

**IMAGE-BASED CHARACTERIZATION OF
MULTISCALE PORE STRUCTURE
USING MACHINE LEARNING**

BY

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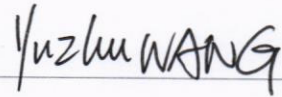


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Dedicated to my family, with love and gratitude

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LIST OF ABBREVIATIONS

NMR	:	Nuclear Magnetic Resonance
DRP	:	Digital Rock Physics
SEM	:	Scanning Electron Microscopy
MIP	:	Mercury Injection Pressure
μ-CT	:	Micro city Image
MCMC	:	Markov Chain Monte Carlo
FIB-SEM	:	Focused ion beam scanning electron microscopy
MRF	:	Markov Random field
RF	:	Random forest
SVM	:	Support vector machine

ABSTRACT

Author Name : Abdullahi Ahmad Jibrin

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Understanding fluid flow and transport mechanisms in porous media requires the characterization of porous structure. Examining a rock's complex pore structure and heterogeneity using traditional experimental methods remains difficult. Conventional core analysis, the main method used to estimate properties of hydrocarbon resources through experiments, provides information such as porosity, permeability, fluid saturation, elasticity, electrical conductivity, magnetic susceptibility, and multi-phase fluid flow properties. However, these measurements offer only a generalized overview of the sample's features and do not yield insights into the microstructural details that exert a substantial impact on the rock's characteristics. Along with the wide use of imaging devices in petroleum industry, reservoir engineers can step into the inner structure of the rock sample and calculate the full set of the reservoir properties directly. This approach provides an innovative method for acquiring a deep knowledge of the pore structure of the rock and can solve the limitations of traditional laboratory studies. This research is aimed to analyze the heterogeneity of the rock pore networks by image-based rock typing and further characterize the pore structure of each rock type. In addition, machine learning will be applied to make the proposed method more accurate, efficient, versatile, and intelligence. The entire workflow can be divided by two steps of image-based rock typing and pore structure characterization, where the image-based rock typing can be further divided by three steps: 1) image pre-processing; 2) feature extraction; 3) rock typing.

The performance of the image-based rock typing highly depends on the selected image features and classifiers, Therefore, eight image features (intensity features, edge features and texture features) and five classifiers are selected to test the rock typing performance. Based on the segmented images, pore structures parameters including porosity, pore size distribution, pore count, perimeter, and pore area will be analyzed. The proposed method would effectively mitigate the limitations of the conventional laboratory studies.

١ ملخص الرسالة

اسم المؤلف: عبد الله أحمد جبرين

عنوان الرسالة: توصيف هيكل المسام متعدد المقاييس المستند إلى الصور باستخدام التعلم الآلي

المجال الرئيسي: هندسة البترول

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يتطلب فهم آليات تدفق السوائل والنقل في الوسائط المسامية توصيف بنية المسام. لا يزال فحص البنية المعقدة للمسام وتفاوتها باستخدام الطرق التجريبية التقليدية صعبًا. يوفر التحليل التقليدي للنواة، وهو الطريقة الرئيسية المستخدمة لتقدير خصائص موارد الهيدروكربونات من خلال التجارب، معلومات مثل المسامية، النفاذية، تشبع السوائل، المرونة، التوصيلية الكهربائية، القابلية المغناطيسية، وخصائص تدفق السوائل متعددة الأطوار. ومع ذلك، فإن هذه القياسات تقدم نظرة عامة فقط على ميزات العينة ولا تقدم تفاصيل دقيقة عن البنية الدقيقة التي تؤثر بشكل كبير على خصائص الصخور. مع الاستخدام الواسع لأجهزة التصوير في صناعة البترول، يمكن لمهندسي الخزانات استكشاف البنية الداخلية لعينة الصخور وحساب مجموعة كاملة من خصائص الخزانات بشكل مباشر. تقدم هذه الطريقة أسلوبًا مبتكرًا لاكتساب معرفة عميقة ببنية المسام في الصخور ويمكن أن تحل القيود التي تفرضها الدراسات المخبرية التقليدية. يهدف هذا البحث إلى تحليل تفاوت شبكات مسام الصخور من خلال تصنيف الصخور المستند إلى الصور وتوصيف هيكل المسام لكل نوع من أنواع الصخور. بالإضافة إلى ذلك، سيتم تطبيق التعلم الآلي لجعل الطريقة المقترحة أكثر دقة وكفاءة ومرونة وذكاء. يمكن تقسيم سير العمل الكامل إلى خطوتين: تصنيف الصخور المستند إلى الصور وتوصيف هيكل المسام، حيث يمكن تقسيم تصنيف الصخور المستند إلى الصور إلى ثلاث خطوات فرعية: (1) معالجة الصور الأولية؛ (2) استخراج الميزات؛ (3) تصنيف الصخور المستند إلى الصور. يعتمد أداء تصنيف الصخور المستند إلى الصور بشكل كبير على الميزات المختارة والمصنفات، ولذلك، تم اختيار ثمانية ميزات للصور (ميزات الكثافة، ميزات الحواف، وميزات الملمس) وخمسة مصنفات لاختبار أداء تصنيف الصخور. بناءً على الصور المقسمة، سيتم تحليل معلمات هيكل المسام بما في ذلك المسامية، توزيع حجم المسام، عدد المسام، المحيط، ومساحة المسام. من المتوقع أن تقلل الطريقة المقترحة بشكل فعال من قيود الدراسات المخبرية التقليدية

CHAPTER 1

INTRODUCTION

The growing desire for fossil fuels has stirred significant attention toward tight sandstone reservoirs, which are recognized for their minimal porosity and permeability [1]. The intricate and irregular pore structure, marked by high heterogeneity, often results in complex and unconventional measurements of overall properties [2]. A good understanding of reservoir characteristics is essential in the evaluation and utilization of oil and gas resources.

The conventional methods to estimate the reservoir properties is core analysis, which involves conducting experiments on rock samples [3]. Convectional techniques such as mercury injection pressure (MIP), CO₂ gas adsorption, and low field nuclear magnetic resonance (NMR) have all been used extensively to describe reservoir pore structure [4]. However, these measurements only give an average representation of the sample's properties and do not provide insight into the microstructural information that has a substantial effect on the rock's characteristics [5]. As a results, the examination of a rock's complex pore structure and heterogeneity using conventional experimental methods remains a challenge [6].

Along with the universal application of various imaging devices (e.g., thin sections, SEM, and μ -CT), digital rock physics (DRP), which incorporates digital imaging methods, has permitted direct observation of rock microstructures across a wide range of length scales, from the nanoscale to the millimeter scale[7]. Researchers may evaluate rock heterogeneity and determine attributes such as porosity, permeability, elasticity, electrical conductivity, and NMR T₂ distribution using imaging devices, image processing technique and numerical flow simulation[8]. This approach offers a

novel means of gaining a comprehensive insight into the rock's pore structure and can overcome the limitations associated with conventional laboratory measurements [9].

A general pore structure characterization workflow can be implemented via four steps. First, some imaging denoising methods are used to remove some typical image noises to improve the quality of the images. Second, image segmentation is carried out to classify the image into different phases such as pore and solid. Third, image-based rock typing is conducted to classify the image into different rock type where each rock type can be treated as a relatively homogeneous porous medium. Fourth, various geometrical and topological features of the pores in each rock type are calculated. This study focuses on image-based rock typing and pore structure characterization due to the quality of the selected SEM images are excellent in terms of signal noise ratio and resolution which results in the image denoising step can be neglected and image segmentation is straightforward.

Based on the various images and image processing techniques, image-based rock typing was proposed to characterize the heterogeneity of the multiscale pore structure of the reservoir rock samples. A typical image-based rock typing can be divided into two steps of feature extraction and rock type classification [10]. The feature extraction can be implemented by manual selection or deep learning. The manual selection of this features is referred to as self-defined features, in this case the user selects the features applicable for the rock typing and this feature include intensity features, edge features and texture features [11]. After feature extraction, a classifier is chosen to categorize the images into various groups. Commonly used classifiers include K-nearest neighbors (KNN)[12], Gaussian Mixture Model [13], support vector machine (SVM)[14], and random forest [15]. In learning-based approach, the selection of features for rock typing is a challenging task that largely depends on the specific material

For example, Yuzhu wang and Shuyu applied random forest [16] as a classifier and GLCM [17] as feature extractor to process the 2D sandstone SEM images with a multiscale pore structures. Their study shows that GLCM properties are highly effective at capturing texture features in different rock fabrics, particularly for classifying porous structures and the accuracy of rock fabric classification decreases as the number of rock fabrics increases. However, they concluded GLCM outperforms commonly used image features like color, edge, and other texture features in fabric description. The method has been successful in classifying the target image into four phases without the need to prepare a training dataset.

Siddharth and Yaukun introduced an automated image-based rock typing methods comparing machine learning models including (random forest, and decision tress) as the classifiers and threshold based methods [18] combined with traditional feature extraction techniques to segment an SEM Image into four different phases including pore space, clay minerals, pyrite and kerogen components. In terms of feature extraction, thirteen image features were extracted, which were later reduced to six features by feature permutation importance. According to their study, the method was trained using 705, 15000, 17373, and 2074 pixels corresponding to the four different components. After the training, the model effectively segmented SEM images in 30 seconds when applied to the unseen data. The individual component classification achieved average F1 scores of 0.94 for pyrite, 0.97 for pores, 0.80 for kerogen, and 0.83 for the rock matrix. Support vector machine model was applied to conduct an image-based rock typing with grain geometry as the input features by wang et al. A sample image rock sample with $600 \times 600 \times 600$ voxels was used to demonstrate their proposed method. The model successfully classified the heterogenous image sample into two different phases with rock type (RT1) and (RT2) having the F1 score of 0.82 and 0.962. [3]

1.1 Significance of the Study

Accurate characterization of pore structures is instrumental in optimizing reservoir performance. This study will provide an approach in using image-based techniques and machine learning to demonstrate reliable understanding of reservoir pore structure characterization.

1.2 Goals and objectives

The goal of this study is to demonstrate the use of image analysis and machine learning at multiple scales to analyze the heterogeneity of the rock pore networks with high-resolution SEM images of a sandstone rock sample. The selected sandstone sample represents a complex pore space resulting from diagenesis processes.

The primary goals of this project include:

- To analyze the effectiveness of different features in rock typing
- To analyses the capability of different classifiers in rock typing
- To characterize the pore structure of each rock type

The proposed methods will be demonstrated using SEM images. In addition, machine learning will be applied to realize the image-based rock typing. The entire workflow can be divided into four steps: 1) image processing (image denoising and resizing); 2) feature Extraction; 3) image-based rock typing; and 4) pore structure characterization

1.3 Thesis outlines

Chapter one introduces the background and concept of conventional image-based rock typing. Chapter two offers a comprehensive review literature on pore structure characterization various imaging techniques, including SEM and μ CT techniques, along with their respective advantages

and limitations. Chapter Three explores into the detailed methodology of the study which include feature extraction and development of five models including K-Means, Gaussian Mixture Model, Support Vector Machine, Random Forest, and U-Net for image-based rock typing. Additionally, this chapter outlines the typical workflow for each classifier

Chapter four presents the pore structure characterization for each rock type, with a focus on geometrical and fractal dimensions. Chapter five presents a detailed analysis of the results and finally, Chapter five concludes the research by summarizing the key findings.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview of Pore Structure Characterization

Geometric features like distribution of pores, shape, size, and throats, their interconnection, and how they are distributed in space is referred to as the pore structure [21]. Tight sandstone reservoirs are known for having intricate pore geometries and throat structures, as well as a wide variety of pore throat dimensions spanning from nano to micro-scale. Pore throat features, for example, are particularly significant for assessing the quality of reservoirs and fluid circulation inside tight sandstones. To increase and sustain petroleum recovery, it is necessary to carefully examine and describe these microscopic pore structures, including pore shapes, size distributions, and connections [22].

Tight sandstones, on the other hand, frequently have poorly linked pore throats on the nano to micro-scale, and the intricacy and irregularity of their shape make characterizing these tiny structures difficult [12]. Pore throats in restricted reservoirs are defined by complex pore structures, extremely small pore diameters, partial inter-connection, and significant variability, indicating complex pore structures [23]. Complex pore systems, very small pore sizes, restricted inter-connection, and substantial variability describe the microscopic properties of pore throats in tight reservoirs, indicating complicated pore structures [24].

Understanding pore structure and connectivity is essential for building porosity-permeability correlations [13]. Pore structure must be defined and quantified in order to evaluate the interactions between porosity, storage, transportation, and reservoir parameters [25]. The microscopic pore system is important in a variety of geological processes, involving the formation of hydrothermal

systems, the transport and subsequent retention of water, gas, or hydrocarbons, and industrial activities such as CO₂ sequestration and increased oil recovery.

As seen in Figure 2.1, the shape of small pore throats has a direct consequence on reservoir quality, petroleum transport and buildup in sandstone tights [26]. Only by completely knowing the microscopic structure of pore systems can petroleum geologists and engineers make more precise estimations about recoverable hydrocarbons and improve the extraction process [27]. Extensive research efforts have recently been dedicated on the analysis of pore-scale morphologies and dimensions inside tight sandstone reservoirs [28].

Thin sections, electron microscopy, X-ray diffraction (XRD) study, X-ray computer tomography (μ CT), small-angle neutron scattering (SANS), low-field nuclear magnetic resonance (NMR), high-pressure mercury injection (HPMI), gas adsorption/desorption measurements and permeability and porosity assessments have all provided valuable insights into the minute structure of pore throats in tight sandstones [22]. These studies have highlighted the significance of quantitatively analyzing pore structure as a critical factor in the exploitation and development of petroleum resources inside tight sandstones [27].

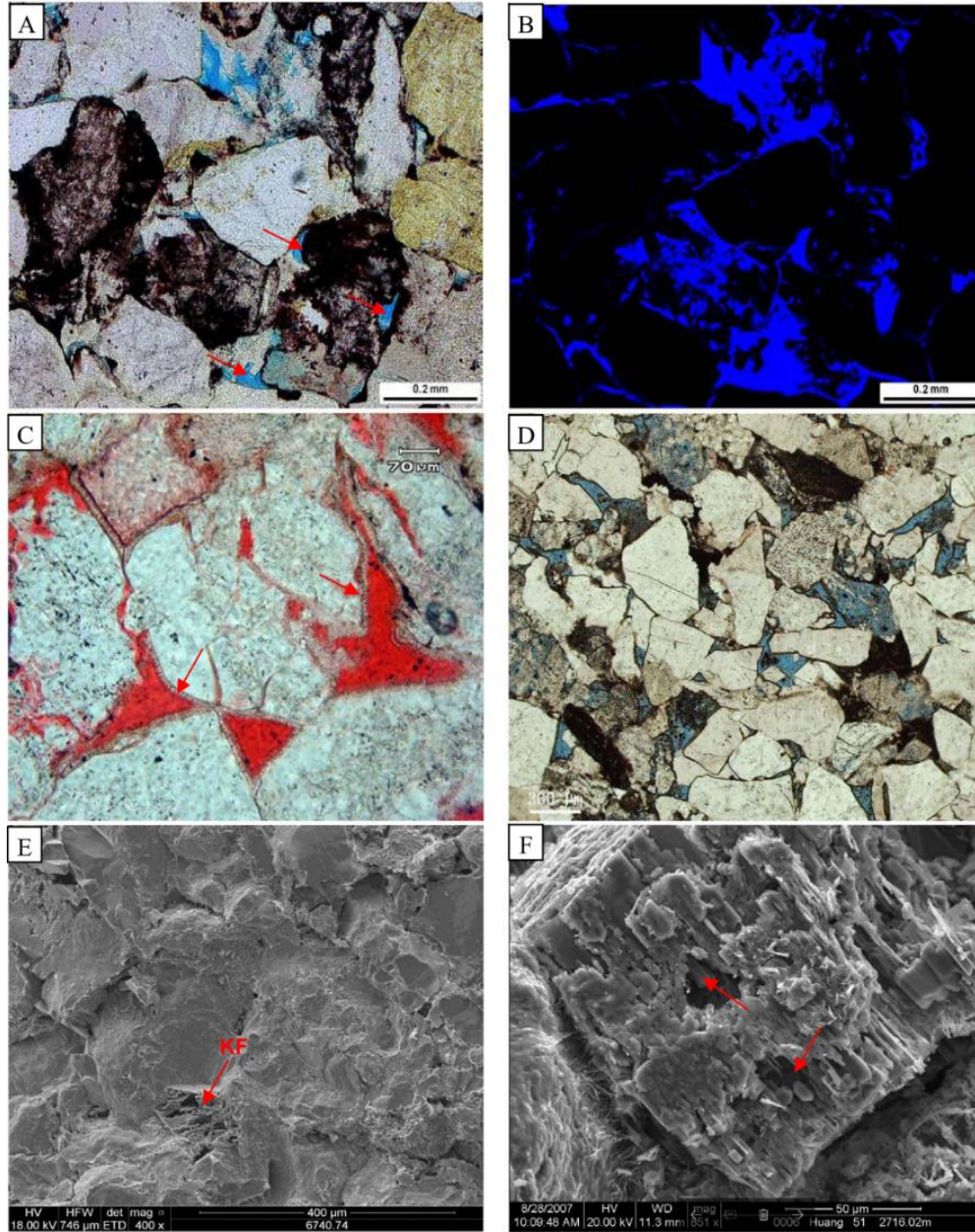


Figure 2.1: Shows photomicrographs of small-scale diagenetic structures [29]

Digital rock physics (DRP), which utilizes high-resolution images of pore structures, is experiencing rapid growth and has the potential to provide useful information into the relationships between rock properties (for instance electrical, elasticity, and transport characteristics) and the underlying pore-scale processes that govern these properties.

