Automatic Classification of Sedimentary Rocks Towards Oil Reservoirs Detection

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Abstract. In technological advancement, there are several techniques have discovered for exact identification of hydrocarbons which is being used by oil industries to detect the oil reservoirs. In this study, we have investigated and proposed system of detection and prediction of hydrocarbons under earth subsurface through microscopic rock image modality. This system presents a robust watershed segmentation approach for determining porosity where convolutional neural networks are used for classification of sandstone and carbonate rock samples. The system is tested on microscopic images of sandstone and carbonate rock samples, and detection observed in rocks is based upon estimation of total porosity. Experimental comparison of proposed system shows outperform over state-of-the-art methods.

Keywords: Oil reservoir · Microscopic rock samples · Convolutional neural network · Watershed · Porosity

1 Introduction

The hydrocarbon detection is to detect the amount of hydrocarbons (i.e. oil and gas) present in earth subsurface. Hydrocarbon deposits are not found in the underground lakes or pools since they are actually located in pore spaces of the porous sedimentary rocks [1, 2]. In this paper, a machine learning based on image processing method has used to analyze the porosity of sedimentary rocks. Edwin drake was the first American person drilled for oil and get a success in 1859 [3]. As time passes, various industries showed interests in drilling and get their success ratio less. Later on, studied on rocks came into a picture for oil observation, and pore size, volume, porosity, permeability are all the key properties associated with the characterization of any hydrocarbon reservoir [1]. Reservoir rock looks solid to the naked eyes but examining the rock through microscope reveals existence the tiny spaces in the rock [4]. By studying porosity of thin section from sedimentary rock samples under the microscopic image is one of the most favorable techniques for prediction and detection of oil reservoir in a rock.

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Sedimentary rocks are basically categorized into three classes, namely, clastic, carbonate, and evaporitic [5]. The hydrocarbon deposits are found in clastic as well as in carbonate sedimentary rocks such as sandstone, limestone, dolomite, breccia, shale, etc. There are several earlier methods to detect oil reservoir such as physical examination, aerial photos, satellite images, and gravitational studies. Among them in gravitational studies, geologist used magnetometers to mark the changes location for finding new sources of oil. Recently, the methods like remote sensing, wildcatting, and geophysical surveys are useful where geophysical surveys have been used around the world for greater than five decades for oil and natural gas exploration. These surveys decide feature of the earth's subsurface by computing the physical divergence between rock types without seeing them directly by digging. The process of oil digging for hydrocarbon can be categorized into two main classes, namely, offshore and onshore [6]. The offshore digging linked with drilling below the seabed, where about 30% of the world fuel production comes from this drilling process. As offshore drilling relates to drilling in the ocean, the seismic imaging plays an important role in creating 3D image of the subsurface rocks. The main problem is that obtaining of the images, because the waves travel faster through salt than in rock. As a result, the final image cannot be accomplished. On the other hand, the onshore digging linked with drilling deep holes under the earth's surface, where about 70% of the global oil production comes from this drilling process. Herewith, it cannot precisely tell what types of rocks are below the surface and it can only predict the presence of hydrocarbons. Oil industries face challenges during drilling are pipe sticking, loss of circulation, pipe failures, mud contamination, hole cleaning, hole deviation, and so on.

To increase the possibility in search of a productive well, oil industries gather more information about the site or field before and after drilling. As a consequence, gathering information about the site or field before and after drilling is very helpful for industries which avoids drilling in unproductive wells. For geologists, it is a quiet challenging to determine the rock categories and the exact percentage of porosity (i.e., hydrocarbon deposits) in each type of rock through their eyes and subjective evaluation. In this paper, we have provided a combination of deep learning and machine learning based technique for classification and detection of oil reservoir by using scanning electron microscopic (SEM) imaging. Therefore, automating the process for detection of oil reservoir is highly needed to reduce the negative influence of subjective evaluation.

