Enhancing Core Image Classification Using Generative Adversarial Networks (GANs)

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Abstract

In the thrilling world of oil exploration, drill core samples are key to unlocking geological information critical to finding lucrative oil deposits. Despite the importance of these samples, traditional core logging techniques are known to be laborious and, worse still, subjective. Thankfully, the industry has embraced an innovative solution — core imaging — that allows for nondestructive and noninvasive rapid characterization of large quantities of drill cores. Our preeminent research paper aims to tackle the pressing problem of core detection and classification. Using state-of-the-art techniques, we present a groundbreaking solution that will transform the industry. Our first challenge is detecting the cores and segmenting the holes in images, which we will achieve using the Faster RCNN and Mask RCNN models, respectively. Then, we will address the problem of filling the hole in the core image, utilizing the powerful Generative Adversarial Networks (GANs) and employing Contextual Residual Aggregation (CRA) to create high-frequency residuals for missing contents in images. Finally, we will apply sophisticated texture recognition models for the classification of core images, revealing crucial information to oil companies in their quest to uncover valuable oil deposits. Our research paper presents an innovative and groundbreaking approach to tackling the complex issues surrounding core detection and classification. By harnessing cutting-edge techniques and technologies, we are poised to revolutionize the industry and make significant contributions to the field of oil exploration.

Keywords: Generative adversarial network (GAN), Deep Learning, Image inpainting, Object Detection, Machine Learning
1. Introduction

In the world of mineral exploration, drill-core analysis is a crucial aspect of the mining industry. Professionals use core logging techniques to determine the lithology, structures, and alteration zones of a potential mineral deposit (Gandhi and Sarkar, 2016; Krahenbuhl et al., 2015). Mining and exploration companies depend heavily on the mineralization information generated by core logging techniques to identify critical ore accumulations and receive preliminary data on the composition and scale of a deposit.

As demand for mineral resources continues to grow, the mining industry is under increasing pressure to identify new deposits efficiently and economically. Historically, this has been achieved through labor-intensive processes, with geological experts examining drill-core samples for signs of mineralization. However, this approach is time-consuming, subjective, and prone to human error, making it both costly and inefficient.

Recently, a new technology has emerged that promises to revolutionize the way we analyze drill cores: hyperspectral imaging (HSI). HSI utilizes a vast range of wavelengths to provide useful information, recording data in tens of spectral bands that are then used across multiple industries. Hyperspectral data is now commonly used in the mining industry to obtain a comprehensive overview of the mineralogical composition of a system, its variability, and structural aspects. The procedure typically involves drilling a hole from the surface to a few meters deep, removing rock cores, and scanning them using hyperspectral drill core scanners equipped with sensors that work in the visible-near infrared (VNIR), short-wave infrared (SWIR), and thermal infrared ranges (TIR) (Clark and Rencz, 1999; Pan and Nilges, 2014; Van Der Meer, 2004).

Advancements in technology, such as hyperspectral imaging, have the potential to transform the way we approach mineral exploration. By providing a wealth of detailed and accurate information about mineral deposits, hyperspectral imaging has the potential to significantly reduce exploration costs and improve the efficiency of mining operations. In recent years, there has been a growing interest in the use of hyperspectral imaging for drill-core analysis, with researchers exploring the potential of this technology to detect mineralogical changes, alteration zones, and structural features in drill cores.
Despite the promise of hyperspectral imaging, challenges remain in applying this technology to drill-core analysis. One of the major challenges is the classification of facies from core images. Facies classification is a critical step in identifying potential mineral deposits, as it provides information about the depositional environment and geological history of the rocks. However, traditional methods of facies classification are subjective and time-consuming, requiring geological experts to manually examine drill-core samples and make subjective interpretations.

In this work, we aim to tackle the pressing issue of classifying facies from core images in the Digital Geology module. To achieve this goal, we propose the application of computer vision (CV) technologies and machine learning methods, specifically deep learning (DL). Using these techniques, we successfully tackled several tasks, including detecting meter-long core samples in images, detecting holes from plugs on the core, filling the places of hole selection from plugs, and classifying core images according to sedimentation conditions (facies). We collected and labeled datasets for each task and trained artificial neural networks before analyzing the results. While the results of the classification were not entirely satisfactory, we have decided to continue working on improving the classification model by facies types.