DRP is based on the image-and-compute principle, which involves photographing the mineral composition and pore space of a rock in 3D and then using computational techniques to mimic physical processes inside the digital representation. This encompasses simulating fluid flow for permeability assessment, modeling electrical current flow for resistivity measurements, and conducting simulations of elastic deformation to determine elastic moduli and wave velocities. Recent advancements in high-resolution 3D imaging and the availability of advanced software and hardware, DRP is poised to make a substantial impact in the field [30].

X-ray computed tomography micro-scale (μ CT) is a cutting-edge technology for imaging pore geometries. It involves assessing the local x-ray absorption inside an extremely small cylindrical rock sample, which is typically a few millimeters in diameter or less. The three-dimensional pictures are built up from a series of radiographs obtained from various angles. The reconstruction yields a grayscale picture with the intensity indicating the CT-number of the substance within the item [31].

Segmenting the 3D rock object obtained by scanning is a vital stage in the DRP method. This method involves separating and naming pore and mineral phases within an image. Manual segmentation is impossible given the normally enormous 3D datasets, necessitating the use of image processing methods for automated segmentation. Noise, artifacts, and spatial filtering, reduction, thresholding, morphological procedures, and cluster analysis are all common 3D segmentation methods. It is vital to remember that grayscale picture segmentation is not a deterministic technique, therefore segmentation algorithms require human oversight and quality control [30].

The investigation of pore structures using 2D images has received a lot of consideration in the literature. This research, however, tend to focus on two key areas: the estimation of permeability

using 2D images and the categorization of multiscale pore networks. For example, a study by [32] suggested a method for estimating permeability using 2D images, with the pore structure modeled as a network of cubic tubes. In addition, a study conducted by [33], used the Lattice Boltzmann approach to predict the permeability of a 3-D porous structure rebuilt from 2D thin sections created using a sequential indication simulation methodology. Furthermore [34] performed a quantitative investigation of numerous characteristics of pore networks in Middle East carbonates. Porosity, pore-throat distribution, coordination number, form factor, aspect ratio, and their distribution, were evaluated at various scales using SEM pictures and physical core measurements. The preceding sources mostly focus on determining permeability using 2 dimensional images and do not account for the multiscale structural properties of the porous sample.

Another method for obtaining 3D representations of rock microstructures is to use statistical approaches, often known as 2D-to-3D reconstruction. This approach includes determining the statistical parameters of the core sample using a two-dimensional image generated by electron microscopy. The 2D-to-3D reconstruction method has the advantage of producing a significant number of digital samples with identical microstructural features. The generated images, though, do not fully represent the complexities observed in real rock samples, limiting their practical value. Process-based strategies have been developed to construct pore geometries that more closely match sedimentary rock formations. These approaches recreate or reproduce the physical and geological processes that occur during rock creation [30].

2.1 Convictional laboratory methods of pore structure measurements

The conventional laboratory techniques such as mercury injection pressure (MIP), CO₂ gas adsorption, and low field nuclear magnetic resonance (NMR) have all been used extensively to describe reservoir pore structure [4]. Nuclear Magnetic Resonance (NMR) is a method utilized to

acquire various geometric and surface characteristics that can describe porous media directly, without the necessity of using model representations. The primary challenge in effectively utilizing NMR lies in interpreting the signals obtained. Specifically, there is a need to determine how NMR measurements can be employed to assess properties crucial in describing the storage and movement of fluids in porous media [35]. However, Mercury Injection Porosimetry (MIP) is an effective method for studying the variation in pore size. The disadvantages of using Mercury Injection Porosimetry (MIP) include its potential toxicity and environmental hazards associated with the use of mercury, as well as the potential for sample damage during the measurement process and limitations in the measurement of extremely small or large pore sizes.

Conventional techniques for characterizing pore structures involve a variety of methods and instruments that have been employed for an extended period in fields such as geology, materials science, and petroleum engineering. These methods are fundamental for gaining insights into the properties of porous materials, including parameters like permeability, porosity, and pore size distribution.

2.1.1 MIP Method

Mercury intrusion pressure (MIP) tests are commonly employed to assess the complexity and heterogeneity of pore throat structures [36]. In MIP analysis, the intricate pore throat networks within tight sandstones can be viewed as a series of interconnected, irregular capillary systems [37]. Capillary pressure is influenced by the pore throat size (see Figure 2.2) and the sorting of these pores, following the relationship between capillary pressure and pore throat radius as shown in equation (2.1)

$$P_c = \frac{2\sigma \cos\theta}{r} \quad (2.1)$$

Where P_c represents the capillary pressure (MPa), r is the pore radius (μm), σ denotes the surface tension, and θ is the contact angle in degrees. The capillary pressure curve provides insights into pore throat structures (Li et al., 2017), assuming the air/mercury surface tension is 485 mN/m and the wetting angle is 140° . An MICP test utilizes a mercury porosimeter to generate high pressure (up to 55,000 psig or 379.31 MPa), forcing mercury into all accessible pores ($> 0.00196 \mu\text{m}$) and measuring pore volumes [37]. MIP is a standard, convenient method for characterizing pore throat structures, particularly in terms of size distributions, spanning from the micron scale (up to approximately $350 \mu\text{m}$) to the nanometer scale (around 2 nm) across five orders of magnitude [25].

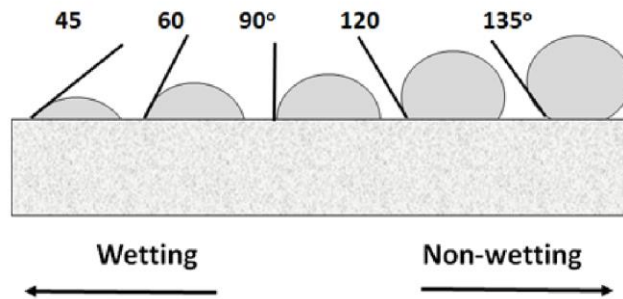


Figure 2.2: Illustrations of contact angles for fluids with varying wettability levels. A contact angle of around 130° is commonly applied for mercury.

Mercury is widely considered the best example of a non-wetting phase because it cannot enter pores via capillary action and can only penetrate interconnected pores. The amount of mercury that can enter the pore space is restricted by the maximum pressure reached during testing, typically up to 60,000 psi for many instruments. Mercury also has a high contact angle (θ) against most solids, ranging from 112° to 142° , with 130° being the most accepted value for advancing stages (imbibition) (Fig. 2.2), while receding (drainage) angles are generally 30° lower, around 80° to 110° . MICP tests can provide various capillary parameters, including entry pressure, displacement pressure, threshold pressure, maximum mercury intrusion saturation (SH_{gmax}), median pore-throat radius (r_{50}), r_{35} , and maximum pore-throat radius (r_{max}) [38]. The r_{50}

represents the pore radius at which 50% of the pore volume is filled by mercury and r_{35} refers to the pore throat at 35% non-wetting phase saturation based on capillary pressure curves [39].

2.1.2 NMR Method

Nuclear Magnetic Resonance (NMR) is an advanced, non-destructive, and quantitative techniques used to evaluate pore structures and fracture characteristics [40]. NMR, which analyzes the relaxation processes of hydrogen nuclei in pore fluids, provides insights into a reservoir's porosity, pore size distribution, fluid types (such as clay-bound water, free water, and hydrocarbons), and permeability [41].

It is one of the most effective methods for non-destructively quantifying the full pore size distribution in reservoir rocks, and NMR experiments on laboratory core samples can guide NMR logging operations [42]. In NMR, the relaxation times of proton spin axes are recorded under pulsed and static magnetic fields (see Fig. 2.3).

Two common types of relaxation times are measured: longitudinal (T_1) and transverse (T_2). T_1 represents the time taken for the system to return to equilibrium, which usually takes longer. T_2 , the time for the secondary magnetic field to lose coherence, is preferred in laboratory measurements due to its faster acquisition [43].

T_2 can provide similar information on pore size distribution as T_1 when low-frequency magnetic fields and short pulse spacings are used [44]. However, T_2 measurements are more complex than T_1 , as they result from three relaxation mechanisms: bulk fluid processes, surface interactions, and diffusion in internal field gradients. This multiexponential process is described in Eq 2.2 [44].

$$\frac{1}{T_2} = \frac{1}{T_{2B}} + \frac{1}{T_{2D}} + \frac{1}{T_{2S}} \quad (2.2)$$

T_2 represents the transverse relaxation time, while T_{2B} , T_{2D} , and T_{2S} correspond to the bulk relaxation time (ms), diffusion-induced relaxation time (ms), and surface relaxation time (ms), respectively. Figure 2.3 illustrates the typical incremental and cumulative distributions of T_2 relaxation times for tight sandstone core plug samples that were fully saturated with brine and centrifuged (with free water removed using a centrifuge)

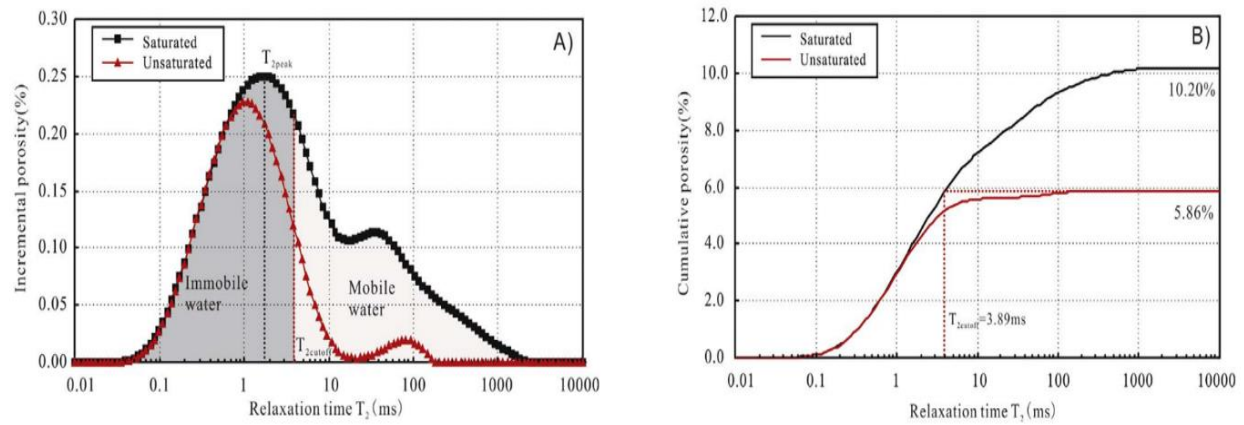


Figure 2.3: The distribution of incremental porosity plotted against the T_2 relaxation time

At larger pore bodies (i.e., higher T_2 values), the diffusion relaxation component plays a more prominent role [41]. Furthermore, proton diffusion between larger and smaller pores leads to a reduction in the proportion of detected smaller pores [45]. A summary of these established methods for pore structure characterization is provided in Table 2.1.

Table 2.1 Summary of the traditional methods of pore structure Determination

S/N	Method	Strengths	Weaknesses	Reference
1	MIP	Can measure pore size distribution over a wide range (from microns to nanometers) and estimate porosity and permeability	Invasive and destructive, may cause damage to the sample and alter the pore structure. Cannot measure isolated pores or pores larger than the maximum applied pressure.	[25]
2	Gas (N ₂ or CO ₂) adsorption	The adsorption isotherm can be utilized to determine the pore size distribution and specific surface area of micropores and mesopores, ranging in size from nanometers to several tens of nanometers	Requires careful sample preparation and pretreatment to avoid errors. Cannot measure macropores or pores smaller than the molecular size of the adsorbate.	[46]
3	NMR	Can measure pore size distribution, porosity, permeability, and fluid saturation in a non-destructive way. Can distinguish between different fluids in the pores.	Sensitive to external magnetic fields and sample orientation. Cannot measure pores smaller than 2 nm or larger than 10 μm . Requires calibration with other methods.	[47]

2.3 Conventional Image base rock typing

The convectional image-based-rock typing including the rock-typing method-based K-means clustering, GMM, SVM, random forest and convolutional neural network. This method relies on extracting and analyzing features such as intensity, texture, and edge features.

Image-based rock typing is conducted to evaluate the heterogeneity of a reservoir rock sample at the pore scale by categorizing images of heterogeneous rock samples into several relatively similar regions [3].

This process can be viewed as a specialized application of texture classification within the digital core domain. SEM image characterization enables the visualization and quantification of the microstructure, topology, morphology, and connectivity of various components in porous geological materials [20].

In recent years, image-based rock typing has made significant advancements with the aid of machine learning. Two major machine learning approaches, supervised and unsupervised learning, are frequently applied in image-based rock typing. In supervised learning, a model is trained to associate specific features of the input data with known outcomes, enabling it to predict results for new, unseen data based on those features [48].

Rock typing with supervised learning can be divided into two main strategies: pixel-wise classification and object-based classification. For instance, Anemone et al. [49] used pixel-wise models with artificial neural networks to detect spectral features across five different land cover classes in remotely sensed images, facilitating the identification of potential fossil sites. Additionally, deep learning has become a powerful tool in image-based rock typing. For example, [50] developed a convolutional neural network with an encoder-decoder architecture for semantic segmentation, effectively segmenting road scene objects, such as cars, trees, and roads, with commendable accuracy and quick processing times [51].

The widespread use of advanced imaging technologies such as (μ -CT) and SEM allows for the direct observation of reservoir heterogeneity at the pore scale, enabling image-based rock typing

analysis. This approach has distinct advantages over traditional rock typing methods that rely on laboratory-measured data. Conventional techniques, including constant speed mercury injection, low-pressure gas adsorption, and low-field nuclear magnetic resonance, typically provide only the overall pore size distribution of a rock sample, lacking insights into the internal structure of each rock type, which is vital for reservoir evaluation. In contrast, image-based rock typing offers an effective means of characterizing the internal structure of each rock type and evaluating its permeability contribution to the overall rock sample [52].

Rock typing is widely employed to differentiate various 2D sections collected from different reservoir zones or to classify reservoir rock samples into distinct types, such as matrix, fractured, and vuggy samples, based on μ -CT images [53]. With the advancements in numerical flow simulation at the pore scale, accurately classifying different rock types within a single image is becoming increasingly important, as different rock types often correspond to varying flow regimes [54].

There are two primary scenarios for applying image-based rock typing. The first involves classifying multiple microscopy sections from different reservoir zones into distinct rock types, each exhibiting relatively homogeneous structural features [55]. For example, rock typing can segment an image of a limestone sample into various types, including fractured, vuggy, and matrix types, based on μ -CT images (Li et al., 2017). The second scenario involves segmenting a single image containing multiple rock types into their respective categories based on textural features [56]

Machine learning is rapidly being used in image-based pore-scale characterization, resulting in considerable advances in our knowledge and prediction of characteristics in porous media [57].

One important application is the use of machine learning for multi-scale pore space investigation using scanning electron microscopy [58]. This includes assessing the geometry and morphology of the pore space inside reservoir rocks at different scales. The complex pore structures, which vary in size, may then be measured and utilized to create a pore network. Using microscopic structure features and fluid physical parameters, machine learning approaches have also proved useful in predicting macroscopic features like porosity, permeability, capillary pressure, and relative permeability. These advancements have significant implications for a variety of subsurface applications, including improved oil and gas recovery, water resource management, and carbon dioxide storage [59]. Another exciting application is the use of Generative Adversarial Networks (GANs) for the generation and reconstruction of digital rock images. This allows for the creation of detailed and accurate models of rock samples based on image data [57].

2.4 Imaging Techniques

For many years, image analysis has been employed to extract useful information from geological photographs [60]. Electron microscopy has been a key milestone in the field of science and engineering for the past 80 years. It has allowed for a deeper understanding of materials at the nanoscale and provided insight into their exceptional properties. The high-resolution capabilities of electron microscopes, capable of imaging objects as small as single atoms, has directed to the growth of new nanotechnologies and made a significant impact in the engineering of large components. Electron microscopy offers a significant advantage over light microscopy in terms of image resolution. Modern transmission electron microscopes have the ability to determine location and chemical composition of individual atoms. Electron microscopes have the ability to magnify objects to a high degree, with the magnification for a scanning electron microscope ranging from

10 to 500,000 and a transmission electron microscope capable of magnifying between 2000 and 1 million times [61].

2.4.1 SEM Device

A scanning electron microscope (SEM) is a powerful tool used in geology to investigate the microscopic features of geological rock samples. SEMs are essential for studying the surface morphology, mineral composition, and various geological processes at a much higher resolution than optical microscopes. Scanning electron microscopy (SEM) is most commonly employed to obtain 2D images at extremely high resolutions, down to a few nanometers. SEM can capture high-resolution two-dimensional images of minerals and the pore space. SEM devices, when furnished with energy-dispersive X-ray spectroscopy EDX capabilities, have the added capacity to furnish chemical data. When appropriately calibrated and equipped with the right software, they can even conduct automated mineralogical assessments [62].

