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Few-Shot Intelligent Identification of Rock Thin Sections Based on SAM

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Abstract: Thin section rock identification is a complex task, primarily constrained by the extraction of complex minerals and the acquisition of large-scale labeled data. This paper proposes a thin section rock identification method designed for few-shot labeled data, which enables the segmentation and identification of various rock minerals with minimal labeled data. The SAM model is used for mineral particle extraction, combined with the focal loss function, transfer learning, and the integration of multiple classification models to identify thin sections. The prediction process is evaluated at multiple levels. Ultimately, the method achieved the extraction and identification of 11 minerals using only 38 labeled data samples, with an identification accuracy of 91%. This approach significantly reduces the cost of manual labeling, requiring only a small amount of labeled data and minimal training effort to identify specific mineral classes. The source code of the proposed method are available at <https://github.com/Xuerenbujianhua/SAMRocks>

Keywords: Few-shot; Rock thin section; Semantic Segmentation; Integrated learning

1. Introduction

Thin section rocks not only reflect the rock type, mineral composition, microstructure, grain size, sorting, and rounding of rocks but also reveal the pore-throat structure and other reservoir characteristics, making them an important basis for analyzing sedimentary environments. They are a crucial tool for geologists in studying rock genesis and geological evolution. Thin section rock identification is an indispensable part of geological research. Traditional thin section identification typically relies on manual visual inspection, which is inefficient and limited by the operator's experience, leading to potential inaccuracies. With the help of deep learning models, the automation of thin section rock analysis can be significantly improved, reducing human errors, minimizing subjective influence on the identification results, and enhancing both efficiency and accuracy. Researchers have employed image processing and deep learning techniques to extract information from thin section rocks, proposing various methods for rock classification, lithology identification, and mineral segmentation. These methods aim to accommodate multiple scenarios and tasks, greatly enhancing analysis speed and consistency, and driving the automation and quantitative progression of geological research.

In recent years, the intelligent identification of thin rock sections has garnered increasing attention in geological engineering and petroleum exploration. Traditional manual identification methods rely heavily on the expertise of geologists, who analyze the microscopic features of rocks under a microscope. These methods, however, suffer from inefficiencies, subjectivity, and difficulties in precise quantification. To improve the efficiency and accuracy of rock thin-section identification, numerous researchers have proposed various machine learning-based automated identification methods. Classification and segmentation are the two primary tasks in intelligent thin-section identification. Classification tasks (Xu et al. 2022Error! Reference source not found.) can be divided into two

categories: one focuses on categorizing entire thin sections by rock type, while the other involves classifying individual minerals. Segmentation refers to extracting mineral particles from an entire thin section and identifying their categories (Izadi et al. 2020; Tang et al. 2020). In terms of classification, methods such as ResNet-18 (Xu et al. 2020), MLP-NN (Borazjani et al. 2016), and the region-growing algorithm (Asmussen et al. 2015) have been effectively employed to identify minerals like sandstone and carbonate rocks. For segmentation tasks, approaches like support vector machine classifiers (Naseri and Resaei Nasab 2023), enhanced SLIC algorithms (Jiang et al. 2018), CNNs (Niu et al. 2020), and extinction consistency perception networks (Zhang et al. 2024) have been utilized to extract and identify minerals such as quartz and feldspar. These studies employ diverse datasets, including CPPID data and multi-angle polarized light images (Zhang et al. 2020; Obara 2007; Zhang et al. 2019). For classification, the Inception-v3 and Xception models (Ma et al. 2021) achieved 90% and 98.65% accuracy using datasets of 5,000 and 10,000 thin sections, respectively. The SENet model (Izadi et al. 2017) achieved 90.89% top-level classification accuracy on a hierarchical dataset containing 105 classes. For segmentation, support vector machine classifiers achieved 99.25% accuracy using 75 thin sections, while a model combining deep forest and K-means SMOTE (Zhu et al. 2023) reached 97.17% accuracy with 3,000 images. Karimpouli and Tahmasebi (Karimpouli and Tahmasebi 2019) generated 20,000 image instances from 20 Berea sandstone images using data augmentation techniques, which enabled the training, validation, and testing of a deep convolutional autoencoder network. Their model achieved 96% classification accuracy on the test set, demonstrating the feasibility of improving accuracy through data augmentation under low-label conditions for sandstone. Previous studies often used data derived from casting thin sections or thin sections of specific minerals (Iglesias et al. 2011). These methods, while effective for certain minerals, lack generalizability and transferability due to the

diverse and complex mineral compositions in rocks. Furthermore, training data requirements for classifying entire thin sections are substantial (Liu et al. 2022), and long training cycles are necessary due to the complexity of mineral compositions. The professional expertise required for semantic segmentation of thin sections adds to the challenge, as generating accurate segmentation labels is labor-intensive and difficult. To address these challenges, this study proposes a generalizable intelligent identification framework for thin rock sections. The proposed approach achieves multi-mineral recognition using only a minimal amount of labeled data, enabling the identification of various minerals with low labor and training costs. This framework is transferable across different study areas and mineral types, making it highly adaptable and cost-effective.