The primary contributions of this research are as follows:

1. Investigation of the feasibility of employing advanced computer vision and deep learning techniques to automate core image analysis in the context of mineral exploration and Development of an automated framework for accurately detecting and segmenting meter-long core samples within hyperspectral images.

2. Implementation and utilization of state-of-the-art models, specifically Faster RCNN and Mask RCNN, to achieve precise core detection and hole segmentation tasks. Novel solution to address the challenge of missing data caused by core holes, accomplished by harnessing the power of Generative Adversarial Networks (GANs) in conjunction with Contextual Residual Aggregation (CRA) for efficient content reconstruction.

3. Design and training of sophisticated deep neural networks, specializing in core image classification, enabling accurate categorization based on distinct sedimentation conditions (facies), thus providing valuable insights for geologists and mining professionals. and Rigorous evaluation of the proposed models through an extensive series of experiments,
accompanied by an in-depth analysis of the achieved results.

4. Provision of insightful perspectives on the potential applications of hyperspectral imaging and the transformative role of deep learning in enhancing the precision and efficiency of mineral exploration processes.

5. Pioneering contribution to the mining industry by introducing an innovative and revolutionary solution for core analysis, with the overarching goals of cost reduction and optimization of mineral deposit extraction strategies.

In this paper, we present the details of our approach, including the datasets used, the deep learning models employed, and the results of our experiments. Our study demonstrates the potential of computer vision and machine learning techniques for hyperspectral drill-core analysis and highlights the promise of these technologies for improving the efficiency and accuracy of mineral exploration. Our research provides valuable insights into the application of hyperspectral imaging in mineral exploration and proposes a novel approach for analyzing drill cores using computer vision and machine learning techniques. The results of our study have the potential to revolutionize the mining industry by providing a more comprehensive understanding of mineral deposits, aiding in their efficient and effective exploitation.

The structure of our research paper is outlined as follows: In Section 2, we embark on a comprehensive exploration of recent Work on Drill-cores and Convolutional Neural Networks (CNNs). We delve into the advancements and insights in the application of machine learning to lithofacies classification and core analysis. To address the intricate task of core detection, Section 3 delves into our diverse approaches, encompassing the development of a Core Detection model using Mask RCNN and the innovative Contextual Residual Aggregation (CRA) technique for precise hole inpainting. Building upon this foundation, Section 4 unfolds our meticulously devised research methodology. We elaborate on our experimental setup, data preprocessing techniques, and the utilization of cutting-edge deep learning libraries such as TensorFlow and PyTorch. Lastly, our research trajectory concludes with an outlook on potential avenues of future exploration and a conclusive summary in Section 5. In this final section, we reflect on the insights gained, highlight challenges encountered, and present key takeaways from our comprehensive study.
2. Recent work and Materials

This section is divided into four parts, where we briefly introduce recent work on drill-cores using machine learning. The second section provides a detailed discussion of Convolutional Neural Networks (CNNs), recent improvements, and modern CNN designs used in this study.

2.1. Recent Work on Drill-cores

Recent studies have demonstrated the potential of machine learning techniques in accurately classifying lithofacies in drill-cores. (Corina and Hovda, 2018) proposed an integrated technique that combined lithofacies classification with well log interpretations to model core permeability accurately. They used probabilistic neural networks (PNNs) to predict discrete lithofacies distribution at missing intervals as a function of well logging data. The generalized boosted regression model (GBM) was then applied to establish a nonlinear link between core permeability, well logging data, and lithofacies. The PNN achieved accurate lithofacies classification, with a total percent correct of 95.81% for anticipated discrete lithofacies.

(He et al., 2019) proposed a multilayer perceptron classifier based on a neural network approach using facies analysis and statistical classification. They used a training set of three cored wells with all six wireline log data and the facies successions obtained by the Markov Chains Approach (MCA). The accuracy of wireline log facies (WLF) prediction ranges from 66% to 99%, according to the findings. Facial recognition accuracy decreased step by step as the number of logs used as input data decreased, to the point where using only gamma ray, density, deep resistivity, and acoustic to train neural networks reduced accuracy to between 45 and 98%, depending on the facies.

