



## Text 1

**Adapted from: Rail Kadyrov, Evgeny Statsenko, Thanh Hung Nguyen, 2024. Integrating  $\mu$ CT imaging of core plugs and transfer learning for automated reservoir rock characterization and tomofacies identification.**

X-ray computed tomography (CT) and microtomography ( $\mu$ CT) imaging have proven to be valuable tools in geology and rock physics due to their non-destructive nature and ability to provide detailed 3D representations of rock structure. This technique has been applied to examine the internal arrangement, mineral content, and physical properties, as well as to simulate natural processes in the rocks. One technique that has emerged from the application of CT to geology is tomofacies analysis, which involves the use of tomography imaging techniques to identify the different types of rock or sediment layers present in a geological formation. It can provide a detailed understanding of the internal structure and composition of rock formations, and can be used to map the distribution of minerals, fossils, cavities, or other features detectable on CT images.

Machine learning (ML) has increasingly been applied to examine tomography images of rocks, allowing automatic and effective identification of rock properties. Traditional methods of core characterization are time-consuming and require the considerable effort of a large number of experts. At the same time, it is quite difficult to readily detect small but important elements in reservoir rocks, especially inside the core volume, that can have a strong impact on assessing reservoir potential and hydrodynamic properties. This research explores the integration of high-resolution micro-computed tomography ( $\mu$ CT) imaging and transfer learning for the automated characterization of reservoir rocks and tomofacies identification.

The study involved collecting and marking a dataset containing 66,560  $\mu$ CT images of 130 standard core plugs containing all major reservoir rock types. Using this dataset of 2D  $\mu$ CT images of core plugs, the researchers applied convolutional neural networks (CNNs) pre-trained on ImageNet and fine-tuned them for rock classification tasks. Applying a transfer learning approach, they trained seven ResNet-50 models capable of identifying and classifying reservoir rock features in  $\mu$ CT images.

The results showed an average classification accuracy of over 94%, indicating the effectiveness of transfer learning in enhancing rock characterization. The developed models demonstrated the ability for rapid detection of subtle details that might otherwise have been missed during manual inspection. In addition, the concept of tomofacies, resulting from the integration of  $\mu$ CT images and machine learning predictions, proved useful in highlighting different reservoir zones and understanding their heterogeneity.

Fonte: <https://doi.org/10.1016/j.marpetgeo.2024.107014>

**1. According to the text, one limitation of traditional core characterization methods is that they:**

- a) require advanced renewable energy systems.
- b) are unable to classify rock types.
- c) may fail to detect small but important internal rock features.**
- d) depend entirely on manual drilling operations.

**2. The main purpose of integrating  $\mu$ CT imaging with transfer learning was to:**

- a) replace geological exploration with satellite imaging.
- b) automate reservoir rock characterization and tomofacies identification.**
- c) reduce the size of rock core samples.
- d) improve fossil fuel extraction methods only.

**3. The text states that the dataset used in the study contained:**

- a) 130  $\mu$ CT images of sandstone samples only.
- b) 66,560 images from different reservoir rock types.**
- c) 94 images classified manually by geologists.
- d) 2D seismic images from offshore reservoirs.

**4. According to the passage, the ResNet-50 models were:**

- a) developed without previous training data.
- b) trained exclusively for medical imaging applications.
- c) pre-trained on ImageNet and adapted for rock classification tasks.**
- d) used only to measure porosity in carbonate rocks.

**5. The term “heterogeneity” in the final paragraph refers to:**

- a) the uniformity of reservoir rock properties.
- b) the differences and variability between reservoir zones.**
- c) the replacement of machine learning by manual inspection.
- d) the reduction of classification accuracy in  $\mu$ CT images.

## Text 2

### **Fatima Ezzahra Arhouni, et al., 2025. Artificial intelligence-driven advances in nuclear technology: Exploring innovations, applications, and future prospects**

Artificial Intelligence is a branch of computer science dedicated to creating systems and machines that can perform tasks requiring human-like intelligence. These tasks range from learning from experience and reasoning to problem-solving, understanding natural language, and recognizing patterns. AI encompasses subfields such as machine learning (ML), where algorithms improve through experience, and deep learning (DL), which involves multi-layered neural networks. At its core, AI involves software-based technologies designed to tackle complex problems by mimicking human cognitive abilities, such as logical thinking and decision-making. These systems interact with their environment by receiving signals, processing them, and producing outputs like predictions, recommendations, classifications, or decisions. The ultimate aim is to develop autonomous systems that can adapt to new inputs and execute complex tasks efficiently.

AI has transformed several scientific fields. This revolution extends into nuclear physics. In recent years, the adoption of artificial intelligence AI/ML in the nuclear sector has accelerated, revolutionizing various facets of nuclear operations. AI's capabilities in handling vast datasets, recognizing complex patterns, and predicting outcomes have become indispensable for improving reactor design, monitoring systems, and safety protocols in various aspects of nuclear operations. This technological integration has led to significant advancements, such as enhancing predictive maintenance, refining reactor efficiency, and streamlining nuclear fuel production processes, thereby lowering operational costs.

In nuclear security, AI has the potential to enhance the analysis of spectroscopic and geospatial data for better detection of nuclear materials outside regulatory oversight, strengthen nuclear material accounting and control systems, and enable the identification of both internal and external threats at nuclear facilities. Furthermore, AI-driven approaches are increasingly being used alongside traditional simulation tools, offering innovative methods for simplifying complex models in areas like thermal-hydraulics and neutronics. These advancements not only contribute to safer and more reliable nuclear power plants but also open new avenues for AI applications. The synergy between AI and nuclear technology is setting the stage for future innovations that could have profound impacts on energy production, national security, and medical advancements.

However, despite the potential benefits of AI in strengthening security, these technologies also introduce significant ethical challenges within the field. The adoption of AI/ML technologies brings with it new risks and uncertainties, particularly as human operators might overlook potential vulnerabilities or the risk of algorithmic biases. These biases, stemming from data, model assumptions, or training methods, can lead to skewed findings and substantial mistakes, particularly in a field where accuracy is crucial. Given the potential for widespread use of these technologies, it is essential to understand their limitations thoroughly.

Fonte: <https://doi.org/10.1016/j.anucene.2024.111151>

**1. According to the text, the main objective of Artificial Intelligence is to:**

- a) replace all human workers in scientific research.
- b) create autonomous systems capable of adapting to new inputs and performing complex tasks.**
- c) eliminate the need for decision-making in industrial systems.
- d) develop only language-processing applications.

**2. The text states that AI has become indispensable in nuclear operations mainly because it can:**

- a) reduce the production of radioactive materials.
- b) completely replace traditional simulation tools.
- c) handle large datasets, recognize patterns, and predict outcomes.**
- d) simplify all reactor designs without human supervision.

**3. According to the passage, one consequence of integrating AI into nuclear technology is:**

- a) increased operational costs in fuel production.
- b) reduced efficiency in monitoring systems.
- c) advancements in predictive maintenance and reactor efficiency.**
- d) the elimination of safety protocols in nuclear facilities.

**4. The text suggests that AI can contribute to nuclear security by:**

- a) replacing international nuclear agreements.
- b) detecting nuclear materials and identifying potential threats.**
- c) reducing the need for regulatory oversight.
- d) preventing the use of spectroscopic data.

**5. The expression “algorithmic biases” refers to:**

- a) errors caused by excessive reactor temperatures.
- b) intentional sabotage of nuclear facilities.
- c) distortions or mistakes resulting from biased data or model assumptions.**
- d) improvements in machine learning performance.

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Good luck and success!