The contributions of this paper are summarized below:

I. The paper provides the research community with annotated ground truth (GT) images of microscopic sandstone and carbonate samples from the DRSDR1 [7] dataset for pore space analysis which is previously not done.

II. The paper provides a proposed schematic system flow for estimating porosity of microscopic samples of hydrocarbon stones. The system flow is covering two portions as follows:

   II.1. First portion analyses the classification performances of reservoir stones using state-of-the-art deep convolutional neural networks (CNN).

   II.2. Second portion provides the segmentation output of pore spaces of reservoir stones using a robust watershed algorithm for pore space analysis.

III. The segmented microscopic reservoir stone images are then compared with ground truth via several performance evaluation metrics.
IV. Finally, estimated the porosity values and evaluated comparison of our proposed system with most widely used state-of-the-art hydrocarbon detection methods.

Rest of the paper is organized as follows: Sect. 2 discusses the review on oil reservoirs using multimodal imaging and in Sect. 3 discusses the methodology and the workflow of the proposed system. Section 4 is about experimental results and discussions. Finally, Sect. 5 consists of conclusion and future work.

2 Related Work

Image processing has been used in the field of geoscience for a long time. The scientists have been tried to use image processing in study of rock properties for prediction of porosity and permeability that are essential for petroleum industry. Image is a key feature due to its higher resolution where pores are visible more helps for correct determination of porosity. Image analysis by scientists all over the world have been brought revolution for oil industries in order to take out more important information from geological images [1]. Microscopic and Computer Tomography (CT) rock images are mostly used to analyze the samples for porosity and permeability calculations in computer vision for automate process. The seismic hyperspectral infrared spectroscopy images are also used. At the present time, computer vision is a revolution for oil industries as using new advance techniques help them to reduce cost and gives an accurate value. In order to conduct a systematic review, we have taxonomized the survey over three categories: conventional machine learning, deep learning approaches, and well-known rock datasets.

Timur et al. [8] had utilized scanning electron microscope (SEM) for studying pore spaces in rocks like sandstone, limestone, dolomite, shale, etc. The main advantage of using SEM that it works with a large depth of focus and magnification to show the detail structure of pore spaces. H. Taud et al. [9] presented a segmentation approach studying the hydrocarbon properties of pore spaces for porosity calculation over X-ray CT imaging. To classify carbonate rocks from thin sections, Marmo et al. [10] introduced a technique based on principle component analysis (PCA) over microscopic image analysis and multi-layer perceptron. In 2011, Grove et al. [3] developed a software, namely, ImageJ for calculating total optical porosity of blue resin saturated thin sections. The porosity of rock samples can also be measured directly as explained by Yusuf et al. [11] where they have examined 20 samples of rocks porosity ranging from 14.29% to 51.92%. The limitation of their study is that it cannot differentiate between different types of rocks. Zhang et al. [12] proved that the sandstone CT image analysis with Ostu thresholding gives better results for the oil reservoir detection. In 2012, Ghiasi-Freez et al. [2] proposed a semi-automated method for recognized and categorized five unalike types of porosity in microscopic samples i.e. interparticle, intraparticle, oomoldic, biomoldic, and vuggy using discriminant classifier such as linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA). For estimating porosity automatically in carbonate and terrigenous rock samples of CCD camera, Mazurkiewicz et al. [13] also proposed an image analysis-based algorithm. The Ostu thresholding also used by Datta et al. [1]

for estimating porosity of different types of rocks like limestone, sandstone. Recently in 2017, Nurgalieva et al. [14] presented an approach called ISODATA algorithm which was preferred because it is iterative and correct to process microscopic images of carbonate rock.