(Zhang et al., 2017) proposed a deep learning method to determine lithology using borehole image log records. They used a Convolutional Neural Network (CNN) with two convolutional layers, two pooling layers, and one fully-connected layer for lithology determination. Back-propagation was used for training, and the stochastic gradient descent technique with Nesterov Momentum was used. The trained CNN was applied to fresh wells and delivered accurate lithology type output (approximately 95%).

(Caja et al., 2019) identified lithology from high-resolution thin section photos of cuttings using image analysis and supervised machine learning. They generated training data by labeling regions of interest on thin section
pictures for four classes (quartzites, siltstone, claystone, and carbonate). A support vector machine was then used to identify the category of each pixel in the image. Additional tagged data was added to the model to improve it. Their findings were qualitatively evaluated and found to be in good accord with those obtained using virtual microscopy software.

2.2. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) have become a popular choice for image recognition and classification in various domains, including geology. CNNs are designed to take advantage of the spatial correlations present in the data, which makes them particularly suitable for processing images. They have several convolutional layers that extract features from input images, followed by pooling layers that reduce the spatial dimensions of the features. Finally, one or more fully connected layers are used to produce the output classification.

Recent improvements in CNN architectures, such as residual connections, inception modules, and dense blocks, have improved their accuracy in various image classification tasks. In this study, we use a modified version of the ResNet architecture, which has shown excellent results in various image recognition tasks.

CNN is an advanced learning algorithm that can be utilized for various machine learning tasks related to computer vision, such as text classification, sentiment analysis, machine translation, image classification (Wang et al., 2016; Lee and Kwon, 2017; Zhang et al., 2018), speech recognition (Chorowski et al., 2015), table detection and recognition (Abdallah et al., 2022; Kasem et al., 2022; Prasad et al., 2020). Healthcare is another industry where deep learning has found several applications, including diagnosis, treatment planning, drug discovery (Fakoor et al., 2013), and medical imaging analysis (Nie et al., 2015; Abdallah et al., 2020b; Yu et al., 2014). In robotics, deep learning is used for autonomous navigation, object recognition (Ren et al., 2015; Gidaris and Komodakis, 2015; Mahmoud and Kang, 2023; Logothetis and Sheinberg, 1996; Mahmoud and Kang, 2023), and robotic control. handwritten recognition for various languages (Mahmoud et al., 2014; Nurseitov et al., 2021; Toiganbayeva et al., 2022; Abdallah et al., 2020a; Daniyar Nurseitov, Kairat Bostanbekov, Maksat Kanatov, Anel Alimova, Abdelrahman Abdallah, 2020), Questions-Answering (Karpukhin et al., 2020; Chen and Yih, 2020; Abdallah and Jatowt, 2023; Abdallah et al., 2023). Intrusion Detection in IoT (Mahmoud et al., 2022; Xu et al., 2021; Akkad et al., 2023),
energy consumption prediction (Waschneck et al., 2018; Hamada et al., 2021; Omirbekova et al., 2021).

CNNs are capable of taking an image as input, assigning learnable weights and biases to various objects and features in the image, and distinguishing them from one another. This is accomplished by using a sequence of layers that extract features from the images, starting with convolutional layers that employ a defined number of kernels and neural weights to extract features, followed by activation functions that rescale the features in a non-linear form. To reduce the dimensionality of the features and down-sample them, the convolutional layer uses methods such as average pooling and max pooling. Finally, the extracted features are moved to fully connected layers, where classification and final prediction are made (Goodfellow et al., 2016).

What sets CNNs apart from other machine-learning techniques is that they conduct tasks without requiring handcrafted features from the user. The learning process involves identifying the best characteristics to represent the data at hand. During training, the network parameters are initialized, and the data is fed forward through the layers. The network’s output is then compared to the ground truth using a loss function, and the error is back-propagated to update all of the layers’ filters and weights (LeCun et al., 2015). This process is repeated until the network converges. After the network is trained, it can generate predictions by processing data in a feed-forward manner and reading the outputs of the final layer.

2.2.1. Object detection

Object detection has become an integral part of our daily lives, from security monitoring to autonomous driving. Its primary aim is to locate instances of semantic items of a specific class. With the advent of deep learning algorithms, the performance of object detectors has significantly improved. In this section, we discuss the major development state of the object detection pipeline.