Unlike electron microscope, SEM is primarily geared toward imaging rather than chemical analysis. The images generated by SEM result from the scanning of a sample with an electron beam, and the signal detected by an electron sensor is then displayed on a television or computer screen. Figure 2.4 provides a visual representation of a high-energy electron beam penetrating the surface of materials under scrutiny in SEM.

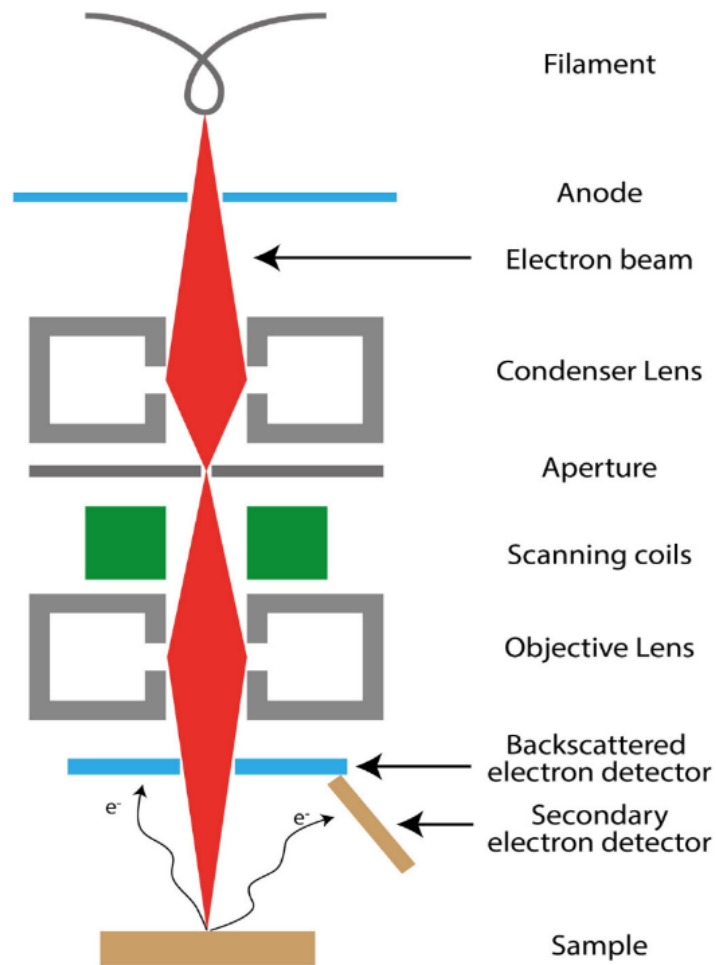


Figure 2.4: Schematic representation of SEM device

These electrons engage with the atoms in the sample, generating signals that carry information about the sample's surface properties and composition [63].

One significant drawback of utilizing SEM for geological materials is that many samples must be pre-treated. Because the vast majority of geological rock samples are electrical insulators, they normally require a conductive covering to avoid charge when subjected to electron bombardment, unless an environmental or low-vacuum SEM is utilized. It is feasible to achieve topographic or compositional difference based on the mean atomic number by selecting the appropriate detection mode. Because electron microprobe (EMP) equipment include electron-imaging capabilities,

which are mostly utilized for identifying sites for chemical investigation, there is substantial functionality overlap between EMP and SEM. SEM's imaging capabilities, which provide numerous advantages, make it a valuable tool in a variety of geological fields, including paleontology (for studying the morphology of fossils, particularly microfossils), sedimentology (to generate data on fabric and porosity and capture images of separate grains and intergrowths), mineralogy (for examining micro-scale crystal morphology), and others. Back-scattered electrons (BSE), secondary electrons (SE), and distinctive X-rays are among the signals generated by SEM (see Figure 2.5).

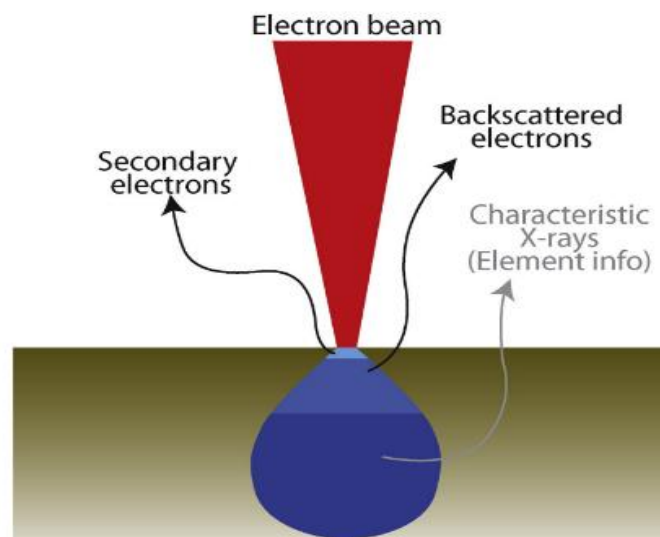


Figure 2.5: Interactions between electron beams and specimens [64]

Secondary electrons (SE) appear once an incoming electron induces an electron within the rock. The excited electron travels towards the material's surface, allowing it to escape and eventually reach the detector. These secondary electrons can only be emitted from the rock if they develop within a very small distance, generally around 5 nm, from the surface. Furthermore, they have relatively modest energies, often up to 50 eV. Figure 2.6 depicts a clear image of Indiana limestones and carbonate obtained by SEM device [18].

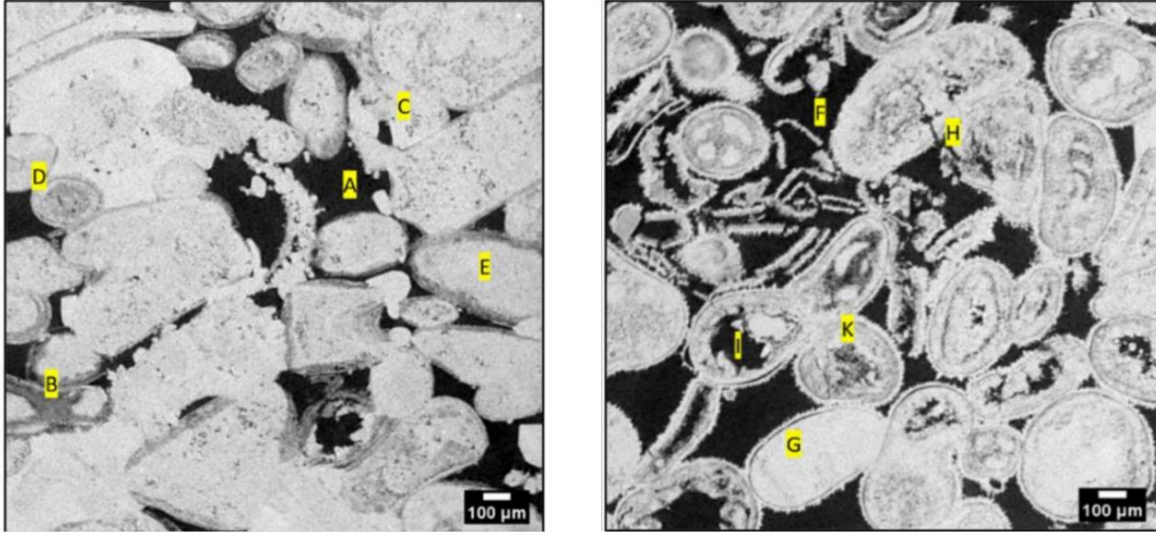


Figure 2.6: Sample of SEM Images, first one is Indiana limestone and the second is carbonate presenting a multiscale pore structure as represented by the lettered labeled A-G [64]

Secondary electron (SE) images, with their exceptional resolution, serve as an excellent tool for the examination of microstructures and micro-porosity in diverse fields, including geosciences, soil science, and concrete research applications [65]. BSE photographs of refined segments of geological samples are very useful for analyzing structure and permeability. Pores are dark in these photos, whereas heavier materials are bright. For optimal spatial resolution, a low accelerating energy is suggested.

X-rays are often employed to identify the composition and number of elements in a sample when an electron beam dislodges an inner-shell electron from the material. Energy-dispersive X-ray spectroscopy (EDS or EDX) is used by researchers to analyze these different X-rays. EDS or EDX is a material elemental analysis and chemical characterization analytical method. SEM has been used to study pore networks and limestone morphology since 1971 [66]. Lloyd presented a detailed analysis of utilizing BSE images to differentiate distinct mineral phases in 1987.

Furthermore, SEM has been used to investigate significant geological processes like as diagenesis and weathering. Longman and Mench (1978), for example, utilized this approach to explore the diagenesis of limestone, whereas others used it to investigate distinct forms of extremely fine-grained clay minerals formed by feldspar weathering. In reservoir geology, SEMs have been used to examine nanoporous cap rocks and tight shales [67]. In recent years, the principal applications of SEM in geological study have been microporous limestones and fine-grained clay stones, which have gained a lot of attention in terms of research and imaging. The automated mineralogy of rock samples is possible because to automated EDS study techniques for instances Qemscan and MLA [68].

2.4.2 X-ray micro-CT.

In 1895, Wilhelm Conrad Rontgen made the groundbreaking discovery of X-ray radiation, and X-ray computed tomography (CT) became a part of clinical applications in 1972, offering a standard resolution of 300 μm [69]. Since then, advances in equipment and processing power have enabled true 3-dimensional imaging of interior structures, rapidly expanding its applicability to a general range of industries. At sizes ranging from submicron to millimeters, X-ray CT provides 3-dimensional structural insights into geomaterials. Algorithms are then used to rebuild a series of 2D radiographs into 3-dimensional digital images. Cormack and Godfrey Hounsfield were the first to use John Radon's mathematical transformation techniques created in 1907 to generate 3 dimensional reconstructed pictures for medical evaluations of patients. In medical CT settings, an X-ray source and detector circle around the sample, but in normal laboratory micro CT configurations, they are commonly fixed with a revolving sample (see to Figure 2.7).

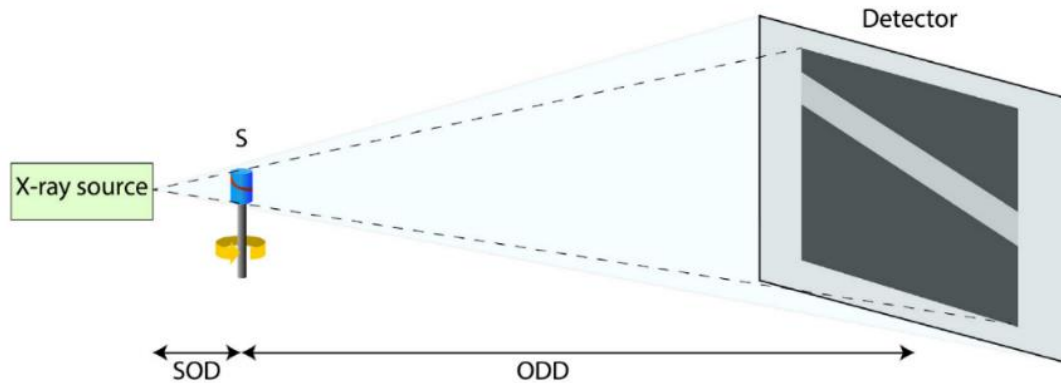


Figure 2.7: Representation of a micro-CT device in a laboratory using an X-ray tube and a cone-beam arrangement

The sample S is shown in Figure 2.7 within the X-ray source and the detector. X-rays interact with the sample, resulting in the detector capturing a 2D projection (radiograph). A 3D volume may be rebuilt by combining data from hundreds of radiographs taken throughout a 360° range. The ability to perform non-destructive 3-dimensional imaging is one of the primary benefits of CT. It provides a three-dimensional representation of the local linear attenuation coefficient, which is often kept as a series of virtual two-dimensional slices for ease of display. Visual study of this three-dimensional volume using specialist rendering tools such as Fiji, Avizo is conceivable. This feature is especially significant since it allows for the examination of unique or expensive objects [70]. The imaged volume adopts the shape of a cylinder with a specified diameter due to the rotating action.

CHAPTER 3

METHODOLOGY

The objective of this study is to characterize the geometrical and fractal properties of multiscale pore structures and assess the porosity contribution of various rock types. The study's methodology involves several key steps: performing image-based rock typing by comparing multiple machine learning models; conducting two-phase conventional image segmentation using watershed algorithm to differentiate pore and solid phases in grayscale images from the subsections extracted in Figure (3.2b to 3.2d); calculating geometry and fractal features of the pore structures of each rock type. The methodological framework employed for this study is briefly summarized as follows (see Figure 3.1).

- I. Image-based rock typing is performed using five different models: K-means, Gaussian Mixture Model, Random Forest, Support Vector Machine, and U-net. These models are applied to quantitatively evaluate the heterogeneity of the reservoir sample at the pore scale by segmenting the image of a heterogeneous rock into relatively homogeneous regions, including macropores, grains, feldspar, rock fragments, and clay [3]. This process can be viewed as a specialized form of texture classification within the field of digital core analysis. In this study, the grain is considered a completely solid rock matrix with zero porosity, while the macropore is treated as a porous medium with a porosity of one.
- II. Watershed method is applied to further classify each rock type into pore- and solid-phase.
- III. Pore structure characterization is then carried out to characterized the pore structural and geometrical features including pore size distribution, pore perimeter, pore area and pore counts by using a popular region pros package from Sk-image image. Sk-image image library provide a versatile algorithms and tools for image analysis. After then, subsections of the 2D

images were extracted from original SEM image from Figure 3.2a. These subsections are shown from 3.2b to 3.2d and were utilized for the geometrical and fractal analysis of the pore structure. A 2-Phase conventional erosion watershed (EW) segmentation based on Figure 3.2b, 3.2c and 3.2d were carried out to distinguish the pore spaces and the solid phases in the subsection of the images

- IV. Then fractal dimension of each of the subsection of Figure 3.2b, 3.2c and 3.2d was carried out using a popular box counting method. The procedure involves super imposing of grids of different calibration size over the pore space, then recording the number of blocks the pore space passes through each caliber.

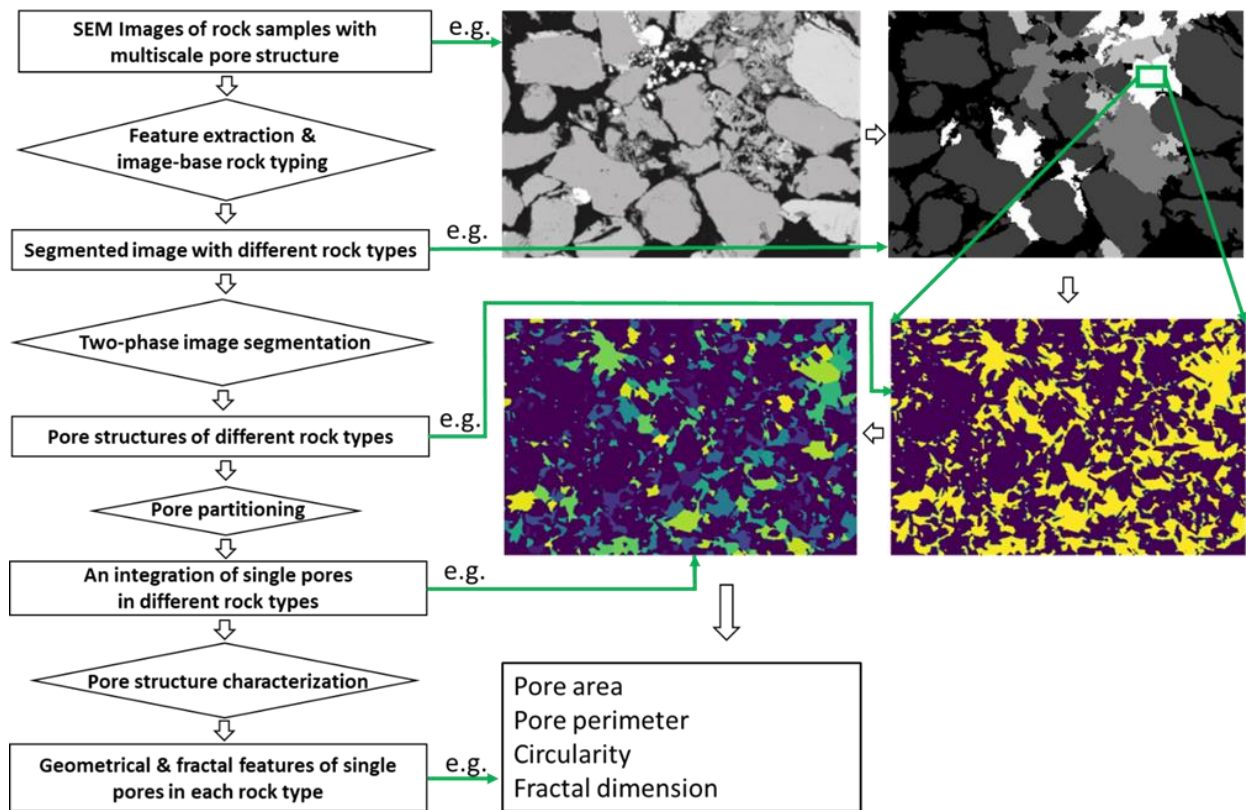


Figure 3.1. workflow for image-based rock typing and pore structure characterization

3.1 Dataset

Scanning electron microscope (SEM) images of the Leman sandstone at high resolution with $0.174 \times 0.174 \mu\text{m}$ per pixel were obtained from an online digital rock portal [19], and used in this study to demonstrate the proposed technique. Because of the complexity of the demonstration rock sample, it has been divided into five unique components: (1) Grain, (2) Macropores, and micropores. The micropore system can be classified into three types namely (3) natural micropores which are present within the rock fragment, (4) residual pores formed due to partial filling by clay and (5) pores generated by erosion of rock matrix which are usually present in feldspar minerals like silica and kaolinite seen in Figure 3b.