Nowadays, petroleum industries are using deep learning-based models to rapidly predict porous media properties from images in a supervised learning process. Recently, Wu et al. [15] presented a convolutional based neural network (CNN) method for porosity calculation from microscopic images which achieved significant success. The main objective was to teach a deep learning framework for fast prediction of permeability. M. Abedini et al. [16] introduced two intelligent frameworks, namely, back-propagation network (BPN) and stacked autoencoder (SAE) that for detection types of porosity. The feature extracted from the rock sample of 682 pores were used for training. N. Alquahtani et al. [17] also utilized a CNN model to rapidly predict several porous media properties from micro-CT images of different sandstones. The deep CNN model trained and validated in an end-to-end regression scheme with input greyscale micro-CT images and output of several computed porous properties. O. Sudakov et al. [18] introduced a deep learning-based descriptors pore network approach on 3D scans of Berea sandstone subsamples images with X-ray micro-CT, and analyzed the predictive power of various descriptors where deep descriptor outperforms. In 2020, Y. Niu et al. [19] used a CNN to segment digital sandstone data based on high-resolution micro-CT and corresponding SEM. The results are evaluated in terms of porosity, permeability and pore size distribution from segmented data.

There are few related datasets of rock stones available.

DRSRD1 [20]: Digital Rocks Super Resolution Dataset 1 (DRSRD1) dataset which is consists of organized 2D slices and 3D samples of Bentheimer Sandstone and Estaillades Carbonate. 800 samples are accessible for training, 100 for validation and 100 for testing.

GIAS [21]: Geological Image Analysis Software (GIAS) is an image processing package written in MATLAB which facilitates the analysis of vesicle images. Nikon LS-2000 digital film was used to directly collected an sample of 320x256 petrographic thin sections.

LANDMASS 2 [22]: Large North-Sea Dataset of Migrated Aggregated Seismic Structures (LANDMASS) is a high quality seismic data used for oil and gas exploration which consists of total 4000 samples (1000 horizon, 1000 samples, 1000 samples and 1000 salt dome) of dimensions 150x300 pixels.

OMS [23]: Offshore Miocene Sandstone (OMS) thin section with resolution for all samples and all magnifications is 0.24 μm per pixel.

LS X-RAY [24]: A Large Scale X-RAY (LS X-RAY) micro-tomography dataset (LS X-RAY) dataset comprises of raw samples and segmented X-ray micro-tomography samples.

Oil reservoir detection one of the most fundamental and challenging problems in computer vision. Machine learning techniques have emerged as a powerful strategy for learning and classification rock feature representations but lack in accuracy. Whereas deep CNN remarkable break through recently and unexplored in the field of oil reservoir detection.

3 Methodology

Figure 1 shows a schematic diagram of our proposed workflow for oil reservoir detection. A dataset of 2D microscopic images of sandstone and carbonate samples are inputted for the training of CNN models. The stone sample images are then segmented using a modified robust watershed segmentation algorithm which is a required further phase to distinguish pores from the pores space. Then the pores are evaluated through performance metrics and porosity from the processed images.

3.1 Deep Nets for Classification of Different Rocks

In this study, we have used different CNN architectures for classification of rocks before segmentation to analyze rock samples.

The accomplishment of deep convolutional neural networks is accredited to their capability to learn rich image depictions, but they rely on assessing millions of parameters as well as necessitate a very bulk number of images. In our case, we have very less volume of rock samples data as compared to the requirements of CNN. An alternative which has been extensively used is to fine-tune and transfer learning the CNNs, that are pre-trained using large amount of image datasets such as ImageNet. The renowned CNN models in literature are VGG, ResNet, AlexNet and so on. The rock samples cannot be explored in a concrete way by small networks such as AlexNet sometimes. On the other-hand, the VGG16, VGG19, and ResNet50 makes improvement over AlexNet by substituting large number of filters, convolutional layers with multiple tiny 3×3 size kernels. These multiple stacked tiny size kernels along multiple non-linear layers increases depth of the architecture, which enables it to learn more concrete and complex features of rock samples. However, our trail experiments demonstration that only the usage of pre-trained networks with fine-tuning cannot deliver pleasing performance in a small rock dataset. Furthermore, the custom VGG16, VGG19, and ResNet50 based rock features progresses