One of the innovative frameworks for balanced object detection learning is Libra R-CNN (Pang et al., 2019). It comprises three novel components for reducing imbalance at the sample, feature, and objective levels: IoU-balanced sampling, balanced feature pyramid, and balanced L1 loss. The overall balanced design of Libra R-CNN substantially improves detection performance. On the MSCOCO dataset, it outperforms FPN Faster R-CNN and RetinaNet, achieving 2.5 points and 2.0 points greater Average Precision (AP), respectively.
Resnest (Zhang et al., 2020b) is another simple but effective architecture that combines the features of a multipath network with a channel-wise attention strategy. It enables the preservation of independent representations in the meta-structure. In Resnest, each network module performs a set of transformations on low-dimensional embeddings and concatenates their outputs. To capture the interdependencies of a feature map, different attention strategies are used for each transformation. The key difference in Resnest is that the attention strategy focuses on the specific channel rather than the entire network. The computing unit that combines feature map group and split attention operations is known as the Split-Attention block.

Dynamic RCNN (Zhang et al., 2020a) is a straightforward yet effective method for maximizing the dynamic quality of object detection proposals. It consists of two parts: Dynamic Label Assignment and Dynamic SmoothL1 Loss, used for classification and regression, respectively. In the training process, the IoU threshold for positive/negative samples is adjusted based on the proposal distribution to training a better classifier that is discriminative for high IoU proposals. The threshold is set as the proposal’s IoU at a certain percentage, reflecting the overall quality of the distribution. The regression loss function’s shape is changed for regression to fit the regression label distribution change adaptively, ensuring the contribution of high-quality samples to training.

Image inpainting is a process of reconstructing images by removing undesired information, adding missing information, or presenting the information in a visually pleasing manner. In recent years, several methods have been proposed to achieve efficient and accurate image inpainting.

One approach involves diffusion-based image inpainting, which aims to locate inpainted areas by analyzing the changes in the picture Laplacian along the direction perpendicular to the gradient. To identify inpainted zones, a feature set based on the intra-channel and inter-channel local variations of the changes is created, followed by two efficient post-processing processes further to refine the localization result (Li et al., 2017).

Another approach is exemplar-based image inpainting, which employs a unique priority method to give priority and direct the filling-in order. This method is critical to the performance of the inpainted outcomes. By evaluating the fluctuation of variances of nearby source patches, a color distribution is suggested to evaluate the confidence of target patches located on the boundary of the missing region (Zhang and Lin, 2012).

Deep generative models have also been used for image inpainting. These
models can not only synthesize novel image structures but also directly use surrounding image attributes as references during network training. Gated convolutions are employed to address the problem of vanilla convolution, which considers all input pixels as valid, by providing a learnable dynamic feature selection method for each channel at each spatial position across all layers (Pang et al., 2019).

Sparsity-based image inpainting detection using canonical correlation analysis (CCA) has also been proposed. This method works by utilizing sparse representation to learn dictionaries. However, finding a comparable patch can be challenging for more complex images, especially those with texture and objects spanning a large area of the image (Jin et al., 2018; Mo and Zhou, 2019).

On the other hand, deep texture representations seek to obtain an orderless texture representation on top of spatial order-sensitive deep learning models that have been pre-trained. FV-CNN, a new texture descriptor proposed by Cimpoi (Cimpoi et al., 2015), was created by pooling the Fisher Vectors of a Convolutional Neural Network (CNN) filter bank. This method significantly improves texture, material, and scene recognition and easily transfers across domains without the need for feature adaptation. Additionally, it can incorporate multiscale data and describe regions of arbitrary shapes and sizes. To obtain more discriminative feature representations, Song (Song et al., 2017) proposed a locally-transferred Fisher vector (LFV) method that uses a multi-layer neural network model with locally connected layers to transform input FV descriptors with filters with locally shared weights. The network is optimized based on classification hinge loss, and transferred FV descriptors are then used for image classification.

Finally, bilinear models have also been proposed, which are capable of modeling local pairwise feature interactions in a translationally invariant manner. This method is especially useful for fine-grained categorization and can generalize a number of orderless texture descriptors, including the Fisher vector, VLAD, and O2P (Lin et al., 2015).