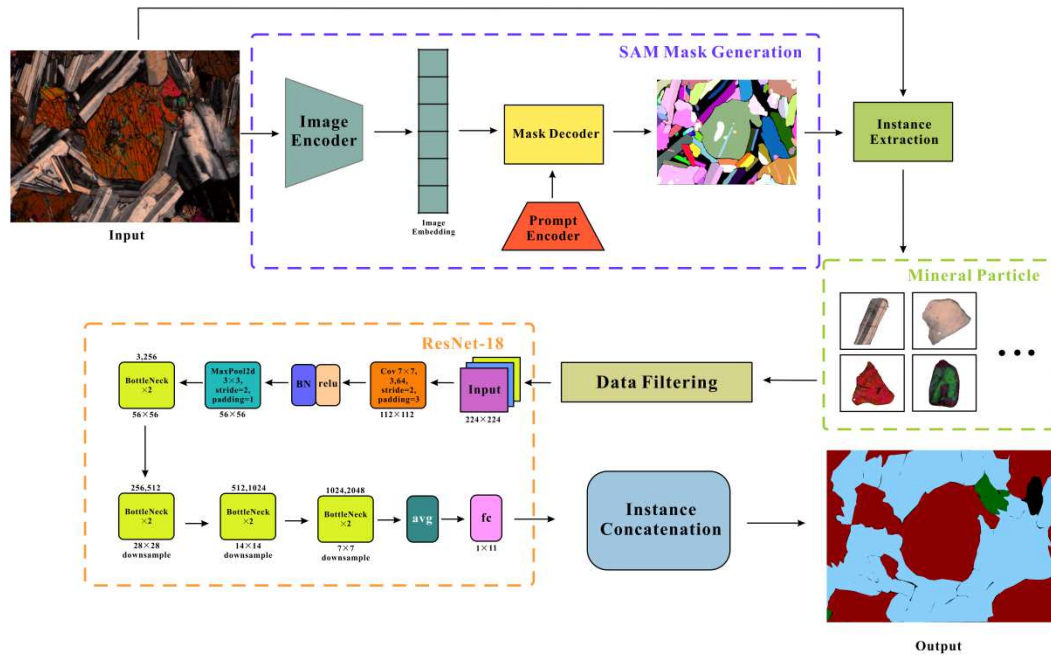


Fig.1: Model Architecture. Image extraction using pre-trained models, taking ResNet-18 as an example.

2. Materials and Methods

2.1 Dataset

To validate the adaptability and transferability of the proposed approach, the datasets used in this study were sourced from public available collections, covering multiple regions and different geological environments. These datasets include a wide range of thin section rock images, ensuring that the model can adapt to the geological characteristics of different areas and improve its generalization ability in real-world applications. The data was reorganized, classified, and statistically analyzed, with a selection of representative mineral types labeled manually by geological experts. The labeling process for each image took an average of 1.5 hours. A total of 38 labeled training images were obtained, containing 11 mineral types. The list of mineral categories and their corresponding labels is shown in Table 1.

2.2 Introduction to SAM

SAM (Segment Anything Model) is a general-purpose image segmentation model based on the Vision Transformer (ViT) architecture, which has been trained on large-scale datasets. The goal of the model is to simplify the image segmentation process, enabling users to quickly segment semantic information from images in various applications. Currently, SAM has been applied in multiple fields, such as tumor segmentation, organ recognition, autonomous driving, and virtual reality (VR), among others. Therefore, the model architecture for image identification of rock thin sections has been designed based on SAM model (Fig 1).

Although SAM has the capability for zero-shot segmentation, it still has many limitations in downstream tasks. As shown in Fig 2, for fine-grained segmentation tasks, some particles can be well segmented, while the segmentation performance degrades when the surrounding environment is darker.

However, there are many obstacles to overcome in order to improve the SAM model in the absence of labeled thin section rock data. Additionally, the segmentation results from SAM do not include semantic information, meaning the categories of mineral particles are not identified, which poses a severe challenge for rock thin section identification.

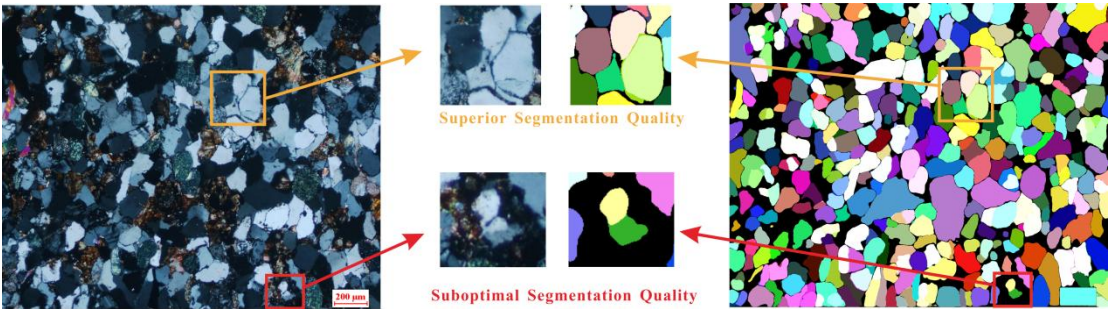


Fig.2: SAM particle segmentation results.

Table 1: Mineral types and thin section label count statistics.

Primary Category	Secondary Category	Tertiary Category	Fourth-Level Classification
Sedimentary Rock	Clastic Rock	Quartz Sandstone	Quartz
		Glaucinite Quartz Sandstone	Quartz
			Plagioclase
		Arkose	Muscovite
			Quartz
			Plagioclase
	Carbonate Rock	Feldspathic Sandstone	Quartz
		Dolomitic Rock	Plagioclase
			Muscovite
		Igneous Rock	Crystalline Rock
Dolomite			
Limestone	Quartz		
	Anhydrite		
Ultramafic Rock	Peridotite		Calcite
	Mafic Rock		Dolomite
Gabbro		Olivine	
		Quartz	
			Olivine
			Pyroxene

Metamorphic Rock	Intermediate Rock	Diorite	Plagioclase Hornblende Pyroxene Plagioclase Quartz Quartz
	Felsic Rock	Granite	Plagioclase Muscovite
	Hornfels	Andalusite Hornfels	Aphanocrystalline Cordierite
		Cordierite Hornfels	Aphanocrystalline
	Schist	Muscovite Schist	Quartz Muscovite

3. Experimental Process

3.1 Particle Extraction and Preprocessing

First, the SAM model is used to segment the rock thin section images, and mineral particles are extracted from the segmented images (Chen et al. 2023). However, SAM performs poorly in downstream tasks and suffers from over-segmentation, resulting in substantial noise in the particle extraction, such as 1x1 pixel images or mineral lines that do not contain meaningful mineral characteristic information. This increases the training burden and negatively impacts model performance. Therefore, it is necessary to filter the extracted mineral particle data. This is achieved by calculating the particle pixel area size and the proportion of valid information in the entire image, followed by area (pixel) filtering and line threshold filtering.

