THE DETAILED STUDY ABOUT THE ALGORITHMS AND METHODOLOGIES USED FOR SYSTEMATIC LITHOLOGY CHARACTERIZATION

Dr. P. Rajasundaram[1] & Dr. S. Punithavathi[2]

1st Assistant Professor, Dept. of Computer Science, School of Computational Studies, Hindustan College of Arts & Science, Padur, Kelambakkam, Chennai 603 103.
2nd Assistant Professor, Dept. of Computer Science, School of Computational Studies, Hindustan College of Arts & Science, Padur, Kelambakkam, Chennai 603 103.

ABSTRACT

Automated and rapid rock type identification plays a crucial role in modern intelligent geological and geotechnical fields, deep learning techniques - particularly **Convolutional Neural Networks (CNNs)** and **transfer learning -** are widely used in the field of Lithology for rock classification and interpretation using borehole core images. Nevertheless, current Lithology identification models still exhibit limitations in both accuracy and efficiency so the society is in the need of improving the field Lithology to the next and advanced level. In this study, we first establish a large, systematic rock data framework grounded in the geological rock classification system to generate robust training datasets. The used datasets contains more images of rock specimens, encompassing igneous, sedimentary, and metamorphic categories. Next, an end-to-end image-to-label Lithology classification model is especially developed using a CNN-driven deep transfer learning strategy and some of the preferred algorithm and new methodologies. Finally, generalization tests and core validation demonstrate that some of the proposed intelligent rock recognition model can achieve rapid and accurate rock classification, reaching an accuracy exceeding 95% for commonly encountered engineering rock types. Some of the intelligent Lithology classification model provides an efficient and practical tool for geologists and scientific researchers working in the field.

Keywords: Screening refining and Labeling, Deep Transfer Learning, Convolution Neural Network, Rate of recognition, Depth Learning Model, Chemo metrics, Machine Learning, peridotite, pyroxenite, and metamorphism.

1. INTRODUCTION

Rock classification constitutes a fundamental research domain within contemporary geology and holds substantial importance for precise geological interpretation as well as informed engineering decision-making [5]. Conventionally, two principal methods are employed in lithological identification: visual examination and laboratory-based analysis. Visual examination involves the approximate determination of rock types through direct observation of attributes such as color, surface texture, and hardness. Although rapid and straightforward, some approach is constrained by the observer’s level of geological expertise and that is inherently prone to subjective bias [3]. Laboratory analytical methods, conversely, enable accurate rock classification through the use of specialized instruments, including photoelectric microscopes; however, these procedures are often labor-intensive, time-consuming, and unsuitable for real-time field applications [4]. Consequently, the development of an automatic, efficient, and highly accurate means of rock identification remains a critical and unresolved challenge within the geological sciences [1, 2].

Automatic rock recognition can be regarded as an image classification task within the field of computer vision. The integration of intelligent technologies enables automated assistance in rock identification, and notable progress has been made in existing studies, with various methods and models being developed. For instance, Li et al. [7], Zhang et al. [8], and Guo et al. [9] introduced rock image classification algorithms capable of categorizing sandstone microscopic images from different regions. Zhou et al. [12] proposed a novel Convolutional Neural Network (CNN) architecture named HKUDES_Net, which successfully classified seven common rock types in Hong Kong and achieved a precision of 90.9%. Koeshidayatullah et al. [11] developed a vision transformer model to enhance both the accuracy and efficiency of lithofacies prediction, reaching an accuracy of 87.3%. Additionally, Li et al. [10] trained and compared four CNN-based models for rock identification.

However, these models are limited to identifying only one to five rock types, primarily due to the small size of the available rock image datasets. Li et al. [13], Xu et al. [14, 15], and Zhou et al. [12] proposed a series of multitype rock identification methods based on convolutional neural networks (CNNs). Fan et al. [16] evaluated the classification performance of CNNs in comparison with three other machine learning algorithms, demonstrating that CNN-based chemometric techniques can serve as an effective tool for rock recognition. However, the model achieved a prediction accuracy of only 87.65%. Wei et al. [17] employed hyper spectral data as a technical approach for coal and rock identification and developed an algorithm that utilizes hyper spectral bands for this purpose. Overall, the accuracies reported for these models remain relatively low.