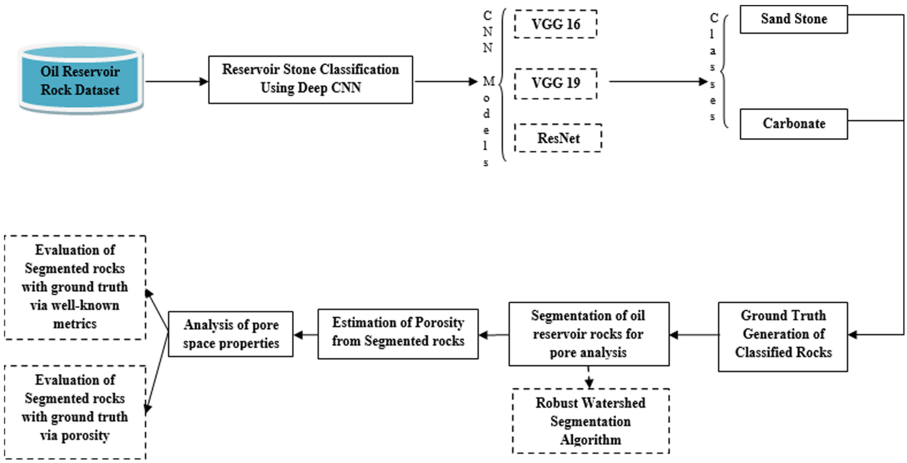

Fig. 1. Proposed schematic work flow for oil reservoir detection.

to a very great degree the performance of classification of microscopic rock samples. In custom models, the last Dense classification Softmax layer has been changed according to the number of rock types (classes) as presents in our rock dataset, and modified the fully connected layers according to our problem domain, and used the rest of pre-trained model as a fixed feature extractor.

3.2 Robust Rock Segmentation Approach for Pore Space Analysis

In watershed transform, we correspond to catchment basins as 'pore space' and ridgelines as 'grain' in sedimentary rocks, as shown in Fig. 2. The steps of our modified robust watershed algorithm as follow:

(i) Add neighbors to priority queue, sorted by value.
(ii) Choose local minima as region seeds.
(iii) Take top priority pixel from queue.
(a) If all labeled neighbors have same label, assign to pixel. If we think pixel as center pixel, and calculate distance between all labeled neighbors with center and assigned to nearest one. At a time, a center and a labeled neighbor is considered while other neighbors compete as candidate neighbors.
(b) Add all non-marked neighbors.
(iv) Repeat step (iii) until finished.

For better visualization, few segmented output samples are shown in Fig. 3.

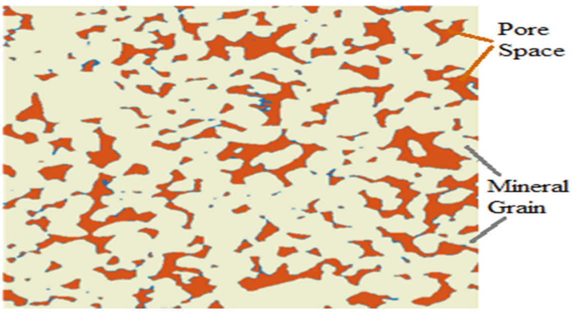

Fig. 2. A sedimentary microscopic rock sample [20].

4 Performance Evaluation

In this study, we have used the DRSRD1 [20] which is a dataset of total 2000 2D images with high resolution of 800 × 800 pixels of 1000 from sandstone and 1000 from carbonate samples. Those were cropped samples from the centre of the original cylindrical lens images of.PNG files. For experimental purpose, a total of 1600 images (i.e. 800 from sandstone and 800 from carbonate) are used for training, and rest of 200 images from each type of samples used for validation/testing during training of CNN models.