Additionally, due to the limited number of original labels and the small number of extracted particles, data augmentation is necessary to ensure the model's generalizability (Wang et al. 2022). The choice of data augmentation methods and the extent of augmentation can significantly affect model performance. Considering that the interference colors and shape features of different minerals under the microscope are critical for mineral identification, this study employs contrast, clarity, translation,

zooming, and rotation of five augmentation techniques (Fig 3) to increase the sample size and introduce noise without altering the crystal optical properties of the minerals.

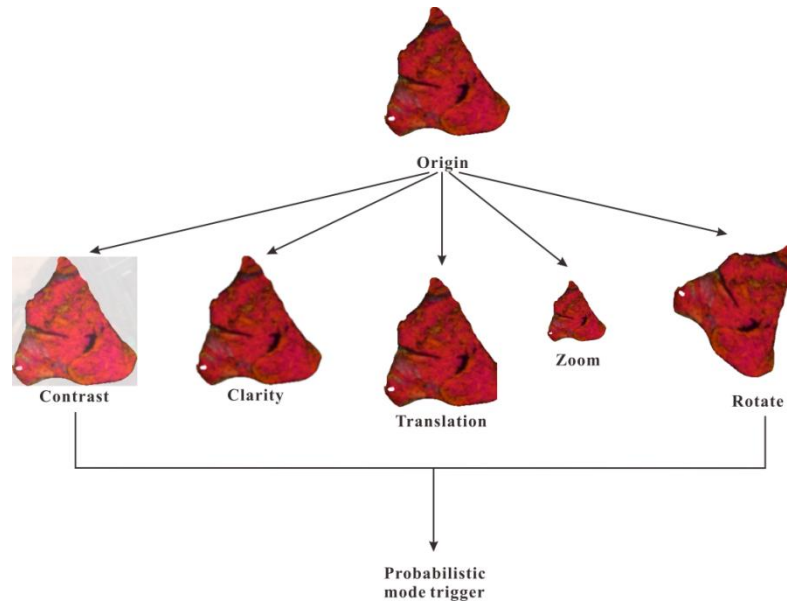


Fig.3: Data Augmentation Methods

3.2 Training Set Division

The scarcity of labeled data adds complexity to the evaluation of prediction results. To enable a reasonable assessment of the prediction outcomes, the data is divided in detail, and training and evaluation are conducted at three levels (Table 2).

First, the 38 thin section images are divided into a primary training set and test set. Thirty thin section images are used as the training set, while the remaining eight thin sections are used as the test set. The mineral species in both the training and test sets are consistent, and the training and test sets for the same mineral species are from the same region.

Next, particle extraction is performed on the 30 thin section images, which contain 12 categories (11 mineral species and 1 scale bar), resulting in the extraction of 4,129 mineral particles. These

particles are then divided into a secondary training set and test set in an 8:2 ratio, with the training set containing 3,303 mineral particles.

Finally, the secondary training set is augmented five times, and the augmented data is then divided into a tertiary training set and validation set in an 8:2 ratio. As a result, the training set contains 12,012 mineral particles. This division method evaluates the prediction quality at both the particle level (granular level) and the thin section level (pixel level), allowing for a more comprehensive assessment of the prediction results and model performance.

Table 2: Dataset division method.

Thin Section-Level Division	Number of Thin Sections	Particle-Level Division	Number of Particles	Data Augmentation	Quantity	Evaluation Level
First-Level Training Set	30	Second-Level Training Set	3,003	Third-Level Training Set	12,012	Particle-Level
				Third-Level Validation Set	3,003	Particle-Level
First-Level Test Set	8	Second-Level Test Set	751	\	\	Particle-Level
		\	\	\	\	Particle-Level

3.3 Particle Classification

3.3.1 Loss Function

The loss function plays a crucial role in the model, as it directly determines the optimization direction and final performance. Before constructing the model, the number of occurrences for each mineral category was counted. It was found that the frequency of different mineral particles in the thin sections varies significantly, resulting in severe data imbalance (Fig 4). This imbalance causes the model to focus more on the minerals that appear more frequently during training, while neglecting

those that appear less often, which severely impacts the model's generalization ability, training performance, and evaluation method. Therefore, we chose the focal loss as the model's loss function.

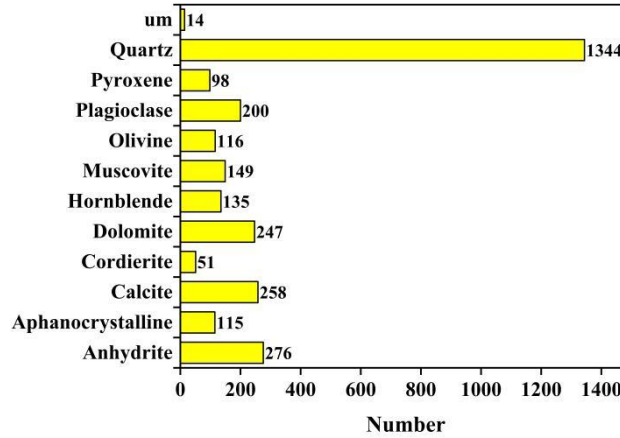


Fig.4: Bar chart of mineral categories and quantities in the Secondary Training Set before data augmentation.