Vasilionak et al. [18], Wang et al. [19], Fu et al. [20], and Liu et al. [21] introduced methods for extracting quantitative features from macroscopic rock images and for performing mineral classification. Zhang et al. [22] developed an Inception v3–based model for rock image classification using a large-scale rock image dataset, achieving an accuracy exceeding 90%.Ran et al. [23] proposed a highly accurate rock identification method based on deep CNNs, capable of classifying six common rock types with an accuracy of 97.96%, outperforming other contemporary models as well as traditional linear approaches. Nevertheless, these models still exhibit insufficient generalization capability.

Although numerous methods for automatic rock identification have been proposed, many of them are primarily developed for microscopic image analysis and therefore do not align well with the practical requirements of field-based automatic rock recognition [24, 25]. Several key factors contribute to this limitation: (1) the structure of existing datasets lacks systematic organization and does not adequately consider scalability [26]; (2) the diversity of data samples is insufficient [27]; (3) model accuracy remains relatively low, and performance improvements are needed [28]; and (4) research on model generalization is inadequate, even though the applicability of a model largely depends on its ability to generalize to similar sample types [29]. Consequently, developing a systematically constructed and diverse rock sample dataset, together with an end-to-end model offering high accuracy and robust generalization capability, can provide an effective solution for automatic rock type identification in practical applications.

Cored wells are essential because they provide the only direct ground-truth data for subsurface reservoirs, including lithofacies variability. Core-based rock-type characterization aims to identify key lithofacies and facies associations, assess facies stacking patterns, and interpret depositional environments. It also seeks to evaluate how porosity and permeability relate to lithofacies and assist operators in selecting optimal zones for well completions. However, traditional lithofacies identification from core data is often costly, time-consuming, and subjective—different geologists may describe the same core differently. To help address these challenges, we investigate whether a convolutional neural network (CNN) can support specialists in their image-recognition tasks [32]. The structure of most of the research work organized as follows:

- ✓ Rock Characterization
- ✓ Construction of Learning Model
- ✓ Model Training
- ✓ Model Generation Verification
- ✓ Verification of Drilling Core Identification

2. ROCK CHARACTERIZATION

2.1 Geological Classification of Rock

The geological rock system is primarily composed of igneous, sedimentary, and metamorphic rocks, each of which can be further subdivided. **Igneous rocks** can be classified based on their silicon dioxide (SiO_2) content into four categories: (1) **Ultrabasic rocks**, with SiO_2 content < 45%, including peridotite and pyroxenite; (2) **Basic rocks**, with SiO_2 content between 45% and 52%, including gabbro and basalt; (3) **Intermediate rocks**, with SiO_2 content between 52% and 65%, including diorite, andesite, and syenite; and (4) **Acidic rocks**, with SiO_2 content > 65%, including granite and rhyolite.

Sedimentary rocks, the most common rock type in nature, can be subdivided according to the source of their formation materials into: (1) **Clastic rocks**, formed from detrital materials, such as volcanic agglomerates, volcanic breccia, and tuff; and (2) **Clay rocks**, formed from clay minerals and other substances, including mudstone and limestone.

Metamorphic rocks are categorized based on the type of metamorphism they undergo: (1) **Dynamically metamorphic rocks**, formed under dynamic metamorphism, commonly referred to as structural breccia; (2) **Thermally metamorphic rocks**, formed through thermal contact metamorphism; (3) **Gas–liquid metamorphic rocks**, developed through high-energy gas or solution metasomatism, which alters minerals and structures of the original rock; and (4) **Regionally metamorphic rocks**, formed through regional metamorphism, commonly including slate, phyllite, schist, and gneiss. The following picture illustrates the geological classification of rocks.