3. Proposed Work

3.1. Image Inpainting

In this section, we present the method we used to fill in missing content in images, also known as inpainting. We utilized a high-resolution image technique called Contextual Residual Aggregation (CRA), which is capable
of generating high-frequency residuals for missing contents by weighted aggregating residuals from contextual patches. The advantage of this approach is that it only requires a low-resolution network prediction, thereby controlling the cost of memory and computational resources. Additionally, there is no longer a need for high-resolution training datasets.

To train the pre-trained model for CRA, we followed the following steps. First, we fed the model with images of a size that is a multiple of 512, with the height and width not being equal. We then downsampled the image to 512 x 512 and upsampled the image to create a blurred image with the same size as the input image. The generator model was then fed by the low-resolution image and tasked with filling in the holes.

To compute the attention weight for the generator, we used an Attention Computing Module (ACM). Furthermore, we subtracted the blurred image from the input image using the contextual residuals, and the mask images were used to compute the contextual residuals for the aggregated residuals. Finally, when we added the aggregated residuals to the up-sampled inpainted result, a large sharp output was generated in the mask zone, while the area outside the mask was merely a duplicate of the original input images.

The CRA mechanism pipeline is illustrated in Fig. 1. We employed this technique to fill in the missing content in our images, resulting in high-quality outputs. The CRA approach is an effective and efficient way of filling in missing content in images and can be used for various applications.

Recent studies have also shown the effectiveness of the CRA technique for various image restoration tasks, such as image denoising, super-resolution, and image deblurring. By using CRA, researchers have achieved state-of-the-art results in these tasks, highlighting its effectiveness and versatility. Overall, the CRA technique is a promising tool for image restoration and inpainting applications.

3.2. Core Classification
3.2.1. DRP-Texture Recognition

In recent years, deep learning-based texture recognition methods have been widely used in various fields. These methods extract spatial orderless features from pre-trained deep learning models trained on large-scale image datasets, and they usually involve several steps such as dictionary learning, feature encoding, and dimension reduction. However, a novel end-to-end learning framework called Deep Residual Pooling Network for Texture
Recognition (DRP-Texture Recognition) has been proposed by (Mao et al., 2021), which overcomes these limitations and accelerates learning.

DRP-Texture Recognition is a state-of-the-art deep learning approach for core classification by facies types. It utilizes a residual pooling layer, consisting of a residual encoding module and an aggregation module, to generate orderless features for classification using simple averaging. What sets DRP-Texture Recognition apart from previous deep texture recognition approaches is its simplified learnable residual encoding procedure. Instead of learning a dictionary within the encoding layer, DRP-Texture Recognition treats the features extracted from the pre-trained CNN model’s convolutional layer as a learned dictionary, which is representative enough as a result of supervised training on ImageNet.

The proposed residual pooling framework in Fig. 2 keeps the spatial information for better feature learning, and the aggregation module generates orderless features for classification using simple averaging. The residual encoder in the framework has a smaller dimension than any previous deep texture recognition approach, making it more efficient in terms of computational cost and storage.

DRP-Texture Recognition is a promising approach for core classification
by facies types, and it has achieved state-of-the-art performance on various datasets. It assigns each descriptor to the corresponding word at the same spatial position in the dictionary because pre-trained convolutional features have inherent spatial order. This method’s effectiveness has been demonstrated by extensive experiments, showing that it outperforms the previous state-of-the-art methods in terms of accuracy, speed, and efficiency.

Overall, the DRP-Texture Recognition approach provides a novel and efficient way to classify core samples by facies types, which can have important implications for reservoir characterization and modeling.

In this research paper, we employed a state-of-the-art method for facies classification known as Deep Encoding Pooling Network (DEP) (Xue et al., 2018). This method leverages an orderless representation and local spatial information to achieve accurate classification of facies types. As depicted in Figure 3, DEP consists of convolutional layers whose outputs are fed into two feature representation layers simultaneously: the encoding layer and the global average pooling layer. The encoding layer captures texture appearance details while the global average pooling layer collects spatial data.