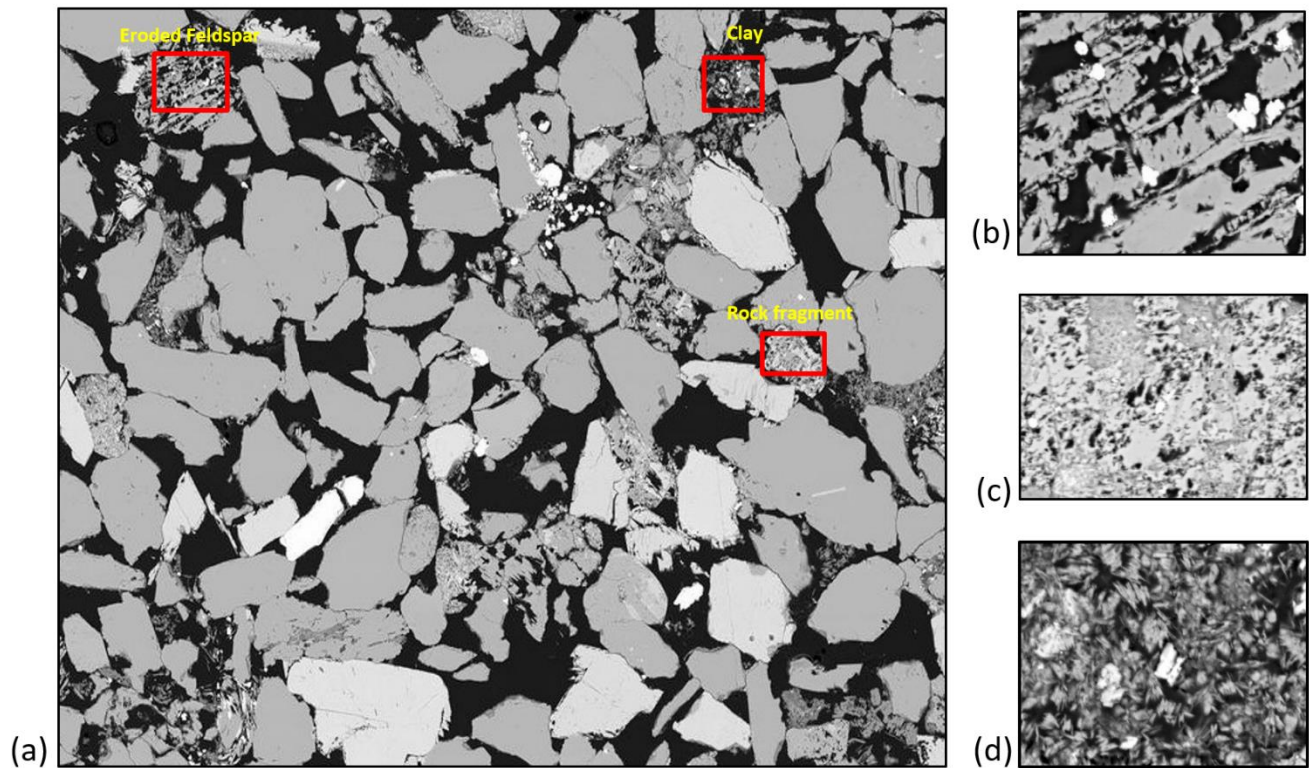


Figure 3.2 Representation of an SEM image with $0.174 \times 0.174 \mu\text{m}^2$ resolution. Part (a) displays the entire view of the demonstrative image, while parts (b), (c), and (d) offer detailed perspectives feldspar, rock fragment and clay respectively

The rock sample exhibits a significant heterogeneity characterized by dual pore systems comprising macro and micropores. Macroscopic pores primarily originate from intragranular spaces, whereas micropores are distributed within microscale porous media, encompassing clay, feldspar, and rock fragment. where EF, C, and RF denote eroded feldspar, clay, and rock fragment, respectively. For convenience, each of these is referred to as a rock type.

3.2 Image-based rock typing models

The image-based rock typing method was implemented using five different models with the popular scikit-learn package in Python, which is known for its comprehensive suite of machine learning tools. The dataset consists of multiple images representing various rock types, which were used to train and evaluate the models.

Each of the five clusters represents a distinct rock type, categorized based on its intensity values. These intensity values reflect variations in brightness and color across the images, which are critical for distinguishing between different rock types. The clustering process thus allows us to group the images into five distinct categories, each corresponding to a specific rock type with unique intensity characteristics.

3.3. Feature extraction

In the image-based rock typing, every pixel will be labelled as a specific rock type according its features which can be categorized into three distinct image features: intensity features, edge detection features, and texture features. Intensity features capture the basic brightness and color information of each pixel, providing a fundamental representation of the image data. Intensity features are essential for distinguishing between different rock types based on their color and lightness variations [20].

3.3.1 Gray level intensity feature

The grayscale value of a pixel in an image can serve as a distinguishing feature for identifying different components or segments. In this study, the scanning electron microscope (SEM) images employ 8-bit integer representation for pixel intensity, ranging from 0 to 255. In this scale, a pixel with an intensity of 0 is black, while 255 represents a white pixel.

3.3.2 Edge detection

Edge detection is a fundamental technique used to identify the boundaries or edges within an image. These edges denote significant variation in the intensity, which can correspond to object boundaries or other features of interest in the image. There are several methods and algorithms for edge detection. In this study, two categories of edge features namely, difference of gaussian and laplacian of gaussian, were applied at varying scale to extract these edge features within the image.

(1) Difference of Gaussian

The Difference of Gaussians (DoG) is computed by finding the disparity between two smoothed renditions of an image, achieved by applying Gaussian kernels with distinct standard deviations (sigma) to the original image. In simpler terms, the DoG transformation involves subtracting a heavily blurred iteration of the original image from a less blurred one see Eq (3.1). This process serves as a band-pass filter, preserving a particular spatial frequency. Fig.3.3 shows a DoG-transformed image at different sigma value.

$$DoG_{mn}(\sigma_1, \sigma_2) = \frac{1}{2\pi} \left[\frac{1}{\sigma_1^2} e^{-\left(\frac{m^2+n^2}{2\sigma_1^2}\right)} - \frac{1}{\sigma_2^2} e^{-\left(\frac{m^2+n^2}{2\sigma_2^2}\right)} \right], \sigma_2 > \sigma_1 \quad (3.1)$$

Where

σ_1, σ_2 = represent the standard deviations of the first and second Gaussian functions, while m and n denote the spatial coordinates within the 2D image.

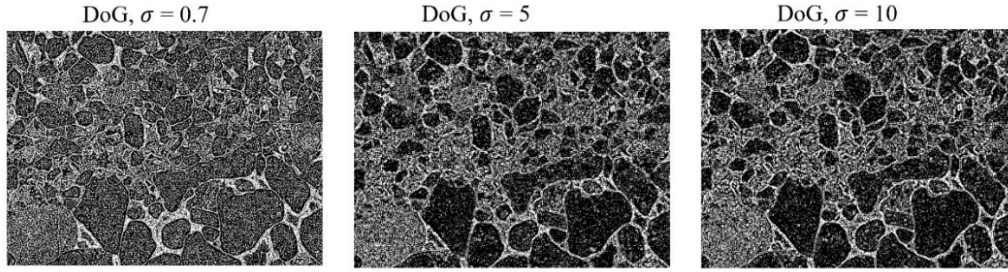


Figure 3.3: Feature map extracted with DoG filter at different sigma values

Difference of Gaussians (DoG) eliminates high-frequency spatial elements corresponding to image noise by smoothing and low-frequency components representing uniform regions in the image through the differencing operation. The DoG algorithm usually operates as an edge enhancement technique, accentuating the high-frequency elements in an image while minimizing the impact of noise. In this study, DoG is defined as the difference between a 2D Gaussian kernel with a sigma value of 5 and another 2D Gaussian kernel with a sigma value of 10.

(2) Laplacian of Gaussian

The Laplacian of Gaussian involves the fusion of two filters: the Gaussian filter and the Laplacian filter see Eq (3.2). This technique combines Gaussian filtering with the Laplacian filter to dissect the image, effectively identifying edges in areas with varying intensity. By doing so, it accurately locates edges and examines a broader region around each pixel for edge detection.

$$LoG(x, y) = -\frac{1}{\pi\sigma^4} \left(1 - \frac{x^2+y^2}{2\sigma^2}\right) e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3.2)$$

Where x and y are the spatial coordinates and sigma is the standard deviation of the gaussian.

This function above can be discretized to obtain a kernel that can be convolved with the image.

The kernel weights can be sampled from the above equation for a given standard deviation. The

gaussian kernel size of 3 x 3 and the sigma value of 0.7, 1.6 and 3 was the optimum kernel used to generate this feature, this because the smaller the gaussian kernel, the noisier feature generated, and larger kernel sized results poor edge localization (see Fig 3.4)

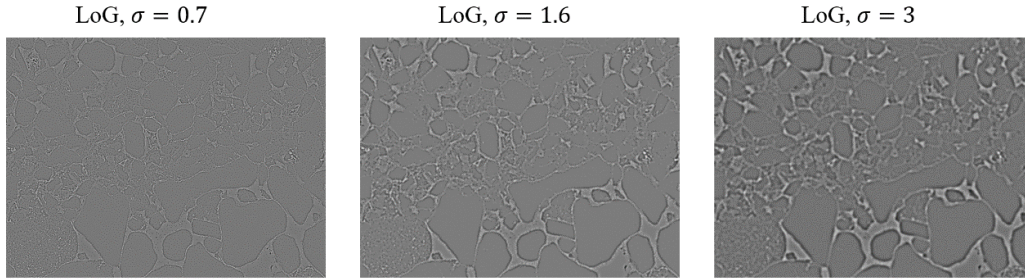


Figure 3.4: Feature map extracted with LoG filter at Different sigma values.

3.3.3. Texture Features

In many cases, images from rock samples usually exhibit wide varieties of textures when captured by a digital imaging device e.g. SEM, because of this problem, some classifiers cannot distinguish texture and untextured regions during rock typing process, for this reason, different texture filters were employed to handle this case and extract this texture from the images directly, for this study, we used hessian of gaussian (HoG) and structure tensor eigen values (STE) to extract this feature.

(3) *Hessian of Gaussian (HoG)*

The Hessian matrix of a Gaussian function is a square matrix of second-order partial derivatives.

For a 2D Gaussian function, the Hessian matrix is given by

$$H = \begin{bmatrix} \frac{\partial^2 G}{\partial x^2} & \frac{\partial^2 G}{\partial x \partial y} \\ \frac{\partial^2 G}{\partial y \partial x} & \frac{\partial^2 G}{\partial y^2} \end{bmatrix}$$

where (G) is the Gaussian function, the eigenvalues of the Hessian matrix can be found by solving the characteristic equation, which is given by (Eq 3.3):

$$\det(H - \lambda I) = 0 \quad (3.3)$$

where I is the identity matrix, and λ are the eigenvalues. The eigenvalues give important information about the image at each point. For example, in a 2D image, if both eigenvalues are large and positive, the point is likely part of a blob-like structure. If one eigenvalue is positive and the other is close to zero, the point is likely part of an edge-like structure. For this study a sigma value of 0.7, 2, and 3.5, and λ value of 0.5 were used to generate this feature (see Fig. 3.5).

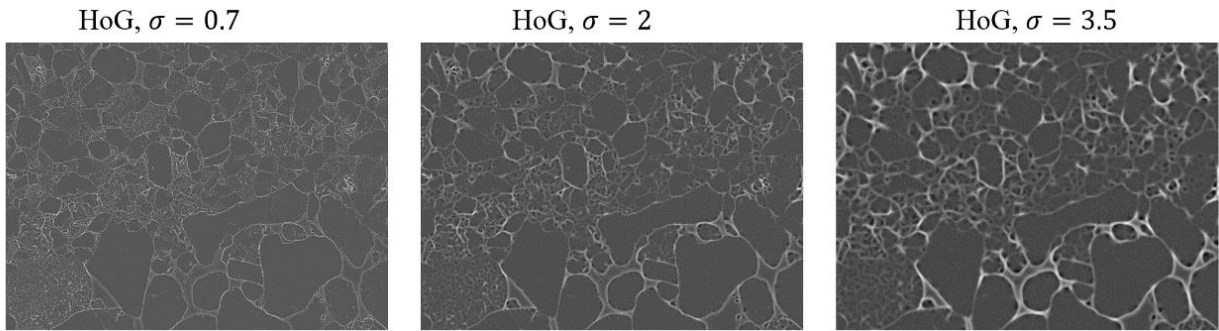


Figure 3.5: Feature map of HoG extracted from SEM image at Different sigma values

(4) Structure Tensor Eigen values.

The gradient structure tensor, second-moment matrix, scatter matrix, interest operator, and windowed covariance matrix are all names for the structure tensor, depending on its application field. Simple windowed smoothing techniques are used to get the structure tensor, and the image is distinguished with sigma values of 1, 1.5, and 2.5, as shown in figure 3.6. Its major function is to detect lines and areas of interest in photos. A first-order Taylor series expansion of the squared difference function yields the first-order structure tensor. The sum of squared changes in point-to-point picture amplitudes between a fixed window W centered on the analysis point (x_0, t_0) and a window moved by (x, t) is computed by this function. The function of squared difference is defined as shown in Eq (3.4).

$$E_{(x_0, t_0)}(\Delta x, \Delta t) \equiv \sum_{(i, j) \in W} w_{i, j} (x_i + \Delta x, t_j + \Delta t) - P(x_i, t_j))^2 \quad (3.4)$$

Where, W represents a window centered at (x_0, t_0) , $w_{i,j}$ denotes non-negative weights, and $P(x, t)$ stands for the image amplitude at the coordinate (x, t) .

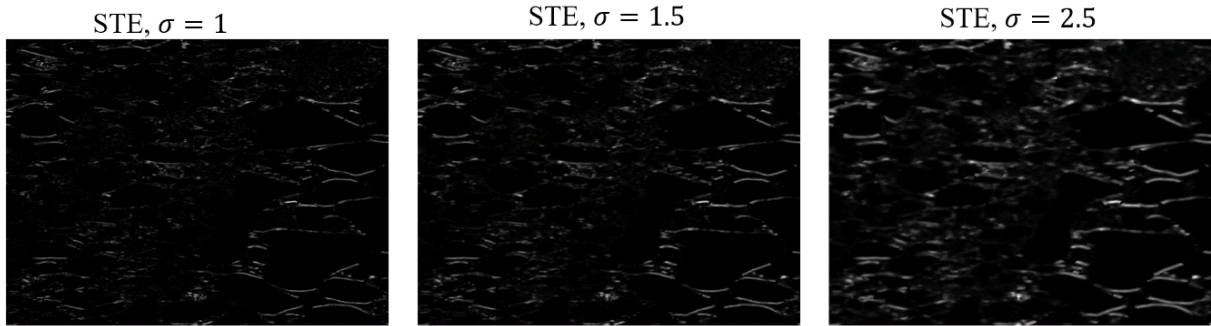


Figure 3.6: Examples of feature map of STE extracted at different sigma values.

(5) *Gaussian Blur*

The Gaussian blur capability is achieved by smoothing an image through the application of a Gaussian function, as illustrated in figure 3.7. This process serves to diminish noise within the image, acting as a nonuniform low-pass filter that retains low spatial frequencies while minimizing image noise and insignificant details. Typically, this effect is accomplished by convolving the image with a Gaussian kernel, represented in 2-D form as expressed below in Eq (3.5).

$$G_{2D}(x, y, z) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3.5)$$

Here, σ represents the standard deviation of the distribution, while x and y denote the location indices. The σ value influences the distribution's variance around a mean, thereby dictating the degree of blurring effect surrounding a pixel. During our evaluation of feature extraction methods, we experimented with sigma values spanning from 1 to 3. As σ increases, the presence of high-frequency information around the pixel diminishes.