Focal loss is a loss function designed to address class imbalance by improving upon the cross-entropy loss. It reduces the loss value for easily classified samples, allowing the model to focus more on hard-to-classify samples. Experiments have shown that focal loss outperforms both the cross-entropy loss function and the weighted cross-entropy loss function. Therefore, focal loss is adopted in model construction to tackle the data imbalance issue.

$$FL(p_t) = -\alpha_t(1 - p_t)^\gamma \log(p_t)$$

3.3.2 Transfer Learning

In the field of deep learning, a pre-trained image classification model refers to a deep neural network architecture that has been trained on a large-scale dataset. These models exhibit significant generalization capabilities by learning feature representations from a vast amount of image data.

Previous research has utilized various neural network architectures to classify rock thin section images.

However, this study focuses on a more detailed particle-level classification task, which has distinct data characteristics compared to previous research, thus requiring a re-evaluation of model performance.

Given this, the study adopts a transfer learning strategy, selecting five pre-trained models that have demonstrated excellent performance in rock thin section image classification. These models include ResNet-18, ResNet-50, ResNet-152, DenseNet-121, and MobileNetV2. These models were further trained and evaluated for performance in the context of this study.

Parameter settings play a crucial role in model training and image processing (Table 3). Specifically, a larger image size (img size) can provide more visual information but increases the computational complexity of the model. The batch size refers to the number of samples processed during each gradient update. A larger batch size helps obtain more stable gradient estimates but requires more memory resources. Conversely, a smaller batch size may speed up model iterations but can lead to larger fluctuations in gradients.

The learning rate controls the step size for each weight update. A learning rate that is too high may cause the model to skip over the global optimum during optimization, preventing convergence, while a learning rate that is too low results in an excessively slow training process and may cause the model to get stuck in a local optimum.

Additionally, the area and line thresholds are used during the data preprocessing phase to filter out unnecessary redundant information, directly influencing the quality of the training data. Due to the limited training data, data augmentation is necessary. However, a too-low augmentation factor may prevent the model from learning mineral features effectively, while a too-high factor may lead to overfitting. Therefore, reasonable parameter settings are essential. Through a series of experiments, this study determined a set of parameters that optimize the use of computational resources while

maintaining model performance. All experiments were conducted using these parameters to ensure the reliability and effectiveness of the results.

Table 3: Model Training Hyperparameter Settings.

Parameter Name	img size	batch size	Parameter Setting	Area	Line Threshold	Data Augmentation Factor
Parameter Setting	224*224	32	0.01	150	0.15	5

Given the complexity and diversity of rock mineral particles, different classification models may exhibit varying performance in the mineral particle recognition task. By analyzing the trends in training accuracy and loss values (Fig 5), it can be observed that all five pre-trained image classification models converge quickly and achieve high accuracy and low loss values in the later stages of training. Furthermore, as shown in Fig 6, although the models perform similarly in terms of accuracy and loss, there are significant differences in their training times.

Therefore, considering both training accuracy and training time as key factors, the ResNet-18, DenseNet-121, and MobileNet_v2 models are able to maintain high classification accuracy over a shorter training period. As shown in Fig 7, the prediction accuracy for all models on the validation set is above 90%. Furthermore, Fig 8 demonstrates that ResNet-18, DenseNet-121, and MobileNet_v2 perform well on the secondary test set, with the accuracy for each mineral exceeding 80%. These models not only effectively extract key data features of mineral particles from rock thin sections but also exhibit stronger generalization capabilities under the same experimental conditions, resulting in superior performance in mineral particle recognition tasks. Additionally, regardless of the length of the mineral test samples, the accuracy remains at a high level, effectively addressing the data imbalance issue.

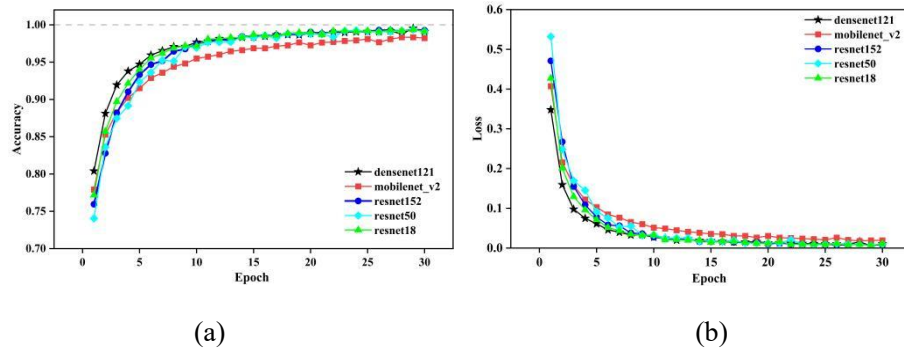


Fig.5: Training Accuracy and Loss Value Changes Across Different Models with Training Epochs..

(a) Training Accuracy Across Different Models with Training Epochs. (b) Loss Value Changes Across Different Models with Training Epochs.

