Exploring Convolutional Neutral Network and Machine Learning for Oil Sands Drill Core Image Analysis

Introduction

Permeability is a measure of the ability of fluids to flow through porous media and is an important factor in characterizing the McMurray oil sands for in-situ recovery. The traditional methods for estimating permeability in oil sands can be challenging due to the presence of immobile bitumen in the cores. However, permeability can be estimated using particle size distribution (PSD), which is a more cost-effective alternative to laboratory experiments (Wilson et al., 2008). The availability of drill cores from several wells in this region makes it possible for geologists to conduct detailed grain size analysis and determine PSD from various sections of the well. In addition, research has shown that there is a linear correlation between permeability and mean grain size (MGS), which can be derived from PSD analysis, providing further insights into permeability through the examination of MGS (Yoneda et al., 2019).

The use of machine learning (ML) and convolutional neural network (CNN) algorithms with digital images has made it possible to automate the traditionally labor-intensive process of grain size analysis in the mining industry (Tran et al., 2022). In this research, we apply these technologies to drill cores from McMurry oil sands, a task previously hindered by the presence of bitumen and difficulties in obtaining physical samples from different depths of many wells. Several thousands of core photos and PSD data were available to this study. This availability facilitates the use of ML and CNN techniques to accurately classify the rock types (facies) and determine the MGS in the drill core samples. We evaluate the effectiveness of CNN techniques to extract features from core photos using a pre-trained VGG-16 CNN model (Tammina, 2019) and then train a Random Forest model to predict the outputs (Rahimi et al., 2022). Using the extracted features, the facies and MGS are accurately estimated with reduced computational time. This work is one of the first research on the application of ML and CNN methods for characterizing oil sands drill core using digital images.

Proposed Methodology

This section outlines the key components of our proposed methodology, including data preparation, feature extraction using a CNN, and the training of a ML model for predicting facies and the mean grain sizes from core images.

Data Preparation

After storing the core samples in the boxes, these are taken to the laboratories, and the photos of the core slabs are captured (Figure 1: left). Information about the drilled well, possible depth, and core ID, among others, are also recorded at this stage. Since the photos contain a collection of core slabs, each core sample is cropped based on the interval points annotated in the core slab photos. The interval starting and ending points have been set to indicate a core sample for measuring the PSD.

Data Annotation with Facies

Cropped photos of core samples are labeled with an appropriate rock type (facies) by the domain experts based on the visual mud index (VMI) logs (Figure 1; right). This index reflects the proportion of mud in the sample. Samples with a VMI below 5% are classified as “F1” (sandstone), and those with a VMI between 5% and 15% are known as “F2” (Sandy Inclined Heterolithic Stratification). Similarly, for VMI between 15% - 30%, the facies are labeled as “F3” or IHS, and the procedure is repeated until 100% VMI. Geologists are interested to identify the reservoir sections with good quality rock for better well placement. “F1” is considered a good quality rock as it contains coarse sands with bitumen, whereas the other facies, such as “F3”, “F4” frequently contain several interbedded sand and mud intervals that can hinder production.

Figure 1 *Photos of a collection of core samples collected by Suncor Energy Inc. (left) and examples of different core samples (right) after cropping the images labeled with facies.*

The data available to this study includes core images labeled as “F1”, “F3”, and “F4” with “F1” being considered good quality and “F3” and “F4” poor quality (F2 was not present in the dataset). These poor-quality images are combined and labeled as “not F1” resulting in a total of 225 “F1” images and 220 “not F1” images. The proposed classification model will predict whether a core sample image is “F1” or “not F1”.

Data Annotation with Mean Grain Size

The drill core dataset includes PSD data for each core sample, determined using sieve analysis and laser diffraction system (LDS) methods (Wilson et al., 2006). The dataset also includes information (e.g., interval points) about the wells from which each sample was collected. To calculate MGS from the PSD, a cumulative probability distribution is created for each sample. This is done by plotting the cumulative mass percentage finer against the midpoint of each size interval. The cumulative mass percentage finer is the total mass of particles that are smaller than or equal to the size of the current size interval being considered. For example, if the current size interval is between 0.1 and 0.2 millimeters, the cumulative mass percentage finer would be the sum of the mass percentages of all particles that are smaller than or equal to 0.2 millimeters. Then, a probability distribution is derived from the cumulative distribution. This probability distribution represents the likelihood of finding particles within a certain size range. Finally, the MGS is calculated for each sample within a specific range, typically between 50 and 300.

Proposed Model Architecture

In this paper, three approaches are explored for facies classification and MGS estimation from drill core photos, including (1) the application of transfer learning on the pre-trained VGG-16 CNN model, (2) fine-tuning a few top layers of VGG-16, and (3) the combination of VGG-16 and traditional machine learning (ML) algorithms. VGG-16 is a CNN model that is trained on over 14 million ImageNet data belonging to 1000 categories (Russakovsky et al., 2015). The reason behind following the VGG architecture is not only the high accuracy but also its efficiency and, more importantly, its adaptability to other image classification problems than ImageNet (Tammina, 2019). Furthermore, the VGG-16 model can extract meaningful features from data due to having many convolutional layers.

VGG-16 structure starts with two convolutional layers, followed by a max-pooling layer. The collection of convolutional layers and the max-pooling layer is called a convolutional (Conv) layer block. For the first two convolutional layer blocks, it follows the same combination. Unlike the first two blocks, the rest of the model architecture contains the combinations of three convolutional layers followed by a max-pooling layer. Overall, the VGG-16 model is designed with five convolutional layer blocks. Finally, after the five convolutional layer blocks, at the top of the model, it contains three fully connected (FC) layers where the last FC layer produces the model's output.