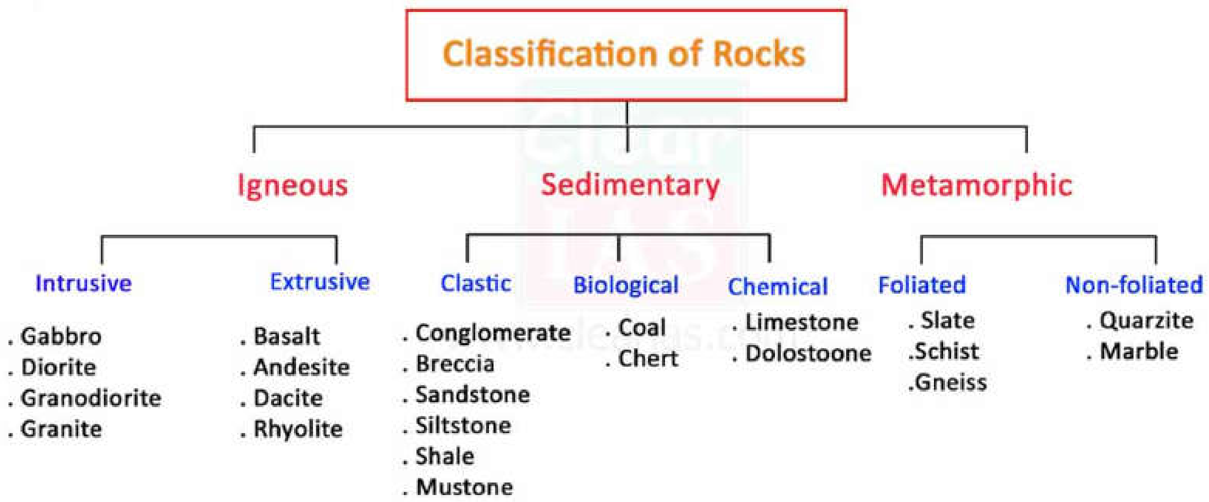

Fig. 2.1: Geological Classification of Rocks

The following picture depicts about the Igneous, Sedimentary and Metamorphic rocks.

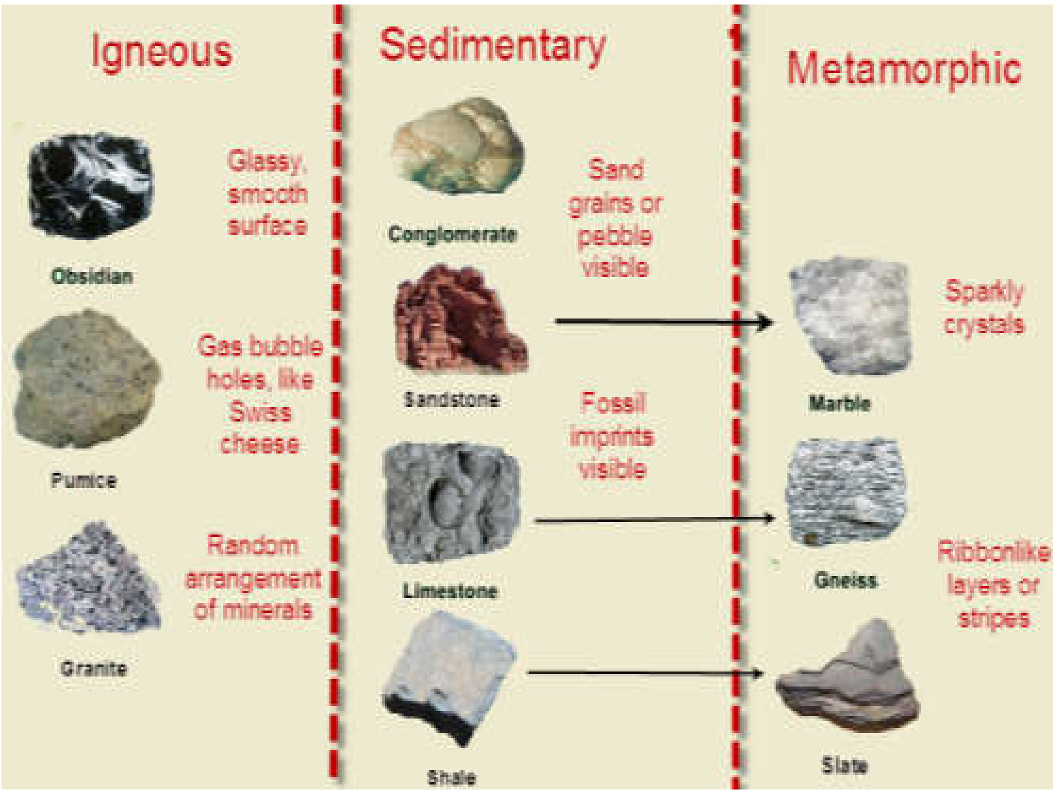

Fig. 2.2: Igneous, Sedimentary and Metamorphic rocks

2.2 Rock Image Acquisition

The rock image dataset used in the existing systems were collected by online or captured in the field area and the researcher have to note about stable camera configuration, Lighting effects of Camera, Clean and Orientation, Background, Focus Resolution, Scale & Orientation and the purpose of image acquisition. The collected images were manually organized and classified into folders corresponding to their respective rock types.

2.3 Rock Image Preprocessing

The collected rock images are must be preprocessed to remove the Noise and some unwanted data and it will be more helpful to enhance the generalization capability of neural network models, each rock class includes multiple samples, allowing the model to learn the general structural features of the rock. After processing and organization, the dataset comprises to several rock types; however, the subsequent experiments focus on the recognition of some common rock types.