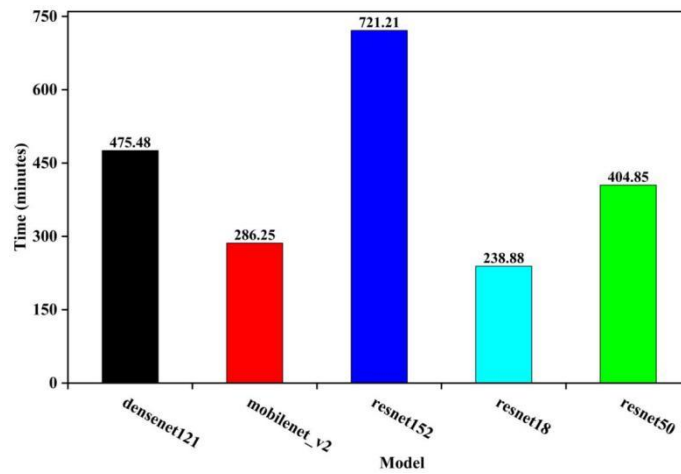


Fig.6: Comparison of Training Time Across Different Models

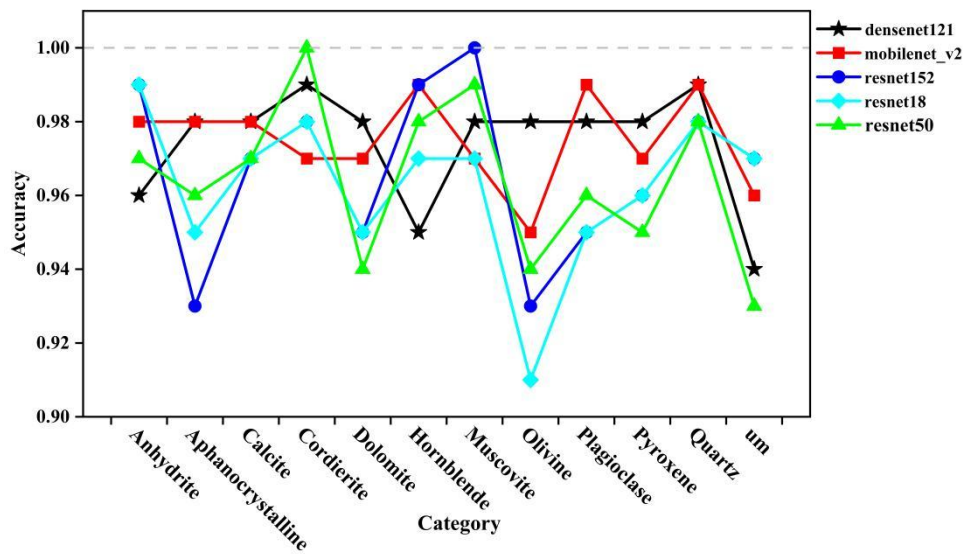


Fig.7: Mineral Particle Classification Accuracy on the Third-Level Validation Set.

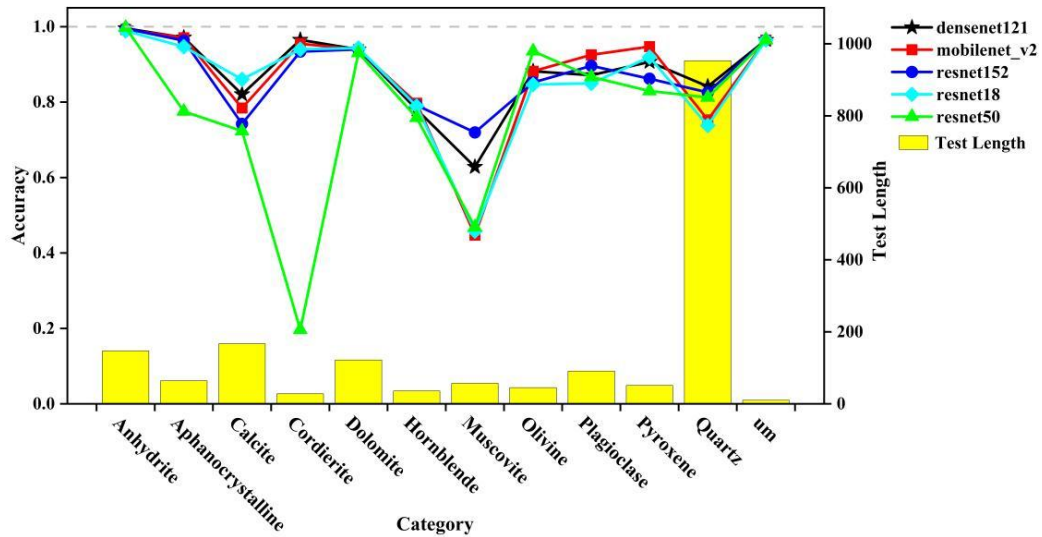


Fig.8: Mineral Particle Classification Accuracy on the Second-Level Test Set.

3.4 Integrated Model

By reintegrating the identified mineral particles back into the original rock thin section images, the particle segmentation and prediction results for the entire thin section can be obtained. Pixel-level evaluation is then performed using the labeled data from the test set. As shown in Fig 9, ResNet-18, MobileNet_v2, and DenseNet-121 perform well in recognizing most mineral categories. However, there are variations in recognition performance across different mineral categories. To enhance the model's generalization ability and improve the accuracy of prediction results, this study adopts a voting method to combine these three well-performing models, creating an ensemble model. This ensemble model achieves the highest recognition accuracy across all mineral categories.

Fig 10 shows the confusion matrix for the ensemble model's classification results, where a large number of elements concentrated along the diagonal indicate the high reliability of the model's classification outcomes. This result further confirms the advantages of the ensemble model in the mineral particle recognition task. By integrating the predictions from multiple models, the ensemble approach effectively improves both the accuracy and robustness of the recognition. This method not only fully leverages the complementary strengths of each model but also reduces the biases that may

239 exist in a single model, thereby yielding more stable and reliable results in the classification and
 240 recognition of mineral particles.