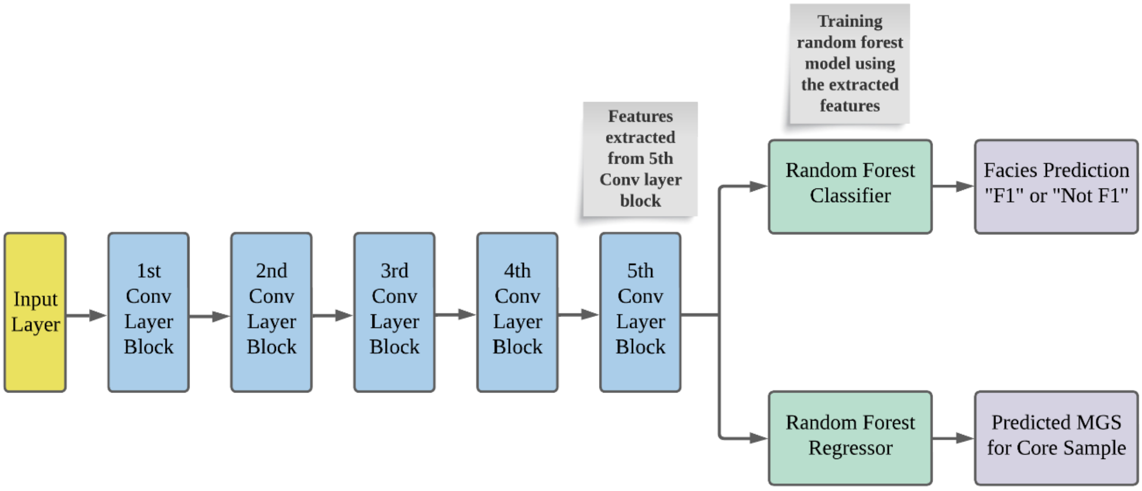

***Figure 2** Block diagram of the proposed facies classification and MGS prediction workflow using the combination of VGG-16 and Random Forest.*

In the first experiment, we freeze the convolutional layer blocks of the VGG-16 model to avoid model weights being updated during the training process. This strategy is implemented to utilize the pre-trained weights of the model and extract the features from the core photos. However, in the second approach, we fine-tune the weights of the last convolutional layer block of the pre-trained VGG-16 model, along with training the top layers. Here, the training process forces the weights to be calibrated to obtain features explicitly associated with the dataset. Therefore, in this approach, we un-freeze the last convolution block of the VGG-16 model and train it along with the layers related to the target.

In the third approach, VGG-16 and RF models are combined. We extract the features from the last convolutional layer block of the VGG-16 model. We use an RF classifier for facies classification, and to predict MGS from core photos, we use an RF regressor. This strategy is illustrated in Figure 2. We also compare the performance of decision tree classification and regression with that of RF models. Facies classification performance is evaluated using precision, recall, accuracy, and F1-score, while mean absolute error (MAE), root mean squared error (RMSE), and percentage error (PE) are used to evaluate MGS prediction performance.

Experiment and Results

Before training the models, we normalize the input data by re-scaling the pixel values from 0-255 to the range 0-1 preferred for the CNN model. As we have all the images and corresponding labels, the data are split into training and testing sets before training the models. A testing set is used to evaluate how the trained model performs on data that the model has never seen before. The performance of the proposed model is further assessed using a 10-fold cross-validation technique. The models are trained for an upward bound of 20 epochs in 64 batches and model checkpoints are used to save the models and weights in a checkpoint file, so that the models or weights can be loaded to continue training from the saved file. Table 1 shows that the proposed approach combining the VGG-16 with the traditional RF model outperforms the other methods by accurately predicting the facies and MGS from the core photos. Experimental results indicates that the features extracted by the VGG-16 are highly informative for classification, further, MGS estimation using the extracted features can provide the best outcome when the RF model is employed.

Table 1 *Summary of the performances of the explored approaches for facies classification and estimating MGS from oil sands drill core photos*

Model Architectures	**Facies Classification**				**MGS Prediction**		
	Accuracy	Recall	Precision	F1-score	RMSE	MAE	PE
Transfer learning on VGG-16	93.15	94.00	94.00	94.00	46.33	36.25	23.54
Fine-tuning VGG-16	96.30	98.00	98.00	98.00	49.29	38.28	24.86
VGG-16 and Decision Tree	94.52	96.38	93.52	94.84	51.60	40.14	26.06
Proposed: VGG-16 and Random Forest	**98.87**	**99.00**	**99.00**	**99.00**	**16.89**	**11.59**	**7.53**

Conclusion and Future Work

Permeability is a key property of the reservoir rocks, which can substantially influence the reservoir performance. Traditional methods for measuring permeability in oil sands, such as laboratory experiments and core analyses, are time-consuming and costly, and do not accurately reflect the in-situ permeability of the rock. Mean grain size (MGS) can be used as an indirect property to estimate permeability, as it contains information about the average pore structure and the ability of fluid to flow within the reservoir. In this paper, we proposed a novel method for predicting the facies and mean grain size (MGS) of drill core samples using digital images and a combination of VGG-16 and random forest (RF) algorithms. Our proposed model showed promising results for accurate estimation of permeability using drill core images. However, this research only considered a binary classification problem using a small library of rock samples. As a potential extension of this work, future research can consider the inclusion of additional facies in the dataset to improve the accuracy and applicability of the model.

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