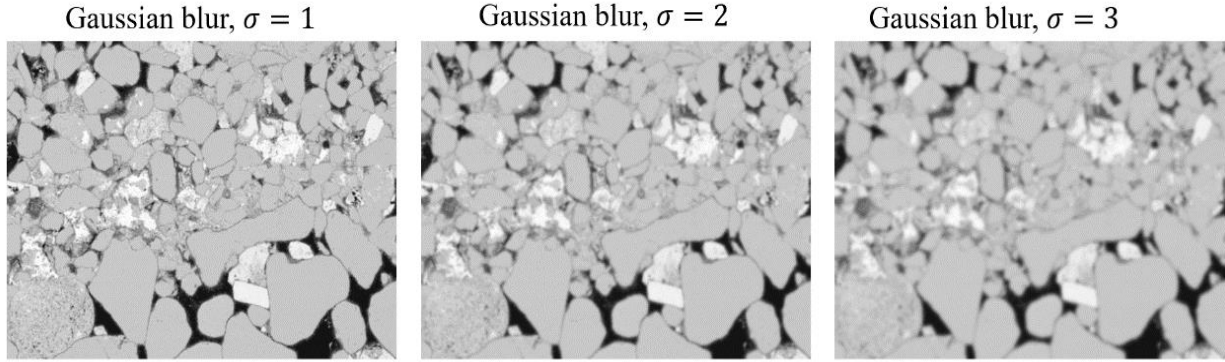


Figure 3.7: Examples of feature map Gaussian blur extracted from at different sigma values

3.1.4. Additional features explored in this study

Various additional characteristics were examined but were ultimately excluded due to their intricate computational demands. For instance, Gabor filter, variance and median filter were tested, it takes a considerable amount of time to run when it was tested on an 8bit unsigned integer 8 (uint8).

3.4 Conventional image-based rock typing

The image-based rock typing method was developed using five different models with the popular sci-kit-learn package in Python, which is known for its comprehensive suite of machine learning tools. The dataset consists of multiple images representing various rock types, which were used to train and evaluate the models. For the clustering algorithms, specifically K-means clustering and Gaussian Mixture Model (GMM), the optimal number of clusters was determined using the Bayesian Information Criterion (BIC). The BIC is a statistical criterion used to evaluate the fit of a model while penalizing for model complexity. By applying this criterion, we identified that five clusters provided the best balance between model fit and complexity for our dataset. Each of the five clusters represents a distinct rock type, categorized based on its intensity values. These intensity values reflect variations in brightness and color across the images, which are critical for

distinguishing between different rock types. The clustering process thus allows us to group the images into five distinct categories, each corresponding to a specific rock type with unique intensity characteristics.

The selection of a training data set significantly impacts the learning and generalization of a machine learning model. Optimal training set choice enhances the learning process, leading to improved rock typing performance and reduced training time. It is crucial that the training samples exhibit high quality, ensuring accurate assignment of component types to pixels. 80% of datasets were used for the training in this study while 20% of the data is used for testing. See Figure 3.8.

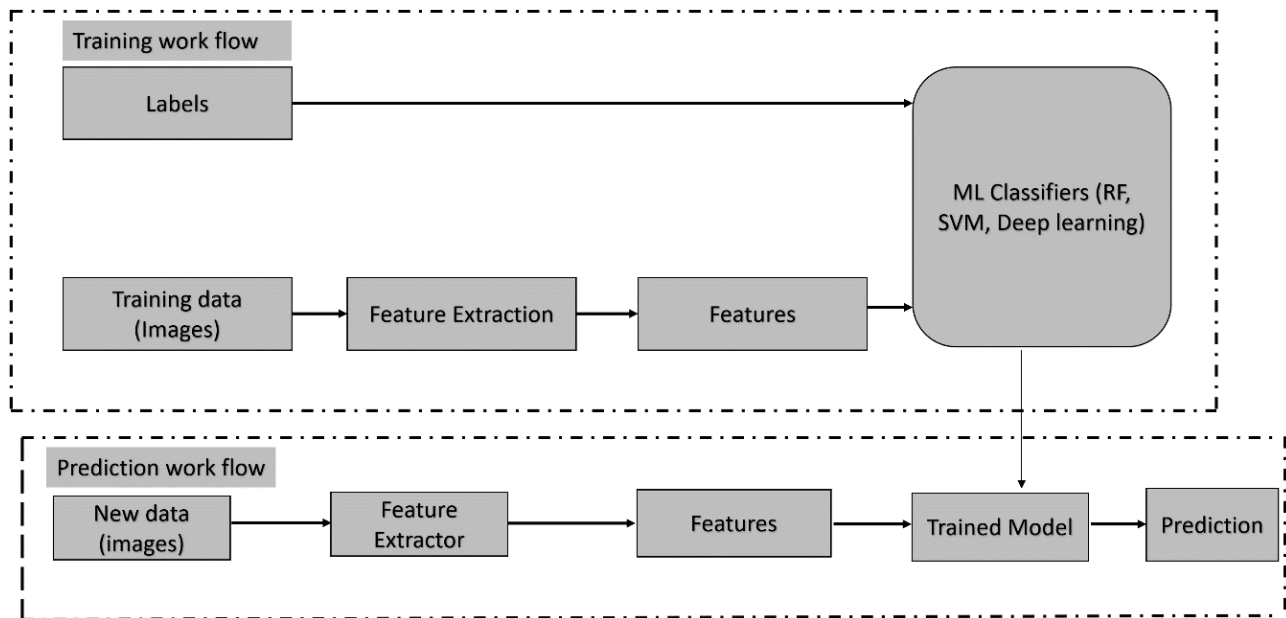


Figure 3.8 Image base machine learning classification workflow for training and testing stages

Table 3.1 Distribution of annotated pixels for training the dataset

S/N	Rock types	No of Pixels
1	Clay	1138
2	EF	9443
3	RF	14971
4	Pore spaces	3371
5	Grain	2412

The annotated pixels of each rock types as shown in Table 3.1 were used as labels to train the classifiers. they serve as the basis for the model to learn and make predictions. In this study the annotations were generated from (Apeer.com) where the images were uploaded and different rock types including grain, pore space, clay, feldspar and rock fragment were annotated and marked as different classes, the result of this annotation of each rock typed is shown in Fig.3.9 and a simple python code was developed to merge all the rock types into a single image which will be used as ground truth/labels for the training of the model.

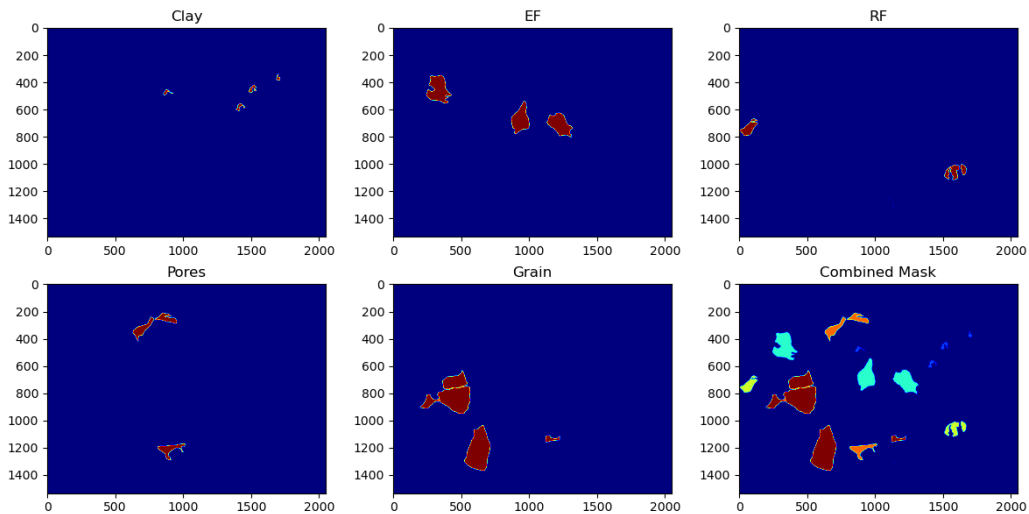


Figure 3.9: corresponding labels of the different rock types and their combined mask

The choice of a training dataset impacts the learning and generalization of a machine learning model. Optimal selection of a training set enhances the learning process, leading to improved rock typing performance and reduced training time. Therefore, it is crucial that the training samples exhibit high quality, ensuring accurate assignment of rock types to pixels.

3.4.1 K-means Clustering

K-means clustering is employed to group image data for rock typing into distinct clusters based on specific features. This clustering method segments the dataset into k different groups, where each group forms a separate cluster (e.g. rock types) [14]. The process consists of two main phases: initially, the calculation of k centroids, and then the assignment of each data point (in this case, pixels in an image) to the cluster whose centroid is closest. The proximity to the nearest centroid is determined using distance metrics like Euclidean distance [24].

After the initial assignment, the algorithm recalculates the centroids for each cluster based on the points within that cluster, and new Euclidean distances are computed to reassign points to their nearest cluster. Each cluster is characterized by both its data points and its centroid, which is the position that minimizes the total distance between all objects in the cluster and the centroid itself. The K-means method iteratively adjusts these centroids to minimize the overall distance between points and their corresponding cluster centroids across all clusters [25-26]. After the initial assignment, the algorithm recalculates the centroids for each cluster based on the points within that cluster, and new Euclidean distances are computed to reassign points to the nearest cluster. Each cluster is characterized by both its data points and its centroid, which is the position that minimizes the total distance between all objects in the cluster and the centroid itself. The K-means method iteratively adjusts these centroids to minimize the overall distance between points and their corresponding cluster centroids across all clusters [14].

3.4.2 Gaussian Mixture Model (GMM)

Gaussian Mixture Model (GMM) is a probabilistic approach commonly applied in image segmentation tasks, especially for multi-class segmentation tasks. It models the pixel intensities or feature vectors as a mixture of several Gaussian distributions, each representing a different class in the image [25]. For multi-class segmentation, GMM assumes that each pixel's feature vector x (e.g intensity) is drawn from mixture of K Gaussian distributions, where each component K corresponds to a class. The likelihood function for GMM is given by Eq (3.6) [26].

$$p(x | \theta) = \sum_{k=1}^K \pi_k \mathcal{N}(x | \mu_k, \Sigma_k) \quad (3.6)$$

where: π_k is the mixture weight for k -th component (class), satisfying $\sum_{k=1}^K \pi_k = 1$. And $\mathcal{N}(x | \mu_k, \Sigma_k)$ is the gaussian probability density function for k -th component with mean μ_k and covariance Σ_k :

$$\mathcal{N}(x | \mu_k, \Sigma_k) = \frac{1}{\sqrt{(2\pi)^d |\Sigma_k|}} \exp\left(-\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k)\right) \quad (3.7)$$

Where d represent the dimensionality of the feature vector x . The model parameters $\theta = \{ \pi_k, \mu_k, \Sigma_k \}$ for each class k are optimized using the Expectation-Maximization (EM) algorithm. More details of which can be found in (T. M. Nguyen et al., 2011) [26].

3.4.3 Support Vector Machine

In this study, Support Vector Machines (SVM) are employed as a supervised learning algorithm to perform image-based rock typing. SVMs are well-suited for this application due to their robustness in handling high-dimensional data and ability to capture nonlinear relationships among image features, which are essential for accurately classifying complex rock structures [76]. The core principle of SVM involves identifying an optimal hyperplane that separates data points, in this case, pixel-level image features, into distinct rock classes [77].

For rock typing, the image data is transformed into a feature space where SVM constructs a decision boundary represented as a line in two-dimensional space and a hyperplane in higher dimensions. The goal of the SVM model is to maximize the margin between the hyperplane and the closest data points from each rock class as shown in figure 3.10, termed support vectors. This maximization enhances the model's ability to generalize to new, unseen data, thus improving the accuracy of rock type classification and minimizing overfitting risks. This approach is particularly valuable for distinguishing subtle differences in texture and composition in rock images, making it effective for rock fabric and pore structure analysis [77].

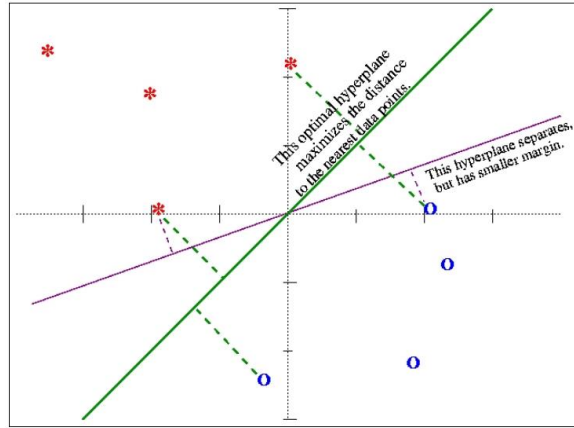


Figure 3.10: Optimal selection of the hyperplane to maximize the margin

To determine the geometric distance from the hyperplane to a data point, it is necessary to normalize by the magnitude of w . The formula for this distance is provided in Eq (3.8).

$$d(w, b, x_i) = \frac{y_i(x_i \cdot w + b)}{\|w\|} \geq \frac{1}{\|w\|} \quad (3.8)$$

where

d represents the distance between a data point and a hyperplane, w is a weight vector defining the hyperplane, b stands for the bias term shifting the hyperplane, and x denotes the data point. In the realm of image-based rock typing, Support Vector Machines (SVMs) have garnered notable attention for their capability to manage intricate patterns and nonlinear connections inherent in rock textures. Through the examination of visual features extracted from rock images, SVMs proficiently categorize rocks into distinct classes based on their mineralogical composition and texture [78].

3.4.4 Random Forest

Random Forest algorithm is employed for image-based rock typing, leveraging its classification capabilities through an ensemble of decision trees. Every tree in the forest independently contributes a vote for the most likely rock class based on the input feature vector [15]. When a new sample is introduced, it is classified by all the trees, and the final class is determined by majority voting see Fig. 3.11. In the context of rock typing, an image features are represented by a feature vector such as average curvature and porosity extracted from the local neighborhood around a specific pixel in the target image. Each class in this system corresponds to a distinct rock type, characterized by unique textural attributes such as geometry, pore connectivity, and porosity [18]. The Random Forest model excels in distinguishing these features to classify different components, such as grains, pores, and clay.

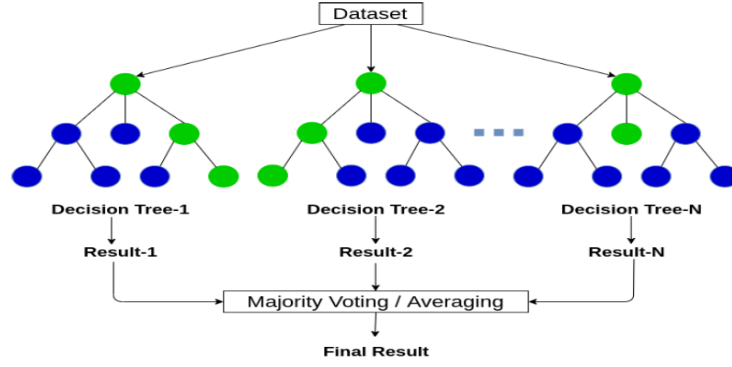


Figure 3.11: Flow Chart of Random Forest classifier

To fully understand the Random Forest, it is required to start by understanding its dynamic building component, which is a decision tree. A decision tree is distinguished by its tree-like structure, which is often a dual tree or a multiple-branch tree. Each non-leaf node indicates a distinct feature test. The several branches that sprout from this non-leaf node correspond to the categorization results of the associated characteristic. Finally, the class labels are found in the leaf nodes [18].

(1) Entropy

The foundation of entropy in a machine learning algorithm is rooted in information theory. It serves as a metric for the uncertainty surrounding a random variable. Shannon entropy is the tool used to quantify this uncertainty, measuring the projected value of information within a message. Eq (3.9) defined the essence of entropy in this context.

$$H(X) = \sum P(x_i)I(x_i) = - \sum P(x_i)\log_b P(x_i) \quad (3.9)$$

Where $H(x)$ is the Shannon entropy of a random variable, $P(x_i)$ is the probability of the occurrence of a particular value (x_i) of the random variable, and $\log_b P(x_i)$ is the logarithms base b of the probability.

(2) Information gain

Information gain evaluates the decrease in entropy resulting from the alteration of a dataset and is commonly employed in the training of decision trees. The computation of information gain involves a comparison of the dataset's entropy before and after the transformation. It signifies the reduction in uncertainty within dataset D when information about a feature is available. In the construction of a decision tree, the preference is to choose the feature with the highest information gain. The formula for calculating information gain for attribute A is expressed as by (Eq 3.91).

$$Gain(A) = Info(D) - Info_A(D) \quad (3.91)$$

Where

$$Info_A(D) = \sum_{j=1}^v \left| \frac{D_j}{D} \right| \times Info_A(D_j) \quad (3.92)$$

(3) Gini Impurity

Gini impurity serves as a metric in the construction of decision trees, guiding the division of nodes based on the features of a dataset. Specifically, Gini impurity is a numerical value ranging between 0 to 0.5, indicating the possibility of misclassifying a new random data point if it were assigned a random class label according to the distribution of classes in the dataset. Let's consider a dataset (D) comprising samples from (K) classes. The possibility of a sample belonging to class (i) at a given node can be represented as p(i). The Gini impurity of (D) is precisely defined by Eq (3.93).

$$Gini(D) = 1 - \sum_{i=1}^k p_i^2 \quad (3.93)$$

Feature reduction with Principal components Analysis (PCA)

In this approach of image-based rock typing, thirteen image features were utilized, the computational runtime for the model's complete execution is 18 minutes and 19 seconds, primarily

influenced by the number of features. A higher count of features results in extended training times. Hence, Principal Component Analysis (PCA) is employed to discern the most significant features. PCA facilitates the transformation of high-dimensional data into a lower-dimensional space while retaining maximal variance. For this study, it was found that the optimum number of principal components which preserved about 90% cumulative explain variance is six components, and only 10% information is lost compared to the entire thirteen initial features see Fig. 3.12.