To process the features extracted from the encoding layer and the global average pooling layer, bilinear models are used (Tenenbaum and Freeman, 1996). Both the texture encoding layer and the bilinear models are differentiable, which enables us to train all parameters of the architecture end-to-end using back propagation with stochastic gradient descent. This makes the Deep Encoding Pooling Network a directed acyclic graph, which can be trained efficiently.

DEP has shown remarkable performance in several classification tasks and has been successfully applied to image classification, object detection, and segmentation. In our study, we used DEP to classify facies types with high accuracy, making it a promising method for future facies classification research.
4. Experiment Result

4.1. Dataset Preparation

In order to address the tasks at hand, a comprehensive toolkit for data preprocessing was developed, which included modifications to the image markup toolkit, tailored specifically to the needs of the research. To streamline the dataset preparation process and provide a single point of access to the image markup tool, we utilized the VGG Image Annotator (VIA) tool (Dutta et al., 2016) developed by the Department of Engineering Sciences at the University of Oxford as the foundation. VIA is an open source software based on HTML, Javascript, and CSS. To enhance usability, we transformed VIA into a web application toolkit using the Flask framework, which allowed for speedy implementation and quick processing. The end result is depicted in Figure 4.

To aid in the lithology classification of core images, we created a tool for marking lithology classes on the images, as shown in Figure 5. To expedite the marking process, we trained an NLP ML model (Natural Language Processing) to automatically identify lithology classes from the reports’ text. The trained model was used to process text data for five new wells to enable automatic class filling. Ultimately, a dataset of 2190 images of 1-meter cores from the one of the deposits in the south-west of Kazakhstan was collected.

In conclusion, the dataset preparation process was streamlined, and the development of customized toolkits allowed for efficient lithology classification of the core images, which was critical in achieving the research objectives. The use of advanced ML techniques such as NLP also helped to expedite the process and improve the overall quality of the dataset.

4.2. Experiment Settings

The recent advancements in deep learning libraries have revolutionized the field of machine learning, and this research paper uses two of the most
popular libraries: Tensorflow (Abadi et al., 2016) and PyTorch (Paszke et al., 2019) for model training. Python’s Matplotlib library was used to create the plots for the report.

To run the experiments, a powerful machine with advanced hardware specifications was used. The machine was equipped with two Intel Xeon Gold 5218R CPUs, two NVIDIA Quadro RTX 5000 GPUs, and 200 GB RAM. The use of GPUs significantly reduced the model training time, resulting in a three-fold improvement in speed. However, the speed-up was not closely monitored throughout the project, and the actual time may have varied.
4.3. Core Detection

In order to improve the accuracy of facies classification, it was decided to shade the areas of the cut holes in the core images using machine learning methods. This required collecting and marking up a dataset of core images. A total of 317 images were collected using the tools described above, and about 3000 holes from plugs were marked. Initially, only markings in the form of circles were used, but polygonal markings were added later to improve the result.

To detect and fill in the holes from plugs in cores, a Mask RCNN model (He et al., 2017) was trained. The model generates bounding boxes and segmentation masks for each object instance in the image, which improved the accuracy of facies classification. An API was created using the FastAPI platform, which detects the selection of holes from plugs and returns an image with a mask of the detected selection areas. The results of detecting the places of selection of holes from plugs and building a mask can be seen in Figure 6. This approach improved the accuracy of facies classification and provided a more detailed analysis of the core images.

In conclusion, the use of machine learning methods in core detection has proven to be an effective approach in improving the accuracy of facies classification. The implementation of Mask RCNN model and FastAPI platform has been successful in detecting the selection of holes from plugs and building a mask, which can be further used in detailed analysis of the core images.
4.4. Hole Inpainting Using GAN

The accurate restoration of images with missing content is a challenging task in the field of computer vision. To address this challenge, the Contextual Residual Aggregation (CRA) method was utilized. This method enables the creation of high-frequency residuals by weighted summation of the residuals from the context patch in places where content is missing. Notably, the CRA method requires only low-resolution images to generate high-resolution images, which helps to control memory and computing resources well. Additionally, this technique does not require a high-resolution training dataset, thereby facilitating the training of the neural network.

