Industrial de Santander                |
| GIT         | Group in Tomography for Reservoir Characterization |
| UAB         | Universidad Autónoma de Barcelona                  |
| Minciencias | Colombian Ministry of Science                      |
| ANH         | Colombian National Hydrocarbons Agency             |
| SGC         | Colombian Geological Survey                        |
| CNN         | Convolutional Neural Network                       |
| CT          | Computed Tomography                                |
| X-CT        | X-ray Computed Tomography                          |
| DECT        | Dual-energy CT                                     |

|        |                                            |
|--------|--------------------------------------------|
| RHOB   | Bulk Density                               |
| PEF    | Photoelectric Effect                       |
| DL     | Deep Learning                              |
| DNS    | Direct Numerical Simulation                |
| MSE    | Mean Squared Error                         |
| MAE    | Mean Absolute Error                        |
| RCAL   | Routine Core Analysis Laboratory           |
| BP-ANN | Back-Propagation Artificial Neural Network |
| ANNs   | Artificial Neural Networks                 |
| FZI    | Flow Zone Indicator                        |

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