From Fig.3.95a. The cumulative explained variance remains almost constant from principal components six upward i.e. it does not add much variance to the components.

Fig 3.12b shows how much information each principal component captures from the original data. It does this by identifying the principal components, which are new variables that are linear combinations of the original variables.

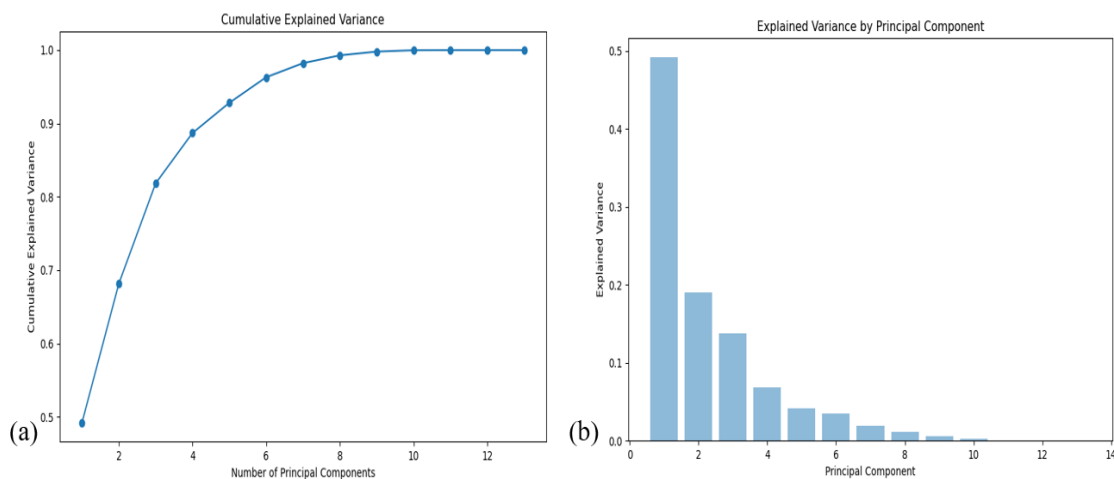


Figure 3.12 Cumulative explained and explained variance plot

In the provided figures, it is evident that principal component one covers 49% of the explained variance. Subsequent principal components, notably PC2, PC3, PC4, PC5, and PC6, exhibit decreasing proportions of variance, with percentages of 18%, 13%, 6%, 4%, and 3%, respectively. Components 7 and above were excluded from consideration due to their low variance ratios.

3.4.5 Convolutional neural networks

Convolutional neural network is extensively used and favored in the field of computer vision for deep learning applications. These networks leverage convolutional operations to effectively obtained features from images. Since their initial success in outperforming other techniques, a multitude of CNNs models have been created to further enhance the feature extraction process [79]. Among the various network designs, the encoder-decoder architecture has been widely used for image rock typing tasks. These networks include an encoder that progressively reduces the size of feature maps to extract high-level features and a decoder that gradually reconstructs the encoded feature maps to recover spatial details [80]. In this study, we adopted U-net as the foundational architecture for the proposed network. U-net is a straightforward and efficient encoder-decoder network initially developed for semantic image segmentation of cells and membranes. Since membrane structures in images are thin and elongated, resembling fractures in rocks, we chose U-net as our baseline model. The original U-net architecture decreases feature map size using pooling layers in the encoder, enhancing the receptive field and enabling it to capture broader spatial information without enlarging the convolution kernel. This connection aids in better image reconstruction during up sampling by leveraging consistent information. The models evaluated in this paper build on the core U-net concept, incorporating several additional techniques to boost performance [79].

Note that random forest is influenced by the number of trees (estimators), and is set to 50, and the maximum depth set at 20. In SVM, radial basis function kernel type was used and regularization parameter (C) impact performance, with C set to 1 and a radial kernel to capture complex decision boundaries. For Unet model, more details more details will be provided in the next section.

(I) Training and validation of the U-net network

When training the model using U-net architecture, the images were preprocessed by converting them to grayscale format and resizing them to 128×128 pixels for uniformity. The U-net architecture applied in this study is shown in Figure 6. The contracting path on the left (blue in Fig. 3.13) serves as the encoder, similar to a typical CNN structure. In each layer, a series of 3×3 convolution operations are applied, followed by a max-pooling with a 2×2 neighborhood, the increased number of feature channels helps the network retain context information at higher resolution layers. The expansive path on the right (green in Fig. 3.13) acts as the decoder, merging both feature and spatial information through up-convolutions, followed by concatenation with high-resolution features from the contracting path [32]. A transposed convolution, with the same kernel size, stride, and dropout rate, is used to reconstruct the segmented feature map back to the original image size. Compared to other fully convolutional networks, U-Net offers better localization, more effective representation learning through subsequent convolutions, and requires fewer training samples [33]. Features embedded in the labeled training image masks allow for effective semantic segmentation within U-net.

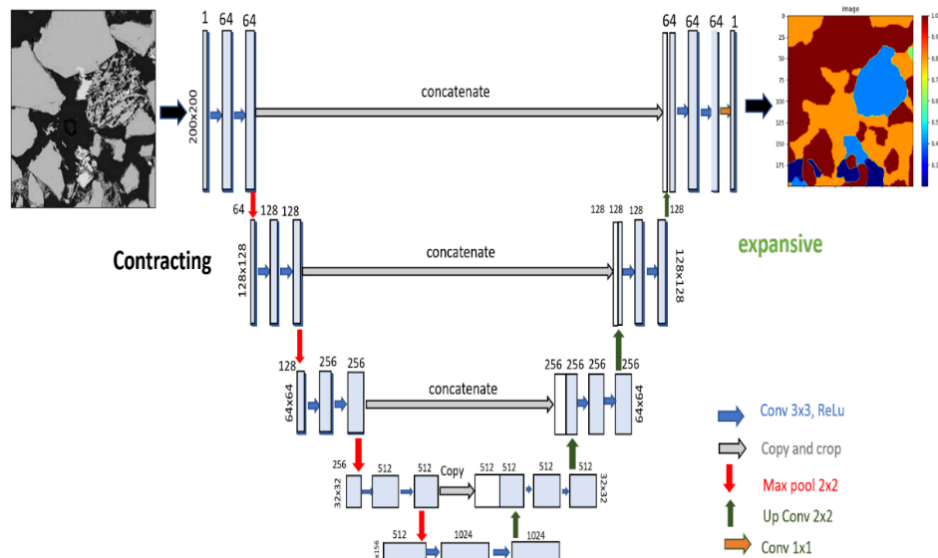


Figure 3.13: A representation of U-net architecture for image-based rock typing

The labelled mask and the corresponding grayscale image (see Figure 3.14) were used to trained the network using Adam optimizer, an advanced form of stochastic gradient descent that has gained popularity in deep learning application [34].

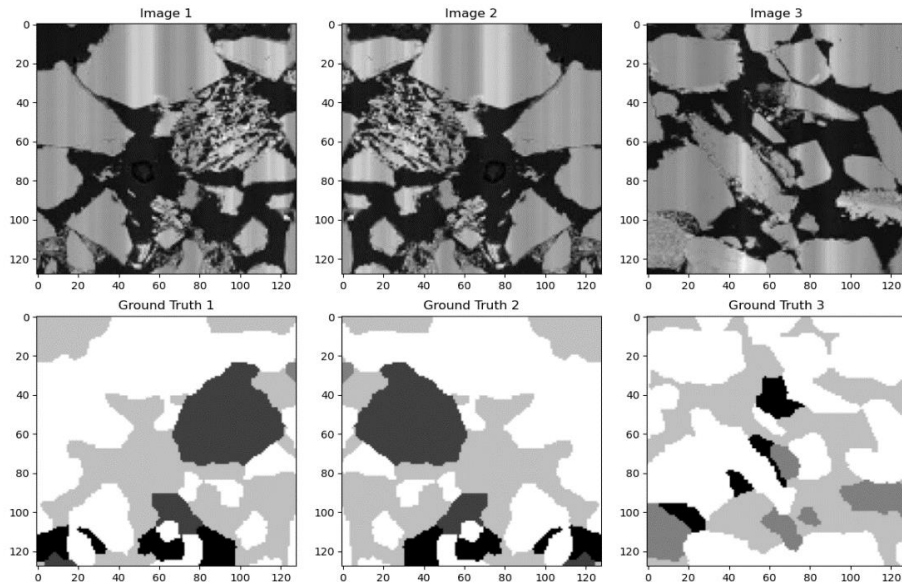


Figure 3.14 An example of the training images is shown in the first row, with the corresponding ground truth displayed in the second row

To address the limited data availability, we applied data augmentation techniques to increase the dataset size and improve model performance. We generated 500 new training samples from the original image by implementing transformations such as rotation, flipping, and zooming. These additional samples increased the dataset size and enhanced the model's representation.

The augmented dataset was then divided into training and validation sets, maintaining an 80:20 ratio, with 400 images allocated for training and 100 for validation. To optimize model learning, we normalized pixel values to a 0 to 1 scale. The model was trained over 50 epochs with a batch size of 16 to ensure stable gradient updates and effective generalization.

To evaluate the performance of the model, we assessed the model on the validation set, comparing predictions against ground truth values. The training and validation losses, as well as accuracy metrics, showed strong alignment, indicating minimal overfitting and solid generalization across data. Figure 3.15 presents this close fit, demonstrating consistent convergence in both training and validation metrics.

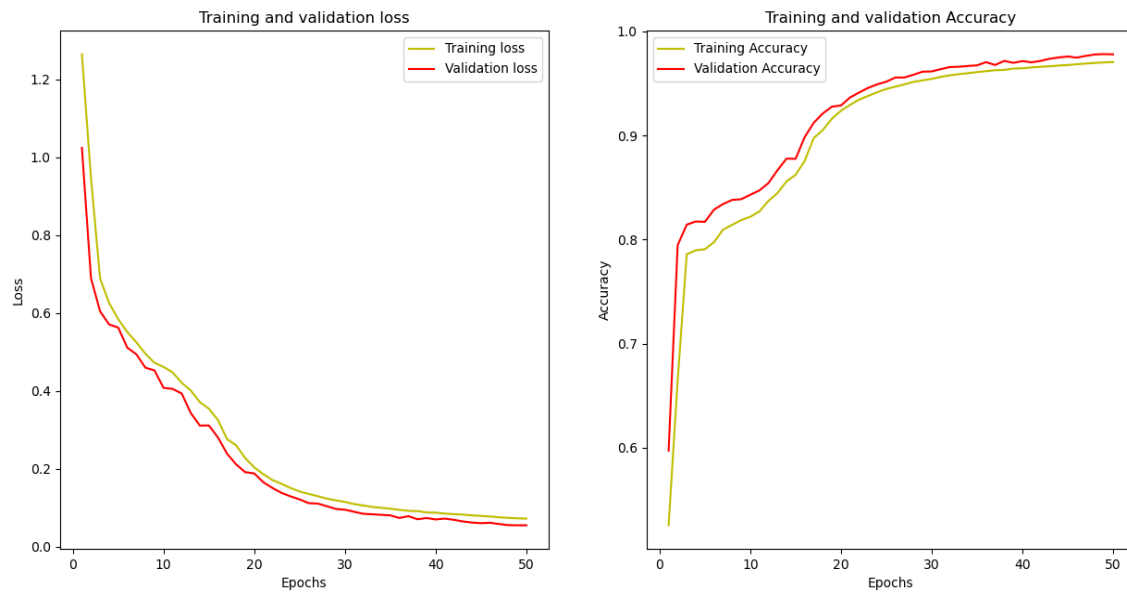


Figure 3.15: Convergence of training and validation metrics

The accuracy curve illustrates a sharp increase in both training and validation accuracy within the first 10 epochs, after which the accuracy continues to improve steadily until it converges around 97% for both training and validation datasets. The close alignment of the training and validation accuracy curves indicates that the model performs consistently well on both datasets, with no significant overfitting or underfitting observed. The loss curve shows a steady decrease in both training and validation loss over the epochs, indicating that the model is learning effectively without overfitting. The gap between the training and validation loss is minimal, which further suggests that the model generalizes well to unseen data. By the end of the 50 epochs, the loss values converge to around 0.1, signifying a high degree of accuracy in segmenting the rock

components. The result of the model prediction and the corresponding ground truth is illustrated in Figure 3.16.

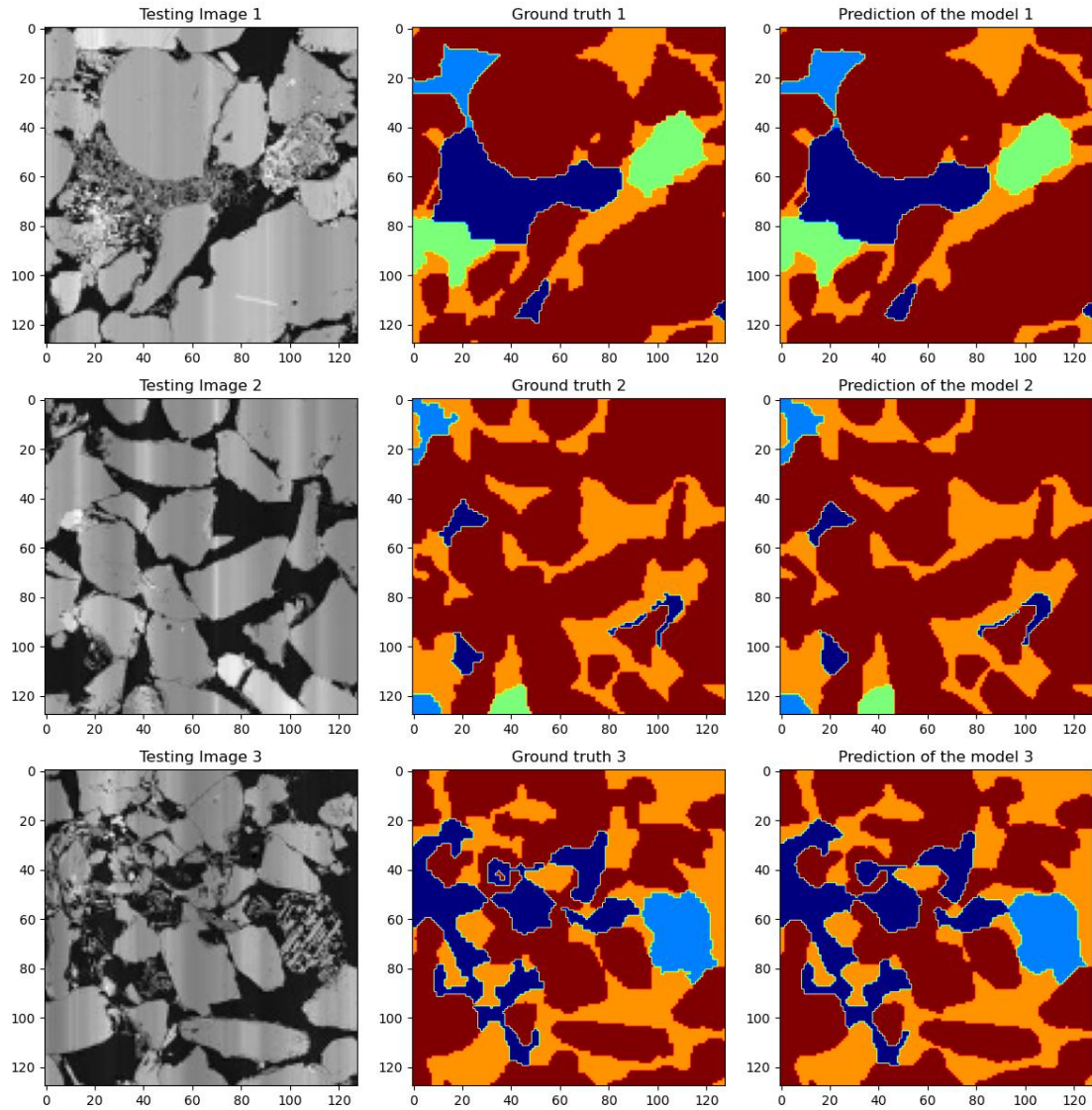


Figure 3.16: Comparison of the original dataset, ground truth and the prediction done by the model

An overall measure of accuracy is computed using intersection over Union (IoU) metrics ($\text{IoU} = \text{Area of overlap} / \text{Area of union}$) resulting in an overall mean IoU of 97%. The results show the objective functions with ADAM optimizer converge with different rates as shown Figure 3.15. The summary of the input parameters used during training of the model can be found in Table 3.2.