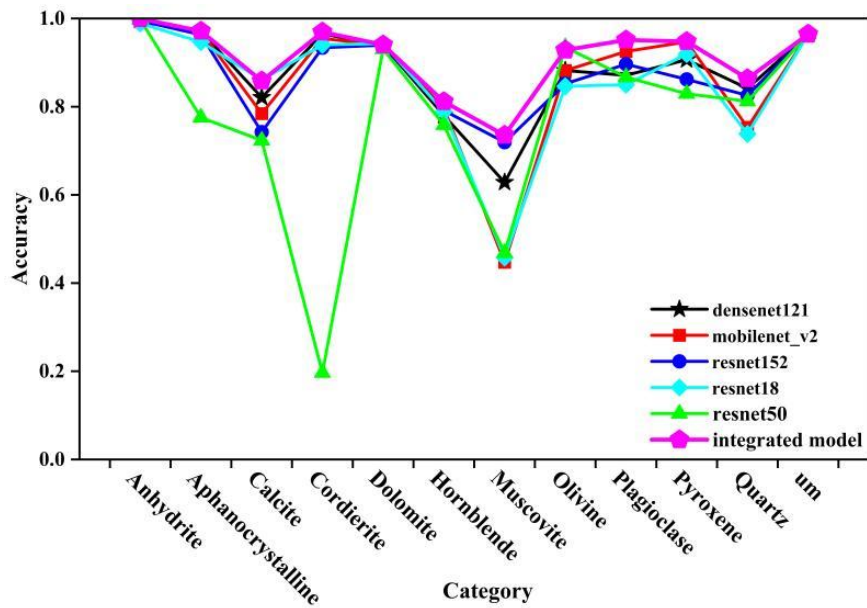


Fig.9: Accuracy on the First-Level Test Set

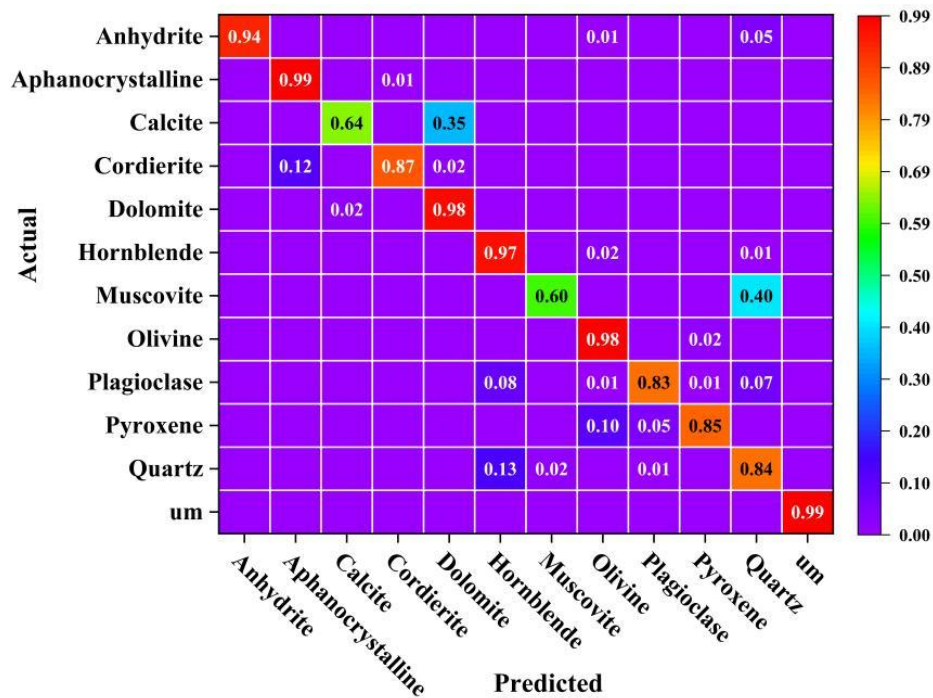


Fig.10: Confusion Matrix of the integrated model

4. Discussion

Based on the analysis above, this study successfully trained and evaluated a model capable of identifying 11 types of minerals using 38 rock thin section images. A multi-level evaluation method was employed to reduce the quantity of training data, which further validated the feasibility and reliability of the proposed approach. Specifically, as shown in Table 4, the highest accuracy for mineral identification at the particle level reached 86.1%, while the pixel-level accuracy was 91.1%.

Fig 11 shows the prediction results for different rock thin sections when SAM is combined with various classification models. Through model integration, the prediction accuracy was significantly improved. This phenomenon indicates that integrating the predictions from multiple models enhances overall recognition performance, bringing the results closer to the true labels.

Through the study, it was found that the lower bound of the final prediction accuracy is mainly constrained by three factors. First, the training images only utilized orthogonal light images of the rock thin sections, without incorporating polarized light images, resulting in a limited amount of information extracted from the images. Additionally, mineral colors in the thin section exhibit certain variations at different angles. The use of only a single orthogonal light image, rather than a sequence of orthogonal light images, leads to the loss of some mineral information, which causes a decrease in accuracy. Moreover, the segmentation results of the SAM model also impose certain limitations on the final accuracy. Some particles were not segmented, leading to incomplete particle coverage in the images and, consequently, a reduction in accuracy.

Nevertheless, overall, compared to the true labels, the ensemble model still achieved excellent prediction results.