4.1 Ground Truth (GT) Generation

To exam the effectiveness of oil reservoir detection methods, the creation of annotation of region of interests in a microscopic rock sample is very crucial. Here we have implemented pixel level binary mask-based annotation to evaluate oil reservoir detection approaches. However, manual annotation of an accurate ground truth data often results in ambiguity and solid subjective bias. All the 2000 images of sandstone and carbonate samples are created binary mask using ImageJ software [25]. It can reliably classify pixels belongings to either pore space or grain: Pore Space - assigned binary value of 0, Grain assigned binary value of 1. Few samples and corresponding generated ground truth have shown in Fig. 3

4.2 Analysis of the Rock Samples Classification Using CNN Models

In this study, CNN models are used for classification to determine the labels: sandstone and carbonate from DRSRD1 dataset microscopic images. We empirically analyze the training and testing loss of CNN models, as shown in Table 1, with the tuning of hyper parameters for training the models are - optimizer: RMSProp, classification loss: weighted sigmoid cross entropy.

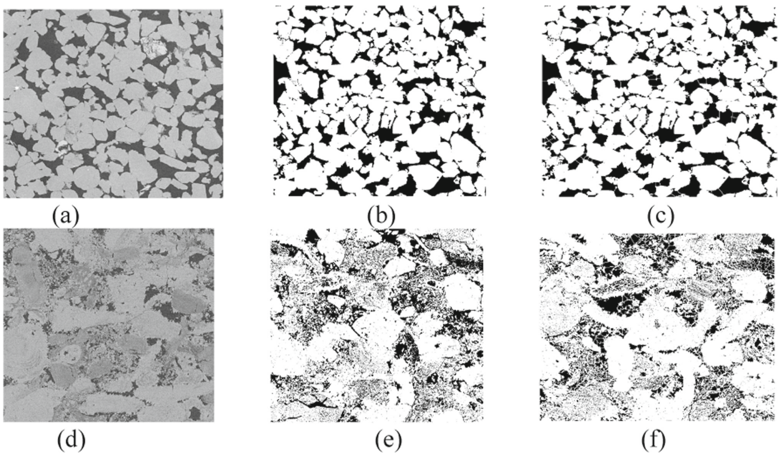

Fig. 3. Ground-truth images from DRSRD1 dataset. (a) sandstone sample (b) corresponding GT (c) segmented output (d) carbonate sample (e) corresponding GT (f) segmented output

We kept pre-trained option true when training the CNN networks to take weights value from the ImageNet multiclass competition dataset. During training, the input convolutional layers reduces the large dimensional original images to a small dimension (224 $\times$ 224) for learning speedup and less memory consumption. We trained the CNN network models for about 100 epochs on the training and validation dataset DRSRD1. Throughout training, a batch size of 32 have used, and the schedule learning rate slowly raises from $1e^{-5} = 0.004$ to $1e^{-2} = 0.135$ in the following order: $1e^{-5}$ for first 25

Table 1. Performance of rock samples classification.

CNN model	No. of epochs	Batch size	Training phase		Testing phase	
			Acc	Loss	Acc	Loss
VGG16	100	32	0.999	0.005	0.983	0.003
VGG19	100	32	0.998	0.027	0.979	0.015
ResNet50	100	32	0.987	0.006	0.972	0.001

epochs, $1e^{-4} = 0.018$ for next 25 epochs, $1e^{-3} = 0.049$ for next 25 epochs, and finally $1e^{-2}$ for last 25 epochs. If we start at a high learning rate our network models often diverges due to unstable gradients.

To overcome the overfitting and data pre-processing issues, first we have turned our data into pytorch dataset where images are randomly shuffled and split into train and validation sets through pytorch DataLoader. Here the training data samples are augmented to improve performance and reduce overfitting issues during training-validation. The data augmentation we have charted here are rotation, zooming, vertical and horizontal flipping.