Table 3.2 Summary of Input parameters used during training of the model

Parameters	Description/values
Model type	Unet
No of classes	5
Image size	128 x 128
Optimizer	Adam
Loss function	Categorical cross entropy
Batch size	16
No of Epochs	50
Pooling layers	MaxPooling2D with pool size (2, 2)
Activation Function	ReLU for Conv2D layers, Softmax for the final output layer

3.5 Image segmentation and Pore Structure Partitioning

In this section, the grayscale images will be classified as pore and solid by image segmentation. Because the pores are connected with each other, a pore structure partitioning process is carried out to separate the pore network into single pores. Then, these single pores can be used for geometrical and fractal analysis. The watershed image segmentation package in the sci-kit-image is applied to classify the grayscale image into pore and solid. Based on the segmented images, the skeleton extension erosion grain partitioning (SEEGP) method [35, 36] is used to separate the single pores.

The SEEGP method can be treated as a modified method based on the erosion-watershed (EW) method. The EW method involves two main steps: first, identifying the pore ‘cores’ by progressively eroding the image with a small structural element until the maximum number of isolated pore cores is achieved; second, applying watershed segmentation to define each pore

region based on the Euclidean distance map of the solid phase, using the pore cores as markers. However, the EW method struggles to separate two partially overlapped grains when their sizes are comparable to the size of the overlapped area.

Furthermore, the conventional EW method faces significant challenges in separating heavily overlapped grains. Recognizing that the endpoints of the pore space skeleton often indicate potential boundaries between adjacent grains, a differential erosion scheme is introduced. This scheme enhances the erosion rate at these potential boundaries, thereby improving partitioning accuracy.

The proposed method is termed SEEGP. In this study, the SEEGP method, originally proposed for grain partitioning, is applied for pore partitioning. As shown in Figure 3.17, the SEEGP method effectively identified the majority of the pores in the target image. After that, the pores detected from each rock types were further analyzed. The colored regions represent the pore space, while the dark areas correspond to the grains.

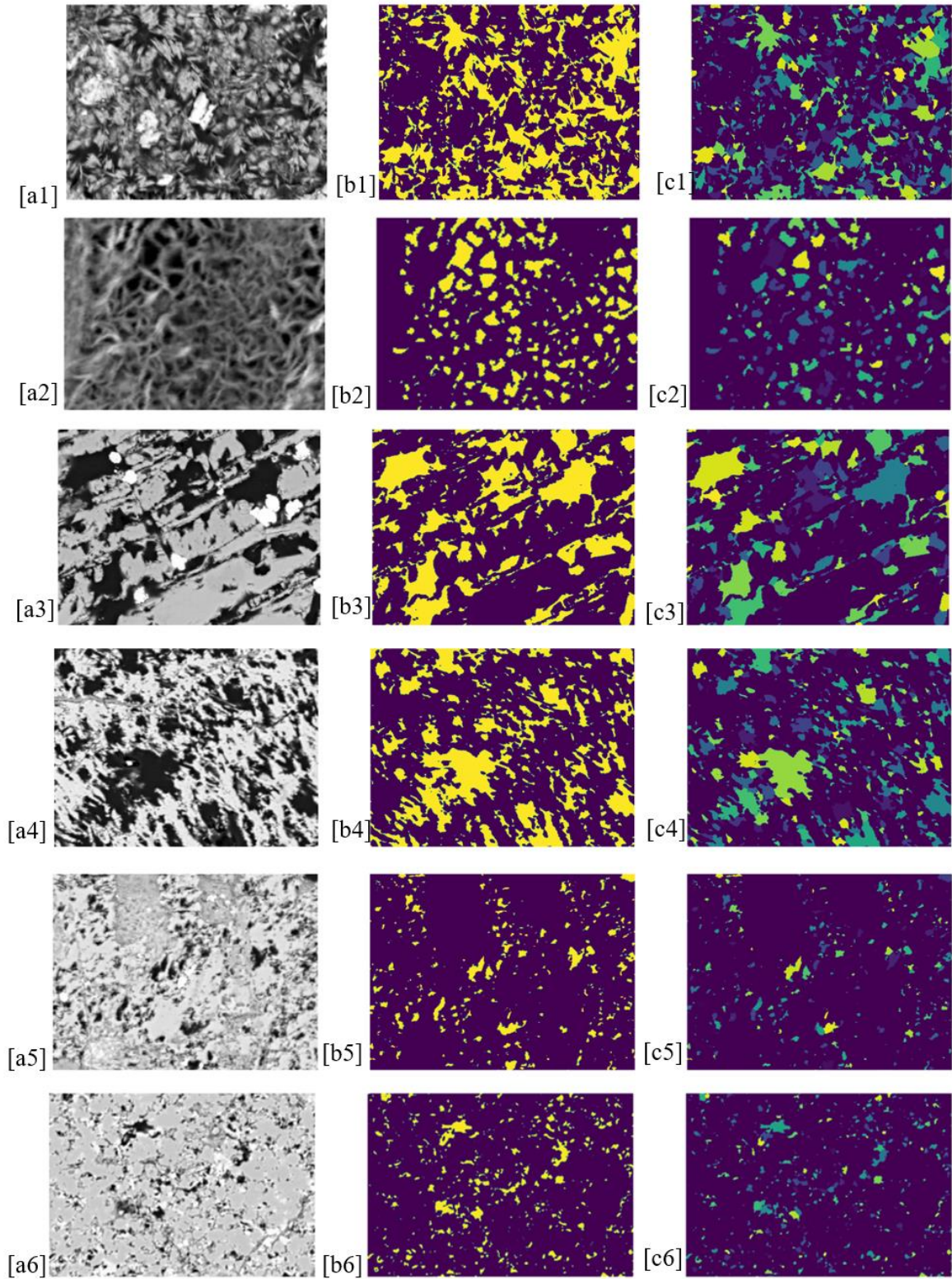


Figure 3.17: Results of the segmentation and pore network partitioning methods. Column [a1] to [a6] display the grayscale images, [b1] to [b6] show the segmented images, and [c1] to [c6] illustrate the pore partitioning results using the skeleton-based extension and erosion method for the first set of samples.

Figure 3.17 shows the illustration segmentation and pore portioning of the subsections of clay, rock fragments, and feldspar extracted from the original grayscale images at different sections with Erosion-Watershed (EW) pore partitioning method. The colored regions represent the pore space, while the dark areas correspond to the grains.

Following the two-phase segmentation process, image analysis was conducted to extract detailed geometrical pore structural information using the widely used sci-kit-image library. Various pore structural parameters were calculated, and the results are plotted and analyzed in the subsequent.

3.6. Pore structure characterization

In this study, several geometrical and fractal dimension features are applied to characterized the pore system in within the rock sample.

3.6.1 Geometrical feature

The pore structural and geometrical features were quantified using the regionprops module from the sci-kit-image library, which provides a comprehensive set of algorithms and tools for image analysis. This package allowed us to measure specific parameters for each pore, as discussed above. Based on the results of the pore partitioning method shown in Figure 3.17 (c1) to (c6), we applied thresholds of 77, 53, and 54 for the first set of samples and thresholds of 55, 87, and 118 for the second set to fully separate pore spaces from grains. To calculate pore area and perimeter, we measured the total area occupied by pixels within the pore spaces and the boundary length around each pore region. This was performed for each individual pore labeled in the image. Additionally, the porosity contribution of each rock type was determined by calculating the total area of the image and comparing it to the area occupied by the pores.

3.6.2 Fractal Dimension

Fractal dimension is a mathematical measure used to quantify the complexity of irregular geometric shapes [84]. The popular methods of calculating the fractal this dimension is the box counting method [85]. Fractal geometry theory has been applied to characterize the pore structure of both conventional and unconventional reservoir rocks [25]. The procedure involves super imposing of grids of different calibration size over the pore space, then recording the number of blocks the pore space passes through each caliber. With a finer grid, more details of the pore system are captured. Therefore, allowing you to find the fractal dimension more effectively [86]. In a fractal structure, the number of elements (N) exhibits a power-law relationship with the element's length scale as shown in equation (3.94) [42].

$$N = CS^D \quad (3.94)$$

Equation (1) represents the relationship between the number of boxes (N), the proportionality constant (C), the scale factor (S), and the fractal dimension (D). Rearranging equation (3.94) by taking the logarithm of both sides allows it to be expressed in a linear form. The gradient of this linear representation corresponds to the fractal dimension [41].

$$\log N = \log cs^D \quad (3.95)$$

$$\log N = \log c + \log s^D \quad (3.96)$$

$$\log N = \log c + D \log s \quad (3.97)$$

Rearranging the equation give the final form of the fractal equation in a straight-line form

$$\log N = D \log s + \log c \quad (3.98)$$

By fitting a linear regression line to the log-log plot, the slope of this line represents the fractal dimension (D) of the pore structure. The fractal dimension is determined as the limit of the ratio of the logarithm of box count to the logarithm of the reciprocal of box size as box size approaches zero. The resulting fractal dimension provides valuable insights into the complexity and space-filling properties of the multiscale pore structure. Higher fractal dimensions indicate greater irregularity and complexity within the pore structure [85]. This analysis will utilize binary SEM images of size $M \times N$. In these images, dark pixels with a gray value of 0 corresponds to pores. The image will be subdivided into a grid of squares with side length of ϕ_m . Subsequently, the number N_k of grids squares containing these dark pixels will be quantified.

CHAPTER 4

DISCUSSION OF RESULTS

4.1 Comparison of rock typing methods

Figure 4.1 illustrate the results of the image-based rock typing using five methods including methods including K-means, Gaussian mixed model, random forest, support vector machine, and U-net. The demonstrated image is segmented into five different rock types containing rock fragments (RF), eroded feldspar (EF), Macropores, clay, and grains.

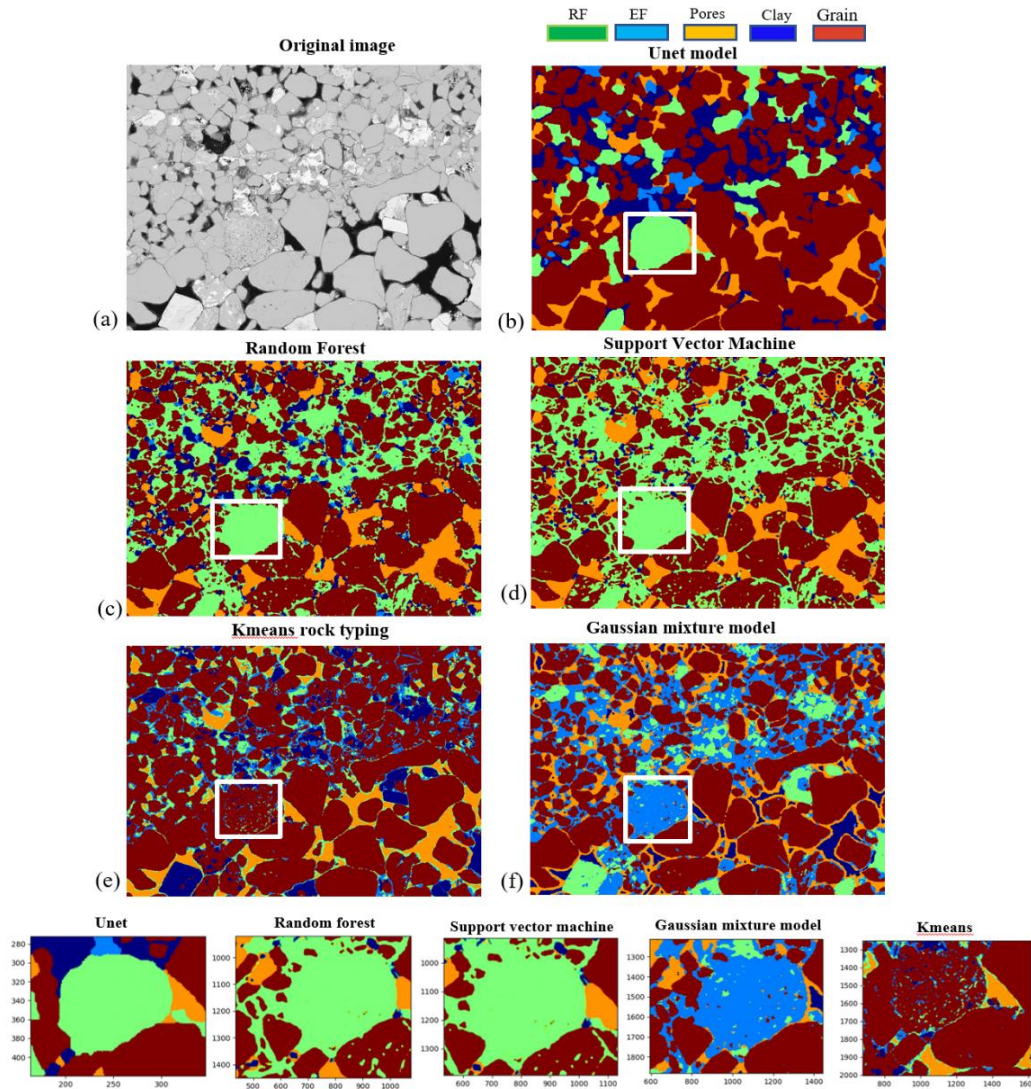


Figure 4.1. Comparison of rock typing methods across different models. Both K-Means and the Gaussian Mixture Model exhibit poor performance in the region highlighted by the white marker. This phenomenon is particularly evident in the cropped section displayed

From Figure 4.1, we can see that U-net demonstrates the strongest performance in identifying the different rock types with an overall accuracy of 97% using intersection over union (IoU) metric. It captures the overall structure of the rock components with precision. The boundaries between the components, especially between pores and grains, are well-defined (see white box in Figure 4.1(b)).

The random forest model produces results that are consistent with the ground truth for most rock types. The model successfully identifies rock fragments, macropore, and grain with high accuracy. However, similar to K-Means, Random Forest shows some limitations in segmenting feldspar and clay, where it tends to merge these components with adjacent rock types. The SVM provides satisfactory segmentation results for rock fragments, macropore space, and grain. However, its performance declines significantly when segmenting feldspar and clay. The model tends to oversimplify the segmentation by grouping multiple components together, leading to less distinct boundaries. This issue is particularly evident in the feldspar regions, where the model struggles to differentiate between feldspar and other components, resulting in blurred or misclassified sections.

GMM, a probabilistic model, provides reasonable segmentation but falls short in capturing the complex structure of the rock sample. The model produces homogeneous regions, and the boundaries between different rock types are not as clearly defined as in U-net, random forest, and SVM. GMM tends to smooth the transitions between components, leading to less accurate segmentation, particularly for feldspar and clay. K-Means clustering, an unsupervised learning model, offers the least accurate segmentation among the five models, it struggles to capture the fine details and boundaries between components, particularly in complex regions containing feldspar and clay.

The performance of the Random Forest and SVM models was further evaluated using quantitative metrics, specifically the F1 score and Intersection over Union (IoU), as presented in Figure 4.2. The random forest model demonstrated strong performance across most rock types, with F1 scores and IoU values exceeding 0.90 for rock fragments, pore space, and grain. This indicates that the model can accurately identify these components with minimal misclassification. The model's performance in segmenting clay (F1 score of 0.87 and IoU of 0.78) and feldspar (F1 score of 0.70 and IoU of 0.54) was slightly lower, suggesting that these components are more challenging to segment, possibly due to their complex morphology and similarity to neighboring rock types.

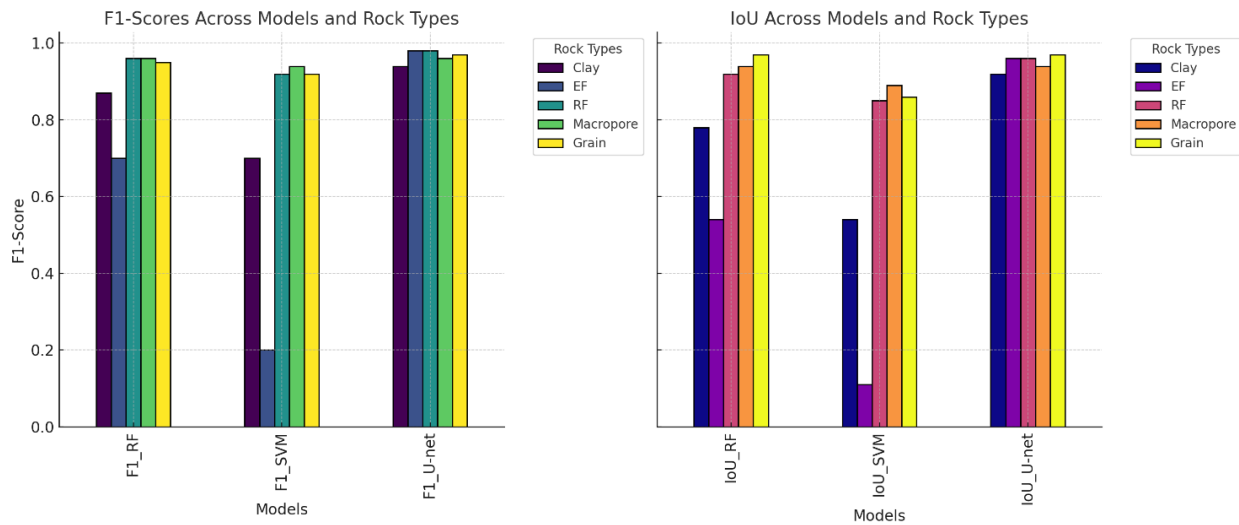


Figure 4.2: Performance of the image base rock typing methods with F1 score and (IoU).