2.4 Rock Image Fragmentation

Due to the limitations of manual image acquisition and field conditions, some of the collected image data are irregular and unsuitable for model training. To address this issue and enhance the model's training performance, recognition accuracy, and generalization capability, the collected images are preprocessed to remove redundant background information, thereby retaining only the rock-specific features for training. The preprocessing techniques applied include Canny edge detection, morphological operations, contour extraction, and image cropping. The following figure demonstrates the complete image processing workflow using granite as an example. As illustrated, the cropped image eliminates background pixels while preserving only the rock pixels for subsequent model training.

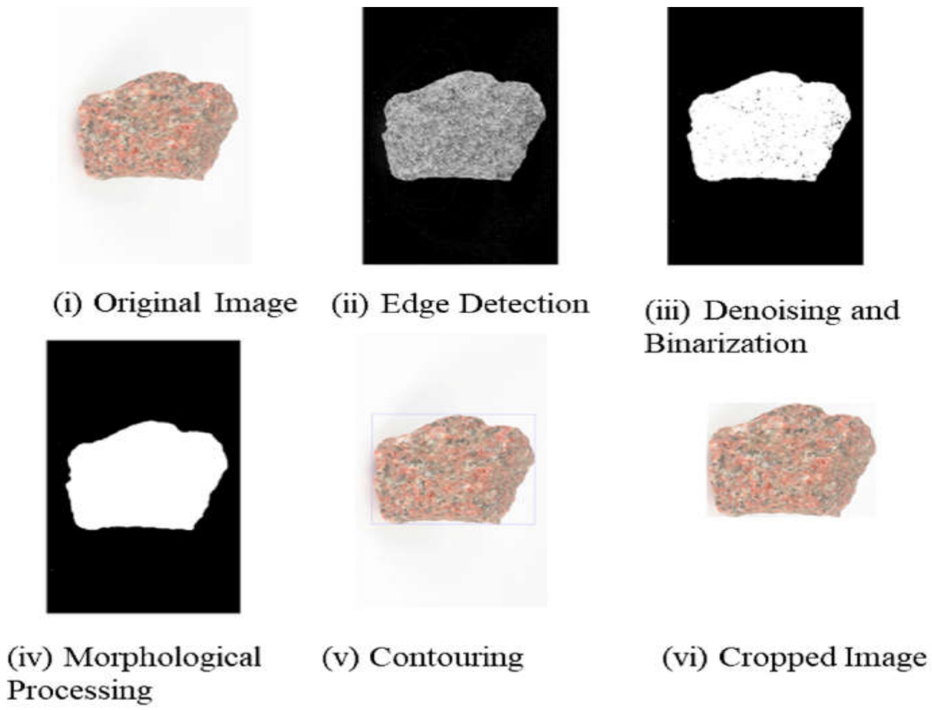

Fig. 2.3: Image Partition Result of a Rock [31].

2.5 Enhancing the acquired image

During model training, data augmentation techniques are employed to expand the rock core image dataset, thereby generating additional training samples and enhancing the model's generalization capability. Data augmentation involves a series of transformations applied to the original dataset to increase both the diversity and volume of rock images. Based on the requirements of model training and the characteristics of rock core images, random cropping and rotation methods are utilized for dataset expansion.

3. Construction of Learning Models

Several authors did the construction of learning models using some CNN, Deep Learning algorithms but here one best strategy is discussed which is developed by Shiliang Li et al. [31] and this rock image recognition model is developed using a CNN-based deep transfer learning approach with the Inception V3 pre-trained model, as illustrated in Fig. 3.1 [31]. The Inception V3 model consists of a total of 47 layers. The lower layers serve as a feature extractor, comprising convolutional network layers, while the upper layers function as a feature classifier, composed of multiple fully connected layers. To utilize the model for feature extraction, the underlying layers are frozen. The original top fully connected layer is removed and replaced with a newly constructed fully connected layer to establish the mapping between extracted features and rock types. The resulting rock recognition model is shown in Fig. 3.2. The model is trained using the rock sample training dataset, and its performance is subsequently validated using a separate set of rock samples.