We have observed that the training accuracy is 0.999 with 0.005 loss rate whereas the testing accuracy is 0.983 for VGG16 with 0.003 loss rate. As compare to VGG16, the training accuracy is slight lower in VGG19 and the testing accuracy correspondingly remains lower but testing loss rate is lesser with 0.015 than training loss 0.027. As compare to VGG16 and VGG19, Resnet50 performs well on training and testing loss whereas accuracy is slightly lower compared to both the architectures.

4.3 Performance Evaluation of the Segmented Pore Spaces

The analysis of segmented pore spaces via our proposed system has done in two ways.

First, we have estimated the correctness of modified robust watershed method for segmentation as compare to ground-truth. For this purpose, the well-known performance metrics such as F_1-score, recall, precision, accuracy, MCC, and sensitivity has been utilized, as shown in Fig. 4. From the Fig. 4, it seems that all the six metrics values for sandstone sample varies from 0.9822 to 1.00. Whereas the performances of segmentation for the carbonate samples are underperform than sandstone samples. The textural microscopic images of sandstone are sharper than carbonate images, which lead to easy segmentation of sandstone and correspondingly outperform in metric values than carbonate.

Second, we have analyzed the porosity values between ground truth and our proposed system via similarity index through Euclidean distance. The porosity is estimated as follows:

$$\mathrm{Porosity}(\mathrm{P_t}) = \mathrm{Pore\ Volume}\left(\mathrm{V_p}\right)/\mathrm{Total\ Volume}(\mathrm{V_t}) \times 100\% \tag{1}$$

From the graph in Fig. 5, we have seen that our proposed system producing nearest porosities against ground truth porosities. And the similarity index also showing analogous

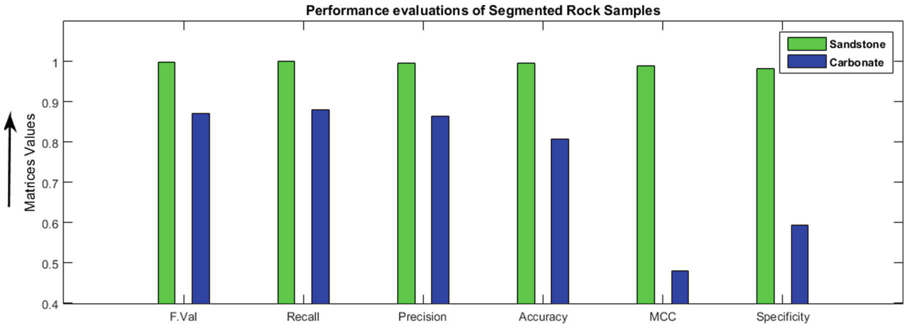

Fig. 4. Segmentation performance correctness measurement.

consequences where value of 0.0264 for carbonate samples and 0.0589 for sandstone samples.

4.4 Comparative Analysis with State-of-the-Arts

Pore spaces segmentation under microscopic medium rock samples has been one of the major research topics to detect the oil reservoirs. Numerous computer aided detection techniques have been proposed in the literature for porosity analysis. In our work, we have used selected most popular methods for comparative study. To provide a better assessment of overall performance and compare the performances among state-of-art methods, we used metrics like porosity. From the comparative analysis in Table 2, we have analyzed our proposed system performances outperform in case of sandstone samples. In case of carbonate samples, M. Abedini et al. [16] approach shows maximum 96.04%.