SVM exhibited a noticeable performance drop when segmenting feldspar, with an F1 score of 0.20 and IoU of 0.11. This indicates that the model struggled significantly in distinguishing feldspar from other components, leading to a high degree of misclassification. For rock fragments, Pore space, and Grain, SVM performance was satisfactory, with F1 scores and IoU values in the 0.85-0.94 range, comparable to Random Forest. However, lower accuracy in segmenting clay (F1 score of 0.70 and IoU of 0.54) further underscores its limitations in handling complex rock structures.

U-net and random forest emerged as the top-performing models in this study, with U-net excelling in capturing fine details of each rock type seen from Figure 4.2, Which shows the plot of intersection over union of each class achieving over 97% accuracy. SVM showed potential but struggled with complex components like feldspar. GMM and K-Means were less suitable for this task due to their inability to accurately segment the diverse components of the sandstone rock sample.

4.2 Geometrical parameters of pore structure

In this section, we presented the results of geometrical and fractal parameters which are obtained by box counting methods (see Table 4.1).

Table 4.1: Pore structural characterization of clay, feldspar and rock fragment using the box counting methods

Parameters	Sample A			Sample B		
	Clay A	Feldspar A	Rock Fragment A	Clay B	Feldspar B	Rock Fragment B
Porosity (%)	5.568	4.872	1.15	2.748	4.698	1.377
Average Pore (um ²)	2.561	5.653	0.92	0.814	7.803	1.977
Average pore perimeter (um)	5.444	7.247	2.777	2.683	9.288	4.392
Circularity	0.856	0.715	0.819	0.775	0.77	0.819
Pore diameter (um)	1.406	1.761	0.866	0.867	2.264	1.28
Pore size area range (um ²)	(0.02-0.057)	(0.02-3.789)	(0.003-0.351)	(0.003-0.579)	(0.002-1.04)	(0.005-0.386)
perimeter range (um)	(0.002- 0.695)	(0.115-95.441)	(0.154-16.159)	(0.154-8.204)	(0.118-47.532)	(0.202-11.892)
Pore count	559	350	354	221	502	598
Perimeter-Area R ²	0.98	0.983	0.986	0.9869	0.986	0.984

The results of porosity contribution across the six rock types revealed significant variation in porosity contribution. As shown in Table 4.1, clay A exhibited the highest porosity at 5.58%, while Rock Fragment B presented the lowest porosity at 1.150%. This observation can be attributed to the high concentration of micropores (size $<10\text{ }\mu\text{m}$) within the Rock Fragment samples. This is further supported by the pore count analysis conducted on all six samples, where Rock Fragments A and B displayed a significant number of micropores. The analysis revealed approximately 354 and 598 small micropores for Rock Fragment A and B, respectively, suggesting a trend of limited porosity contribution due to the predominance of micropores. This wide range of porosity values indicates the heterogeneity in pore structure between the rock types.

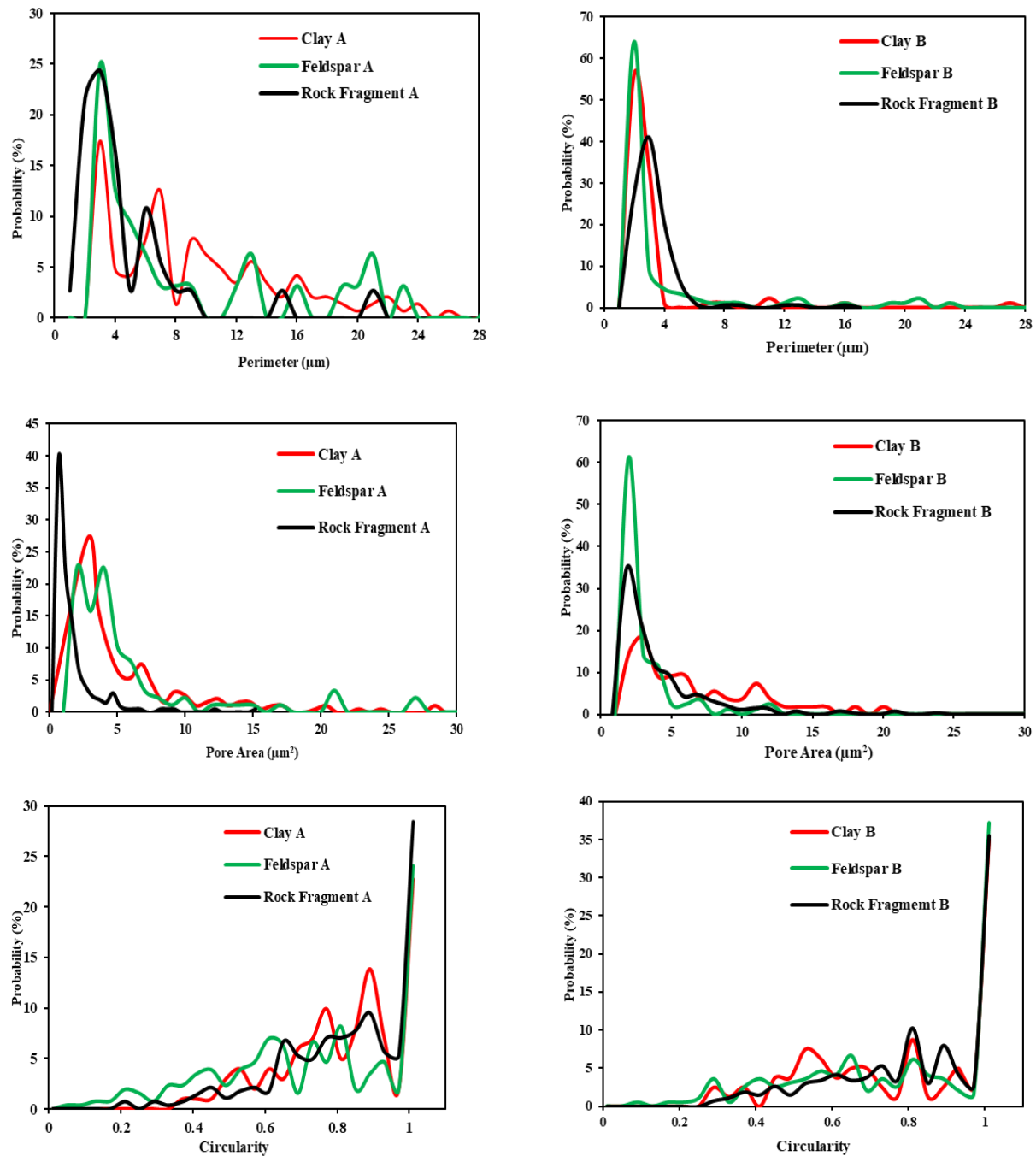
The variation in porosity is likely related to the mineral composition and compaction history of each rock type. Clays, typically fine-grained and prone to forming more extensive pore networks, show higher porosity, while the rock fragments, potentially more indurated or cemented, display reduced porosity. These observations are consistent with the established understanding of pore structure in sedimentary formations where clay tends to retain more pore space than coarser, more lithified materials.

The average pore size varies considerably between the samples, as shown in Table 4.1. Feldspar B has the largest average pore size of $7.80\text{ }\mu\text{m}^2$, followed by Feldspar A at $5.65\text{ }\mu\text{m}^2$. These values are in sharp contrast to Rock Fragment A, which has the smallest average pore size of $0.92\text{ }\mu\text{m}^2$. The larger pore sizes in the feldspar samples suggest more significant fractures or erosion features, potentially caused by chemical weathering processes.

Similarly, the average pore perimeter reflects the size and shape irregularities of the pores. Feldspar B shows the largest perimeter value ($9.29\text{ }\mu\text{m}$), while Rock Fragment A displays the smallest ($2.78\text{ }\mu\text{m}$). Larger perimeters typically correspond to more irregular and complex pore shapes, a

characteristic that is more prominent in feldspar samples compared to the rock fragments, which may have undergone less fracturing or chemical alteration.

A perimeter-area cross-plot was further generated for each of the six rock types, revealing a strong correlation across all samples (see Figure 4.3).



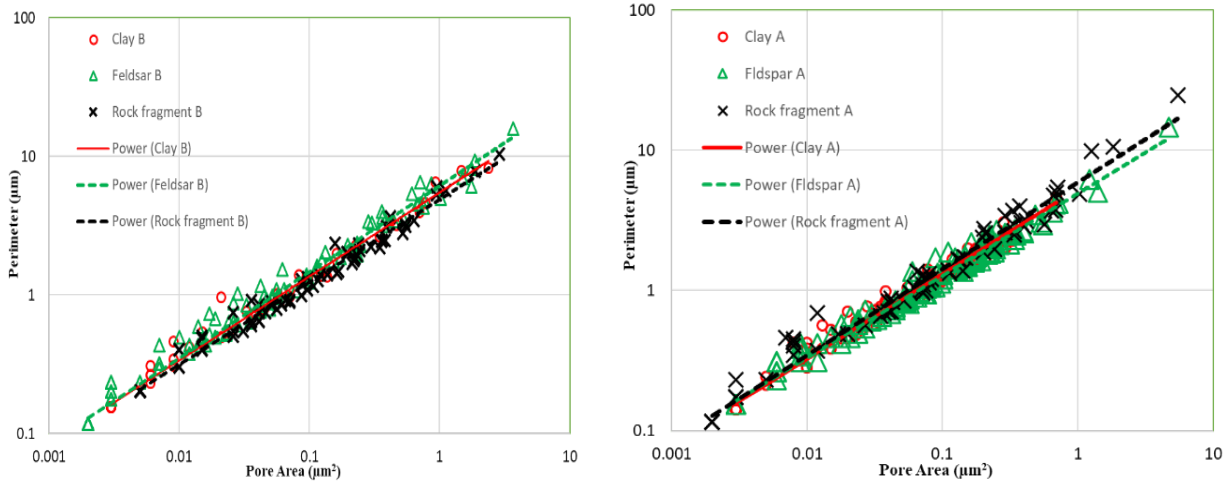


Figure 4.3: Distribution of pore perimeter, pore area, circularity and the relationship between pore area and pore perimeter across different rock types.

Circularity is a measure of the shape of the pores, with values closer to 1 indicating more circular (regular) pore shapes. In this study, clay A shows the highest circularity value of 0.86, indicating that the pores in this sample are relatively more regular and uniform in shape. Conversely, Feldspar A has the lowest circularity (0.72), suggesting more elongated or irregular pores. Interestingly, the circularity values of the other samples, including both rock fragments and clays are relatively similar, ranging from 0.77 to 0.82. The circularity values are consistent with the observed pore shapes, where clay samples tend to have more rounded and well-defined pores, while feldspar samples, likely due to fractures and weathering, show more irregular pore shapes. These variations in pore shape can significantly affect the flow properties of the rocks, with more irregular shapes potentially increasing the resistance to fluid flow.

4.3 Fractal characteristics of the rock samples

Fractal geometry theory was applied to analyze the complexity of the rock types. The fractal dimension of the segmented micropores for each rock type was calculated with box counting method, with the results presented and interpreted in Table 4.2.

Table 4.2: Fractal Characteristics of Different rock types using Box counting methods

Parameters	Sample A			Sample B		
	Clay A	Feldspar A	Rock Fragment A	Clay B	Feldspar B	Rock Fragment B
Fractal dimension (D)	1.9	1.63	1.11	1.42	1.62	1.24

A higher fractal dimension indicates more irregular and complex pore shapes. The relatively high fractal dimension of clay A suggests a more tortuous pore network, which could lead to more complex fluid flow behavior. On the other hand, Rock Fragment B lower fractal dimension implies a simpler and more straightforward pore geometry, potentially facilitating more efficient fluid transport through the matrix.

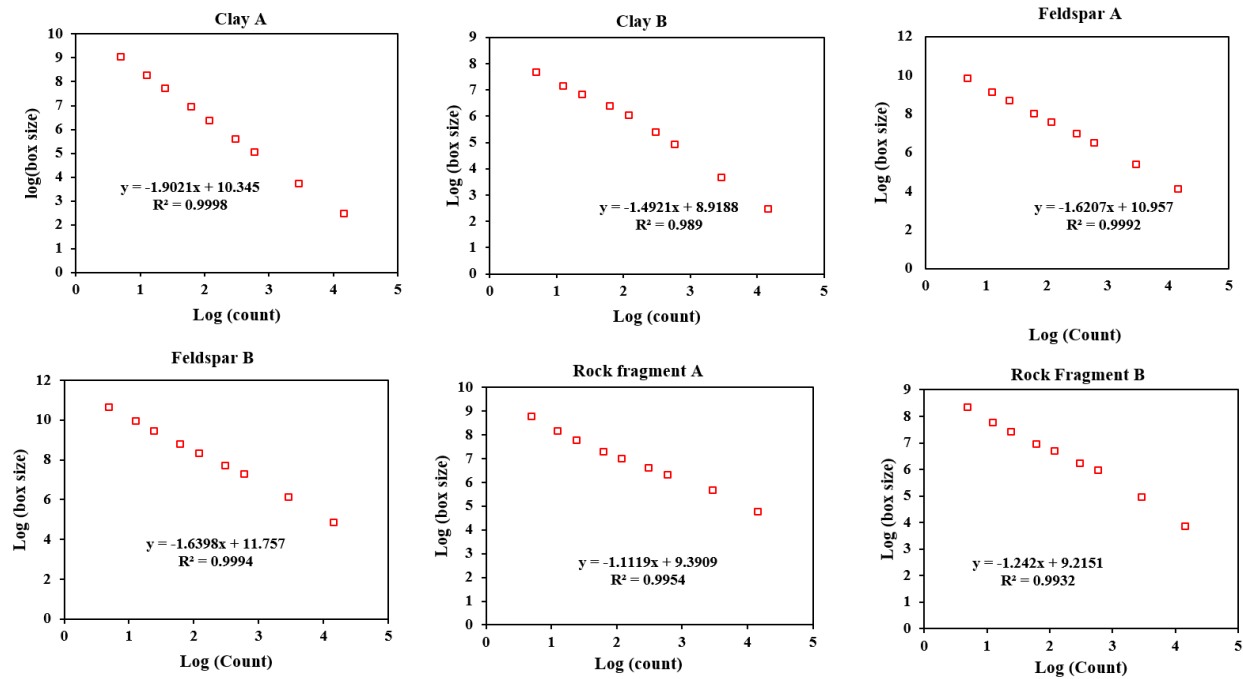


Figure 4.4: Fractal dimension of different rock types from the rock sample images

The plot in Figure 4.4 shows that there existed dissimilar patterns in the pore structural properties of all the rock types for all the six images. This pattern is clearly observed in clay rock types which have the fractal dimension of 1.9 and 1.78, also similar behavior can be observed in feldspar A

and B having the fractal dimension of 1.62 and 1.63 respectively, different pattern is also observed across all the images. The variation in fractal dimension means that the rock types can have different impacts in the reservoir fluid flow system.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This study proposed an effective approach to characterize the geometrical and fractal features of the multiscale pore structures of reservoir rock samples using SEM images. In this study, five different models for image-based rock typing was applied based on SEM images of a rock samples. The study evaluates and compare the capabilities of these models on image-based rock typing for predicting rock types in the SEM images and also conducted 2D pore structure characterization approach based on each individual rock type. The study also analyzed various geometrical features of the pore structures and their impacts on porosity contribution across various rock types, including clay, feldspar, and rock fragments. Additionally, the fractal dimension of each rock type was determined to analyze the complexity and shape properties of the pore spaces. The analysis concluded in the following key findings:

1. Among five applied image-based rock typing methods, the random forest and U-net models presented the best performance, with high accuracy of 88.8% and 97%, respectively.
2. The watershed algorithm and the skeleton extension erosion grain partitioning (SEEPP) methods successfully classify the image into pore and solid, and further separate the connected pore network in to a large number of single pores.
3. According to the demonstrated rock sample, three kinds of rock types with micropore structures contributes a 11.8% proposition of the overall porosity of the rock sample. Among these micropore rock types, Clay rock type, exhibiting the highest porosity

contribution (5.56%) to the reservoir, followed by Feldspar (4.87%) and rock fragments with 1.37%.

4. A variation in pore structural properties was observed across all the rock types. This pattern is particularly evident in the clay samples, which exhibit fractal dimensions of 1.9 and 1.78, while feldspar samples A and B display similar characteristics with fractal dimensions of 1.62 and 1.63, respectively.

5.2 Future Recommendation

While this research has demonstrated the potential of image-based rock typing and pore structure characterization using machine learning, several avenues can be explored to further enhance its accuracy, applicability, and efficiency. Future studies could focus on the following areas:

- Future studies should integrate 3D imaging modalities like micro-CT scans to capture the full complexity of the pore network. This would provide more accurate geometrical and fractal features, enabling better predictions of fluid flow and reservoir properties.
- Combining data from different imaging modalities (e.g., micro-CT, SEM, and NMR) and resolutions would allow for a more comprehensive multiscale analysis of the pore structures. This can help bridge the gap between micro- and macro-scale properties and enhance the predictive capabilities of reservoir models.
- Incorporating uncertainty quantification methods (e.g., Bayesian Neural Networks, Monte Carlo dropout) into the workflow can provide confidence intervals for the machine learning model predictions, allowing for a more robust decision-making process in uncertain reservoir conditions.

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