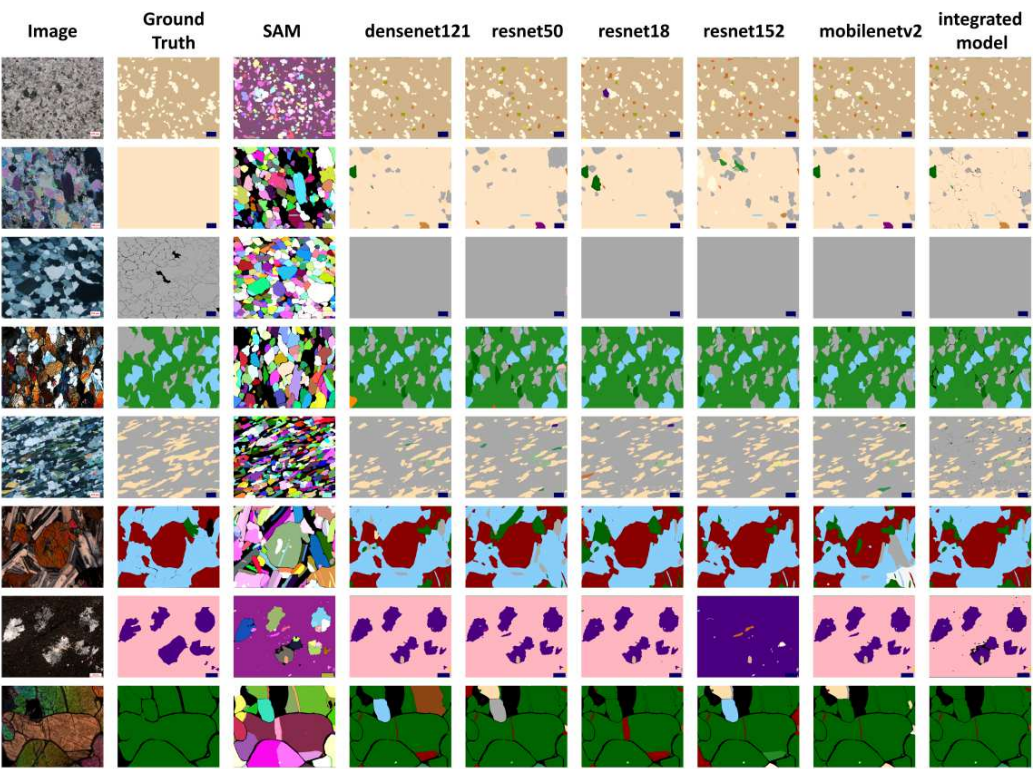


Fig.11: Final Segmentation and Prediction Results

These results indicate that, despite the limited number of training samples, the proposed model and method can effectively identify and classify mineral particles in rock thin sections. The high particle-level and pixel-level accuracy further confirm the model's effectiveness and robustness in mineral identification tasks. By comprehensively utilizing evaluation metrics at different levels, this study not only improved the model's performance but also enhanced the reliability of the results, providing a feasible solution for the automatic recognition of mineral particles in rock thin sections.

Table 4: Overall Accuracy at Different Levels

Thin Section-Level Division	Particle-Level Division	Data Augmentation	Evaluation Levels	densenet1 21	Resnet50	Resnet18	Resnet152	Mobilent_ v2	integrated model
First-Level Training Set	Second-Level Training Set	Third-Level Training Set	Particle-Level	\	\	\	\	\	\
		Third-Level	Particle-Level	0.98	0.97	0.97	0.97	0.98	\

		Validation Set							
First-Level Test Set	\		Particle-Level	0.859	0.846	0.855	0.833	0.855	0.861
	\	\	Pixel-Level	0.843	0.847	0.853	0.825	0.833	0.911
			1						

277 **5. Conclusions**

278 This study focuses on orthogonal light rock microscopic images, combining the SAM semantic
279 segmentation model with pre-trained classification models for mineral segmentation and identification
280 in rock thin sections. The main conclusions are as follows:

281 (1)Efficient Data Utilization: By training with only 30 labeled rock thin section images and testing
282 with 8 labeled images, this study successfully achieved the segmentation and identification of 11 types
283 of minerals. The overall prediction accuracy reached 91.1%, demonstrating the advantage of the
284 proposed method in terms of data utilization efficiency.

285 (2)Comprehensive Evaluation Process: A detailed evaluation process was established, conducting
286 a comprehensive assessment of the model’s prediction results from both particle-level and pixel-level
287 perspectives. This validated the rationality and reliability of the prediction results, providing solid
288 evidence to support the model's performance.

289 (3)Systematic Comparison and Model Integration: A systematic comparison of different image
290 classification models was performed for mineral particle recognition tasks. A voting method was used
291 to integrate the top-performing ResNet-18, MobileNet_v2, and DenseNet-121 models, resulting in an
292 ensemble model with higher prediction accuracy, further optimizing the recognition performance.

293 (4)Few-shot Identification Method: A rock thin section identification method suitable for few-shot
294 data was proposed. This method can complete mineral identification in rock thin sections under
295 conditions of limited thin section image labels and low-cost training.

296 This approach provides a solution to the problem of data augmentation for rock thin section image
297 labels, effectively addressing the difficulty of acquiring labeled thin section data. Through multi-angle
298 evaluation, the reliability of the prediction results was verified, offering new insights for the field of
299 rock thin section image analysis.

300

CRedit authorship contribution statement

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Zhengyu Wei, Qiang Du, Xinlong Li. Implement the training and validation code written by Zhuofeng Zhang. The supervision and manuscript correction were conducted by Qing Li. The first draft of the manuscript was written by Yuan Zhou and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- Asmussen, P., Conrad, O., Günther, A., Kirsch, M., & Riller, U. (2015). Semi-automatic segmentation of petrographic thin section images using a “seeded-region growing algorithm” with an application to characterize weathered subarkose sandstone. *Computers & Geosciences*, 83, 89–99. <https://doi.org/10.1016/j.cageo.2015.05.001>
- Borazjani, O., Ghiasi-Freez, J., & Hatampour, A. (2016). Two intelligent pattern recognition models for automatic identification of textural and pore space characteristics of the carbonate reservoir rocks using thin section images. *Journal of Natural Gas Science and Engineering*, 35, 944–955. <https://doi.org/10.1016/j.jngse.2016.09.048>
- Chen, T., Mai, Z., Li, R., & Chao, W. (2023). Segment Anything Model (SAM) Enhanced Pseudo Labels for Weakly Supervised Semantic Segmentation (No. arXiv:2305.05803). arXiv. <https://doi.org/10.48550/arXiv.2305.05803>
- Iglesias, J. C. A., Gomes, O. D. F. M., & Paciornik, S. (2011). Automatic recognition of hematite grains under polarized reflected light microscopy through image analysis. *Minerals Engineering*, 24(12), 1264–1270. <https://doi.org/10.1016/j.mineng.2011.04.015>
- Izadi, H., Sadri, J., & Bayati, M. (2017). An intelligent system for mineral identification in thin sections based on a cascade approach. *Computers & Geosciences*, 99, 37–49. <https://doi.org/10.1016/j.cageo.2016.10.010>
- Izadi, H., Sadri, J., Hormozzade, F., & Fattahpour, V. (2020). Altered mineral segmentation in thin sections using an incremental-dynamic clustering algorithm. *Engineering Applications of Artificial Intelligence*, 90, 103466. <https://doi.org/10.1016/j.engappai.2019.103466>
- Jiang, F., Gu, Q., Hao, H., Li, N., Wang, B., & Hu, X. (2018). A method for automatic grain