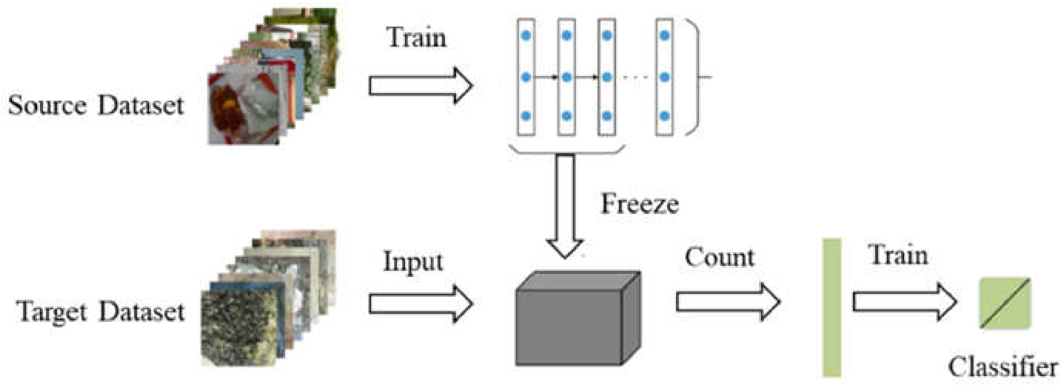

Fig. 3.1: Rock Identification Model based on CNN - Deep Transfer Learning [31].

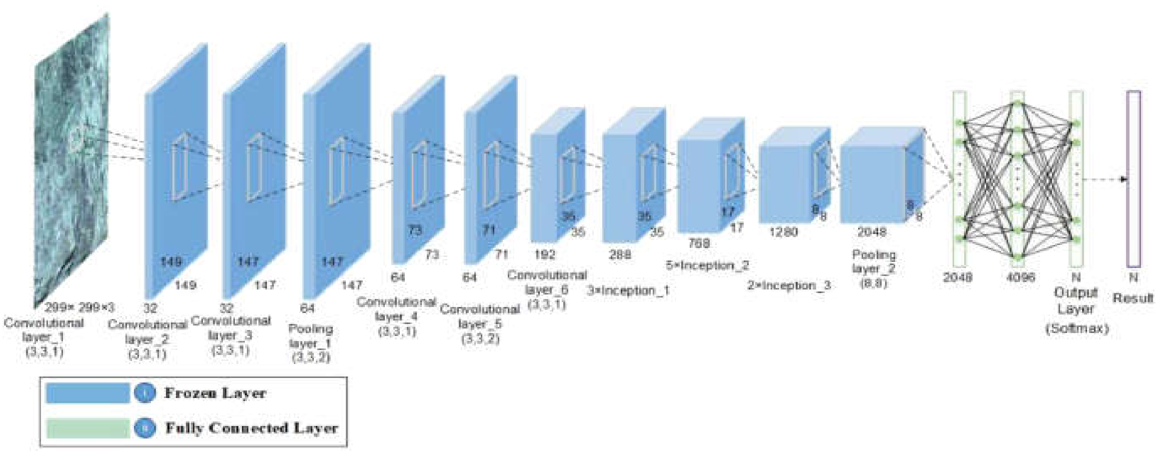

Fig. 3.2: Architecture of Rock Image Recognition Model [31].

As illustrated in Fig. 3.2, one of the existing models [31] comprises three main components: (1) the blue frozen layers transferred from the pre-trained Inception V3 model, (2) the newly constructed green fully connected layer, and (3) the output results. Within the blue block, three specialized Inception modules from the original model are retained, including three 'Inception_1' modules, five 'Inception_2' modules, and two 'Inception_3' modules. Each module, with distinct structural configurations, consists of convolutional and pooling operations with various parameters. During training, these modules automatically facilitate the determination of CNN hyperparameters, such as convolutional kernel sizes.

As shown in Fig. 3.1, the blue module also contains six convolutional layers and two pooling layers. The output of each layer serves as the input to the subsequent layer, with both input and output represented as three-dimensional arrays (h × w × d), where h and w denote the spatial dimensions and d represents the channel dimension or matrix depth. For instance, the leftmost RGB image (299 × 299 × 3) is initially processed through the convolutional layer to produce a three-dimensional array, which is then passed to the next layer. The 'pooling layer 2' within the blue module compresses the features into a 2048-dimensional vector, which is subsequently fed into the green module to establish a mapping between the extracted feature vector and the corresponding rock label. The green fully connected layer functions as a three-layer artificial neural network responsible for global feature classification [31].