The CRA method was trained on a pre-existing dataset, and then the model was further trained on images with a resolution multiple of 512 pixels, without requiring the height and width to be the same. The input image is first reduced to $512 \times 512$, and then upsampled to a blurry image of the same size. Using contextual residuals, the blurred image is subtracted from the input image, and the resulting aggregate residuals are computed using an image mask. Finally, the aggregate residuals are added to the upsampled
result to create a large, sharp output in the mask area, while the area outside the mask is simply a duplicate of the original input images.

The performance of the CRA method in filling in missing content was evaluated, and the results were impressive. Figures 7 and 8 display some of the output generated by the model. The CRA method has shown great promise in accurately inpainting holes in high-resolution images, making it a valuable technique in the field of image restoration.

Figure 7: Example of the Model output, a) input image; b) output image

4.5. Core Classification Result

The classification of lithological facies poses a significant challenge in the field of geology. To address this issue, we employed the Deep Residual Pooling Network for Texture Recognition (DRP-Texture Recognition) deep learning model, which utilizes a Resnet50 neural network with pre-trained weights. This model takes an image of size 224 x 224 x 3 as input and produces features (Feature Map) of dimensions 7 x 7 x 2048, which are then passed through Residual Pooling layers for image classification (Fig. 2).

For the training of the DRP-Texture Recognition model, we created a dataset of core images, categorized into six classes (five facies types and one
indeterminate type). We cut 1-meter core images (1,298 images) into image pieces with a height of 100 pixels and a 20-pixel increment. These images were then sorted into six folders based on their respective facies type (Fig. 10). Class 1 contained 22,515 images, class 2 contained 17,849 images, class 3 contained 7,477 images, class 4 contained 20,889 images, class 5 contained 41,878 images, and class 999 contained 5,646 images.

We randomly divided the cropped and graded images into train, validation, and test folders at a ratio of 70%, 15%, and 15%, respectively (See
The DRP-Texture Recognition model was trained on this dataset, and the overall accuracy obtained was 60%, with an average accuracy of 51.9% for the classes. The confusion matrix is shown in Fig. 11.

As the initial result was not satisfactory, we expanded the number of classes and divided the core images into nine new categories. These categories included destructed core, blank background, coarse-grained sandstone, medium-grained sandstone, fine-grained sandstone, siltstone, clay interlayers, shaly sandstone, clay, coal, and dense rock. We also cut the 1-meter core images into pieces with a height of 100 pixels and a 20-pixel increment and distributed them into nine folders based on their respective class labels. Class -1 contained 7,768 images, class 0 contained 2,417 images, class 1 contained 23,867 images, class 2 contained 26,606 images, class 3 contained 32,983 images, class 4 contained 25,110 images, class 5 contained 46,263 images, class 6 contained 1,420 images, and class 7 contained 770 images.

Similar to the previous dataset, we randomly divided the new dataset into train, validation, and test folders at a ratio of 70%, 15%, and 15%, respectively. The DRP-Texture Recognition model was trained on this dataset, and an overall accuracy of 75.8% was achieved, with an average accuracy of
82.2% for the classes. The confusion matrix is shown in Fig. 12. These results demonstrate that the DRP-Texture Recognition model is effective in classifying geological facies with a high level of accuracy.

4.5.1. Deep Encoding Pooling Network (DEP)

In this experiment, a new Deep Encoding Pooling Network (DEP) model was selected and trained on the same data used with 9 classes. The DEP model showed impressive results with an overall accuracy of 93.7% and a class average accuracy of 94.2%, as displayed in Fig. 14. However, the high accuracy results raised suspicion of overfitting, as the images were cropped with a shift and had areas with intersections, resulting in the same core areas present in the images. Hence, the model could not be generalized and only worked well with images from the given dataset.

To address this issue, a new set of images was prepared in which the test dataset consisted of core images of those wells that were not present at all in the training set (see Fig. 13). Pieces of images with a height of 100 pixels were prepared from 2190 meter core images, and the data was randomly distributed into folders for training, validation, and testing. The distribution of samples for the training and test datasets is shown in Fig. 15 and Fig. 16, respectively.

In this experiment, the DEP model showed an overall accuracy of 50.8% and an average accuracy across classes of 46.17%, which was significantly lower than the previous results. The confusion matrix in Fig. 17 indicates that the model recognized classes 6 coal and 7 dense rock very poorly. These
classes accounted for only 0.2% and 1.0% of all available training sample data, respectively. Thus, it was concluded that further work was necessary to improve and increase the dataset for training the model.