4.5 Discussion of Results Significance

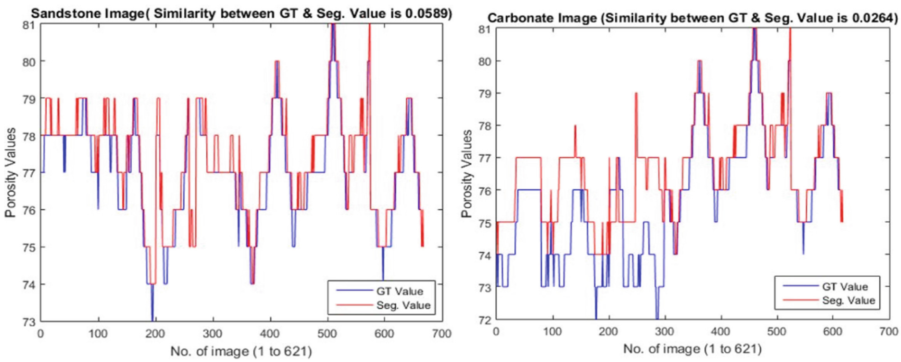

Fig. 5. Segmentation performance via porosity measurement.

Table 2. Comparative performance analysis of state-of-the-art techniques.

State-of-the-art approach	Sample	Max. porosity value
R. Marmo et al. [10]	Carbonate	93.5%
A.D. Yusuf et al. [11]	Sandstone	51.92%
D. Datta et al. [1]	Limestone	30%
	Sandstone	56%
B.S. Nabawy [26]	Sandstone	44.5%
L. Mazurkiewicz et al. [27]	Carbonate (Koscian)	20.1%
	Sandstone (Solec)	24.9%
R. Song et al. [28]	Sandstone	31.8%
	Carbonate	25%
M. Kashif et al. [29]	Sandstone	21.1%
M. Abedini et al. [16]	Carbonate	**96.04%**
Our Proposed System	Sandstone	**98.22%**
	Carbonate	89.02%

One of the factors remarkably influence the accuracy and loss of CNN based classification models is quantity of training microscopic images data. According to objective pursued in any deep learning study, suitable enough amount of input data must be provided. In this research, the collection of data was lesser in amount which creating over-fitting issues during model preparation. Although we have managed these issues via adjustment of hyper-parameters like dropout, batch normalization and most importantly data augmentation. Next influencing factor is convolutional operation through deeper layers investigation and differentiation of several types of attributes such as minerals, colors of minerals, and geometrical characteristics of sample stones. These attributes are utilized as a tool to differentiate and categorize pore spaces. Finally, the intension of this part of classification task is to assess the applicability of CNNs to make accurate predictions of sample labels as carbonate and sandstone.

The second experiment has been identified segmented pore spaces by robust watershed method. The images used in this study are microscopic blue-stain of thin section of sandstone and carbonate rock types with their different pore structures as shown in Fig. 3. Here, we have noticed the micritization, small size, and densely packed unclear boundary grains in some carbonate stones that are complex characteristics than sandstones. As a consequence, the contrast between grains and pore spaces not always result clearly which effects in performance measurement as shown in Fig. 4. Grains must have a well-defined internal structure and a clear boundary.

To assess the correctness of the proposed results in this research work, we need to be compared with the result presented in other publications which present the results of investigations of the same materials with different methods. Table 2 presents the results obtained on samples investigated by sandstone and carbonate analysis. From the comparative analysis in Table 2, we have observed our proposed system performances outperform in case of sandstone rocks. In case of carbonate rocks, M. Abedini et al. [16] approach shows maximum 96.04%.

5 Conclusion and Future Work

This study presents an easy and efficient technique which calculates rocks porosity from images for hydrocarbons for betterment of oil industries. We have used 2D microscopic images dataset for classification and analysis of image samples. For CNN model based classification, the features like minerals, colors of minerals, geometrical characteristics of microscopic samples are utilized to categorize pore spaces of sandstone and carbonate. To segment the pore spaces, a robust watershed method is presented. We have observed, the contrast between carbonate grains and pore spaces not always result clearly than sandstones. To assess the validation of the proposed results, we compared the result presented with other state-of-the-arts. We have observed that our proposed system performances are competitive.

In future, 3D samples from datasets can be used for determining more petro-physical properties.

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