The core function of the convolutional layer in a neural network is to extract image features, and the effectiveness of this extraction depends on the suitability of its parameters. Given the variability among rock images, the model must be capable of capturing the primary features while minimizing the extraction of noise. The outputs of the convolutional layer provide an objective means to evaluate the model's performance. Furthermore, this existing model successfully extracts the porphyritic structures of granite and lamprophyre, as well as the gravel structures of structural breccia and conglomerate.

4. Model Training

4.1 Selection of Model Training Algorithm

The primary objective of model training is to enable the network to effectively extract discriminative features from Lithology images, capturing variations in rock color, texture, and structural patterns. Common optimization strategies employed during training include batch gradient descent, stochastic (random) gradient descent, and mini-batch gradient descent [30]. Among these, mini-batch gradient descent offers a balanced compromise between computational efficiency and learning stability, making it particularly suitable for large-scale datasets and generally more effective than the other two algorithms.

4.2 Learning Rate Debugging

The learning rate is a critical hyper parameter in model training. To determine an appropriate value, multiple learning rates were tested and their corresponding training outcomes were recorded. During the weight-update optimization process, the control-variable method was applied, where the learning rate was the only parameters adjusted while all other hyper parameters—including the training dataset—remained constant.The initial experiment used a relatively small learning rate of 0.1 with 3500 iterations, yielding a test accuracy of 57.6% and only minor parameter updates. This suggests that the value was below the optimal range. In a second trial, the learning rate was increased to 0.8; however, the final test accuracy dropped to 19.8%, and the training curve exhibited severe oscillations, preventing the model from converging. This indicates that the learning rate was excessively high [31].

When the learning rate was set to 0.4, the model achieved a substantially improved test accuracy of 76.5%, implying that this value was closer to the optimal range. To refine the selection further, two additional learning rates between 0.1 and 0.4 and three between 0.4 and 0.8 were evaluated. The trend of accuracy variations with respect to the learning rate is shown in Fig. 8. Overall, the model exhibited a "convex" response: within the range of 0.1–0.5, accuracy improved as the learning rate increased, whereas values above 0.5 led to reduced performance. At a learning rate of 0.8, the model failed to converge altogether [31], some of the existing research only did learning rate debugging and it is processed well in that specified article and it is a good practice to improve the efficiency of the automated system.

4.3 Full Connection Layer Debugging

Optimizing the learning rate alone yielded a maximum model accuracy of about 80%, which remains insufficient for practical on-site rock recognition. Given the wide diversity and complex characteristics of rock types, the inference capability of the classifier was still inadequate. To enhance the model's performance, the number of fully connected layers was increased from two to three, with the newly added layer containing 4096 neurons. Introducing an additional fully connected layer significantly improved the model's classification ability, raising the average accuracy to approximately 96%. This demonstrates that expanding the fully connected structure can effectively boost that model performance [31].

5. Model Generation Verification

With various types of rocks, a certain type of rock may have multiple characteristics, such as granite, which can form subclasses such as biotite granite and hornblende granite due to different mineral contents. Although there are many subclasses of rocks, they have similar texture characteristics. For example, if the model is trained with biotite granite and can recognize hornblende granite during testing, then it can be considered that the model has strong generalization ability. Models with excellent generalization performance can often play an important role in the field, greatly improving the accuracy and reliability of rock identification. ROC (receiver operating characteristic curve) curve is used [31] to evaluate model classification performance. The horizontal axis data of the ROC curve is the false positive rate (*FPR*), and the vertical axis is the true positive rate (*TPR*). The calculations are as follows:

(1) $FPR = \frac{FP}{FP+TN}$, this formula represents the proportion of samples with negative examples that are incorrectly predicted as positive examples.

(2) $TPR = \frac{TP}{TP+FN}$, this formula represents the proportion of positive samples correctly predicted as positive examples.

6. Verification of Drilling Core Identification

The intelligent recognition of drilling core Lithology on construction sites is crucial for enhancing the efficiency of engineering geological investigations. However, onsite conditions—such as complex environments, high noise levels, and inconsistent manual photography—pose considerable challenges to accurately identifying rock core images. To evaluate the effectiveness of the proposed Lithology identification method under real field conditions, drilling-core images from the Shapingba Railway Comprehensive Renovation Project were used for testing [31]. This project, a major redevelopment of the original Shapingba Railway Station, is a key initiative of the Chongqing Municipal Government and plays an important role in improving urban infrastructure and establishing a comprehensive transportation hub in the Shapingba district. Some of the drilled core images are depicted in the following picture.

(a) Sandstone (b) Limestone

(c) Shale

Fig. 6.1: Images of Drilled Core [31].