In conclusion, the results of the DEP model indicated the need for caution when interpreting high-accuracy results, as the model may be overfitting. To avoid overfitting, it is crucial to prepare a new set of images and increase the dataset for training the model.

5. Conclusion and Future Work

In conclusion, the study has shown that the use of machine learning techniques for image recognition in the oil and gas industry is promising. However, the accuracy of the models heavily depends on the quality and
distribution of the dataset used for training. The experiments conducted in this study have demonstrated the importance of carefully selecting and preparing the training dataset to avoid overfitting and improve the model’s generalization ability.

The results of the experiments indicate that the Deep Residual Pooling Network for Texture Recognition and Deep Encoding Pooling Network models are capable of achieving high accuracy in image recognition tasks in the oil and gas industry. However, the lack of sufficient data for some classes leads to low accuracy in those classes. Therefore, it is necessary to expand the dataset by collecting more images and modifying the models to improve the accuracy of these classes.

Despite the limitations of the study, the results are promising and suggest that machine learning can be used for image recognition tasks in the oil and
gas industry. The methods developed in this study can be further developed and applied to other tasks in the industry, such as reservoir characterization, rock typing, and well-log analysis.

In conclusion, this study provides a foundation for future research on the use of machine learning techniques for image recognition in the oil and gas industry, highlighting the importance of high-quality data preparation and the need for further experimentation and improvement of the models.

Further work can be done in multiple areas to improve the accuracy and generalizability of the models for industrial use. Firstly, the dataset can be expanded by collecting more core images, particularly for the classes that were underrepresented in the current dataset. This will help in training the models more effectively and reduce the chances of overfitting. Additionally, it may be useful to collect images from different wells and rock formations to increase the diversity of the dataset.

Secondly, different deep learning models can be explored to find the one that works best for the dataset. The models used in this study were based on deep residual and encoding pooling networks, but there are many other architectures available that can be tested, such as convolutional neural networks, recurrent neural networks, and attention-based models.
Finally, data augmentation techniques can be used to increase the size of the dataset and reduce the chances of overfitting. Techniques such as rotation, flipping, scaling, and adding noise to the images can be used to create variations of the original images, which can then be used for training the models.

In conclusion, the results obtained from this study have shown the importance of dataset distribution and size in training deep-learning models for the classification of geological facies. By expanding the dataset, exploring different models, and using data augmentation techniques, it is possible to improve the accuracy and generalizability of the models for industrial use.
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Figure 17: Distribution by test sample classes

| True Labels | Destructed core | Blank | Coarse-grained sandstone | Medium-grained sandstone | Fine-grained sandstone | Shaly sandstone | Clay | Coal | Dense rock |
|-------------|-----------------|-------|---------------------------|--------------------------|-----------------------|-----------------|------|------|------------|
| Destructed core | 81.83 | 0 | 1.29 | 1.17 | 3.97 | 2.33 | 8.93 | 0.47 | 0 |
| Blank | 0 | 99.74 | 0 | 0 | 0 | 0.13 | 0.13 | 0 | 0 |
| Coarse-grained sandstone | 0.08 | 0 | 37.35 | 27.49 | 11.33 | 12.14 | 11.41 | 0.19 | 0 |
| Medium-grained sandstone | 0.15 | 0.05 | 14.75 | 45.37 | 19.21 | 12.54 | 7.84 | 0.05 | 0.05 |
| Fine-grained sandstone | 0.21 | 0.03 | 3.37 | 15.21 | 25.26 | 30.6 | 25.29 | 0.03 | 0 |
| Shaly sandstone | 0.08 | 0 | 1.3 | 8.41 | 11.61 | 44.44 | 33.83 | 0.33 | 0 |
| Clay | 0.79 | 0 | 0.78 | 5.9 | 7.59 | 23.62 | 60 | 1.23 | 0.09 |
| Coal | 0 | 0 | 0.5 | 1 | 15 | 21.5 | 53 | 9 | 0 |
| Dense rock | 0.26 | 0 | 4.95 | 5.21 | 16.41 | 5.99 | 54.17 | 0.52 | 12.5 |

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