337 segmentation of multi-angle cross-polarized microscopic images of sandstone. *Computers &*
338 *Geosciences*, 115, 143–153. <https://doi.org/10.1016/j.cageo.2018.03.010>

339 Karimpouli, S., & Tahmasebi, P. (2019). Segmentation of digital rock images using deep convolutional
340 autoencoder networks. *Computers & Geosciences*, 126, 142–150.
341 <https://doi.org/10.1016/j.cageo.2019.02.003>

342 Liu, H., Ren, Y.-L., Li, X., Hu, Y.-X., Wu, J.-P., Li, B., Luo, L., Tao, Z., Liu, X., Liang, J., Zhang, Y.-Y.,
343 An, X.-Y., & Fang, W.-K. (2022). Rock thin-section analysis and identification based on artificial
344 intelligent technique. *Petroleum Science*, 19(4), 1605–1621.
345 <https://doi.org/10.1016/j.petsci.2022.03.011>

346 Ma, H., Han, G., Peng, L., Zhu, L., & Shu, J. (2021). Rock thin sections identification based on
347 improved squeeze-and-Excitation Networks model. *Computers & Geosciences*, 152, 104780.
348 <https://doi.org/10.1016/j.cageo.2021.104780>

349 Naseri, A., & Rezaei Nasab, A. (2023). Automatic identification of minerals in thin sections using
350 image processing. *Journal of Ambient Intelligence and Humanized Computing*, 14(4), 3369–3381.
351 <https://doi.org/10.1007/s12652-021-03474-5>

352 Niu, Y., Mostaghimi, P., Shabaninejad, M., Swietojanski, P., & Armstrong, R. T. (2020). Digital Rock
353 Segmentation for Petrophysical Analysis With Reduced User Bias Using Convolutional Neural
354 Networks. *Water Resources Research*, 56(2), e2019WR026597.
355 <https://doi.org/10.1029/2019WR026597>

356 Obara, B. (2007). A new algorithm using image colour system transformation for rock grain
357 segmentation. *Mineralogy and Petrology*, 91(3–4), 271–285.
358 <https://doi.org/10.1007/s00710-007-0200-x>

359 Tang, D. G., Milliken, K. L., & Spikes, K. T. (2020). Machine learning for point counting and
360 segmentation of arenite in thin section. *Marine and Petroleum Geology*, 120, 104518.
361 <https://doi.org/10.1016/j.marpetgeo.2020.104518>

362 Wang, B., Han, G., Ma, H., Zhu, L., Liang, X., & Lu, X. (2022). Rock thin sections identification under
363 harsh conditions across regions based on online transfer method. *Computational Geosciences*,
364 26(6), 1425–1438. <https://doi.org/10.1007/s10596-022-10174-2>

365 Xu, Y., Dai, Z., & Luo, Y. (2020). Research on Application of Image Enhancement Technology in
366 Automatic Recognition of Rock Thin Section. *IOP Conference Series: Earth and Environmental*
367 *Science*, 605(1), 012024. <https://doi.org/10.1088/1755-1315/605/1/012024>

368 , Z., Ma, W., Lin, P., & Hua, Y. (2022). Deep learning of rock microscopic images for intelligent
369 lithology identification: Neural network comparison and selection. *Journal of Rock Mechanics*
370 *and Geotechnical Engineering*, 14(4), 1140–1152. <https://doi.org/10.1016/j.jrmge.2022.05.009>

371 Zhang, P., Zhou, J., Zhao, W., Li, X., & Pu, L. (2024). The edge segmentation of grains in thin-section
372 petrographic images utilising extinction consistency perception network. *Complex & Intelligent*
373 *Systems*, 10(1), 1231–1245. <https://doi.org/10.1007/s40747-023-01208-y>

374 Zhang, Y., Li, M., Han, S., Ren, Q., & Shi, J. (2019). Intelligent Identification for Rock-Mineral
375 Microscopic Images Using Ensemble Machine Learning Algorithms. *Sensors*, 19(18), 3914.
376 <https://doi.org/10.3390/s19183914>

377 Zhang, Y., Zhong, H.-R., Zhang, X., Gao, S.-C., & Zhang, D. (2020). Orthogonal microscopy image
378 acquisition analysis technique for rock sections in polarizer angle domain. *Journal of Structural*
379 *Geology*, 140, 104174. <https://doi.org/10.1016/j.jsg.2020.104174>

380 Zhu, X., Zhang, H., Ren, Q., Zhang, D., Zeng, F., Zhu, X., & Zhang, L. (2023). An automatic

- 381 identification method of imbalanced lithology based on Deep Forest and K-means SMOTE.
- 382 Geoenergy Science and Engineering, 224, 211595. <https://doi.org/10.1016/j.geoen.2023.211595>