7. Conclusion

A deep transfer learning algorithm leverages knowledge learned from a model trained on a large-scale dataset (the source task) to address a new but related problem with limited data (the target task). This is typically achieved by reusing a pre-trained deep neural network—such as a CNN—and fine-tuning its layers so that it can extract task-specific features such as edges or textures. A new classifier is then trained on top of these adapted features [31]. This approach greatly reduces training time and improves accuracy, making it especially valuable in depth estimation and other computer vision applications where data may be scarce, where domain shifts occur, or when bridging the gap between simulated and real environments. And this existing work can be enhanced by using machine learning techniques like Random forest, XG Boost and Decision tree.

8. References

[1]. Han R, Wang Z, Zhang Z, Wang X, Cui Y, Guo Y. Prediction of igneous Lithology and lithofacies based on ensemble learning with data optimization. Geophysics. 2024;89(2):1–11. https://doi.org/10.1190/geo2022-0782.1.

[2]. Shi H, Xu Z, Lin P, Ma W. Refined Lithology identification: Methodology, challenges and prospects. Geoenergy Sci Eng. 2023;231(PartA):212382. https://doi.org/10.1016/j.geoen.2023.212382.

[3]. Zhang Y, Wong L, Tse K. Novel rock image classification: the proposal and implementation of HKUDES_Net. Rock Mech Rock Eng. 2023;56:3825–41. https://doi.org/10.1007/s00603-023-03235-0.

[4]. Zhang W, Ren J, Zhu F, Feng J. Analysis and selection of measurement indexes of MWD in rock Lithology identification. Measurement. 2023;208:112455. https://doi.org/10.1016/j.measurement.2023.112455.

[5]. Kong D, Wu F, Charalampos S. Automatic identification and characterization of discontinuities in rock masses from 3D point clouds. Eng Geol. 2019. https://doi.org/10.1016/j.enggeo.2019.105442.

[6]. Liu Y, Zhang H, Zhang W, Lu G, Tian Q, Ling N. Few-Shot image classification: current Status and research trends. Electronics. 2022;11(11):1752. https://doi.org/10.3390/electronics11111752.

[7]. Li N, Hao H, Gu Q, Wang D, Hu X. A transfer learning method for automatic identification of sandstone microscopic images. Comput Geosci. 2017;103:111–21. https://doi.org/10.1016/j.cageo.2017.03.007.

[8]. Zhang X, Wang Z, Liu T, Sun Q, Wang J. Rock thin section image classification based on depth residuals shrinkage network and attention mechanism. Earth Sci Inf. 2023;16:1449–57. https://doi.org/10.1007/s12145-023-00981-1.

[9]. Guo Y, Li Z, Lin W, Zhou J, Feng S, Zhang L, Liu F. Automatic Lithology identification method based on efficient deep convolutional network. Earth Sci Inf. 2023;16:1359–72. https://doi.org/10.1007/s12145-023-00994-w.

[10]. Li D, Zhao J, Ma J. Experimental studies on rock thin-section image classification by deep learning-based approaches. Mathematics. 2022;10(13):2317. https://doi.org/10.3390/math10132317.

[11]. Koeshidayatullah A, Al-Azani S, Baraboshkin E, Alfarraj M. FaciesViT: vision transformer for an improved core lithofacies prediction. Front Earth Sci. 2022;10:992442. https://doi.org/10.3389/feart.2022.992442.

[12]. Zhou Z, Hang Y, Xin C. Rock thin section image identification based on convolutional neural networks of adaptive and second-order pooling methods. Mathematics. 2023;11(5):1245–1245. https://doi.org/10.3390/math11051245.

[13]. Li D, Zhao J, Liu Z. A Novel method of multitype hybrid rock Lithology classification based on convolutional neural networks. Sensors. 2022;22(4):1574. https://doi.org/10.3390/s22041574.

[14]. Xu Z, Shi H, Lin P, Liu T. Integrated Lithology identification based on images and elemental data from rocks. J Petrol Sci Eng. 2021;205:108853. https://doi.org/10.1016/j.petrol.2021.108853.

[15]. Xu Z, Ma W, Lin P, Shi H, Pan D. Deep learning of rock images for intelligent Lithology identification. Comput Geosci. 2021. https://doi.org/10.1016/j.cageo.2021.104799.

[16]. Fan G, Chen F, Chen D, Li Y, Dong Y. A deep learning model for quick and accurate rock recognition with smartphones. Mobile Inf Syst. 2020;27:1–14. https://doi.org/10.1155/2020/7462524.

[17]. Wei R, Xu L, Meng X, Wu J, Zhang K. Coal and rock identification method based on hyper spectral feature absorption peak. Spectrosc Spectr Anal. 2021;41(6):1942–8. https://doi.org/10.3964/j.issn.1000-0593(2021)06-1942-07.

[18]. Vasilionak AA. Classification of mineral components of granitoid rocks by using methods of digital petrography and machine learning. J Belarusian State Univ Geogr Geol. 2020. https://doi.org/10.33581/2521-6740-2020-1-75-85.

[19]. Wang M, Zhou J, Chen J, Jiang N, Zhang P, Li H. Automatic identification of rock discontinuity and stability analysis of tunnel rock blocks using terrestrial laser scanning. J Rock Mech Geotech Eng. 2023;15(7):1810–25. https://doi.org/10.1016/j.jrmge.2022.12.015.

[20]. Fu X, Sheng Q, Wang L, Chen J, Zhang Z, Du Y, Du W. Spatial topology identification of three-dimensional complex block system of rock masses. Int J Geomech. 2019;19(12):04019127. https://doi.org/10.1061/(ASCE)GM.1943-5622.0001522.

[21]. Liu C, Zheng G, Yang L, Li P, Shahani NM, Wang C, Guo X. Automatic identification of rock formation interface based on borehole imaging. Energy Sour Part A-Recovery Utilization Environ Eff. 2021. https://doi.org/10.1080/15567036.2021.1903121.

[22]. Zhang Y, Li C, Han S. Automatic identification and classification in Lithology based on deep learning in rock images. Acta Petrologica Sinica. 2018;34(2):333–42. https://doi.org/10.1016/j.isprsjprs.2017.05.001.

[23]. Ran X, Xue L, Zhang Y, Liu Z, Sang X, He J. Rock classification from field image patches analyzed using a deep convolutional neural network. Mathematics. 2019;7(8):7080755. https://doi.org/10.3390/math7080755.

[24]. Li Y, Shi D, Bu F. Automatic recognition of rock images based on convolutional neural network and discrete cosine transform. Traitement Du Signal. 2019;36(5):463–9. https://doi.org/10.18280/ts.360512.

[25]. Su C, Xu S, Zhu K, Zhang X. Rock classification in petrographic thin section images based on concatenated convolutional neural networks. Earth Sci Inf. 2020;13(4):1477–84. https://doi.org/10.1007/s12145-020-00505-1.

[26]. Mlynarczuk M, Górszczyk A, Slipe B. The application of pattern recognition in the automatic classification of microscopic rock images. Comput Geosci. 2013;60:126–33. https://doi.org/10.1016/j.cageo.2013.07.015.

[27]. Xu Z, Ma W, Lin P, Hua Y. Deep learning of rock microscopic images for intelligent Lithology identification: neural network comparison and selection. J Rock Mech Geotech Eng. 2022;14(4):1140–52. https://doi.org/10.1016/j.jrmge.2022.05.009.

[28]. Zhang W, Zhang W, Zhang G, Huang J, Li M, Wang X, Ye F, Guan X. Hard-rock tunnel Lithology identification using multi-scale dilated convolutional attention network based on tunnel face images. Front Struct Civ Eng. 2023;17(12):1796–812. https://doi.org/10.1007/s11709-023-0002-1.

[29]. Hou Z, Wei J, Shen J, Liu X, Zhao W. Intelligent Lithology identification methods for rock images based on object detection. Nat Resour Res. 2023;10:1520–7439. https://doi.org/10.1007/s11053-023-10271-8.

[30]. Yang F, Xu W, Cui Z, Liu X, Xu X, Jia L, Chen Y, Shu R, Li L. Convolutional neural network chemometrics for rock identification based on laser-induced breakdown spectroscopy data in tianwen-1 pre-flight experiments. Remote Sens. 2022;14(21):5343–5343. https://doi.org/10.3390/rs14215343.

[31]. Shiliang Li, Yuelong Dong, Zhanrong Zhang, Chengyuan Lin, Huaji Liu, Yafei Wang, Youyan Bian, Feng Xiong, Guohua Zhang. Study on Automatic Lithology Identification Based on Convolutional Neural Network and Deep Transfer Learning. 2024: 6, 322. https://doi.org/10.1007/s42452-024-06020-y.

[32]. Rafael Pires de Lima, Fnu Suriamin, Kurt J. Marfurt, and Matthew J. Pranter. Convolutional neural networks as aid in core lithofacies classification. 2019: 7(3).