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IDENTIFICATION OF ROCK GEOLOGY IN AN IMAGE USING DEEP LEARNING

[1]Mrs.G.SWETHA , [2]P.KEERTHANA, [3]T.KAVYA SREE, [4]S. RAKSHITHA.

[1]Assistant Professor, Teegala Krishna Reddy Engineering College, Hyderabad.

[2,3,4]B,tech scholar, Teegala Krishna Reddy Engineering College, Hyderabad.

Abstract

The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. Deep learning is receiving significant research attention for pattern recognition and machine learning. Its application here has effectively identified rock types from images captured in the field. This paper proposes an accurate approach for identifying rock types in the field based on image analysis using deep convolutional neural networks. The proposed approach can identify six common rock types with an overall classification accuracy of 97.96%, thus outperforming other established deep-learning models and a linear model. The results show that the proposed approach based on deep learning represents an improvement in intelligent rock-type identification and solves several difficulties facing the automated identification of rock types in the field.

KEYWORDS: Deep learning; Convolutional neural network; Rock types; Automatic identification.

1 . INTRODUCTION

Rocks are a fundamental component of Earth. They contain the raw materials for virtually all modern construction and manufacturing and are thus indispensable to almost all the endeavors of an advanced society. In addition to the direct use of rocks, mining, drilling, and excavating provide the material sources for metals, plastics, and fuels. Natural rock types have a variety of origins and uses. The three major groups of rocks (igneous, sedimentary, and metamorphic) are further divided into sub-types according to various characteristics. Rock type identification is a basic part of geological surveying and research, and mineral resources exploration. It is an important technical skill that must be mastered by students of geoscience.

1.1 MOTIVATION

A rock geology project is an exciting opportunity to delve into the fascinating world of rocks and uncover the secrets they hold. By studying different rock formations, you can gain insights into Earth's history and the processes that have shaped our planet over millions of years. In this project, we can analyze the composition, texture, and structure of rocks to understand the geological processes that occurred in a particular area. By examining the minerals present in rocks, we can determine the conditions under which they formed and the forces that acted upon them.

1.2 PROBLEM STATEMENT

Rock geology project is to investigate and analyze different rock formations in order to understand the geological processes that have shaped our planet. By examining the composition, texture, and structure of rocks, we aim to uncover valuable insights into Earth's history and the forces that have influenced its evolution. Through this project, we hope to deepen our understanding of the dynamic nature of our planet and contribute to the field of geology.

1.3 PROJECT OBJECTIVES

1. Understanding Earth's History: By studying different rock formations, you can gain insights into the geological processes that have occurred over time and learn about the changes our planet has undergone.

2. Exploring Rock Formation Processes: Analyzing the composition, texture, and structure of rocks can help you understand how they were formed and the forces that acted upon them, such as weathering, erosion, and tectonic activity.

3. Identifying Geological Features: By studying rocks, you can identify and interpret geological features like fault lines, fossils, and layers in sedimentary rocks, which can provide valuable information about past environments and events.

4. Investigating Earth's Resources: Geology plays a crucial role in identifying and assessing Earth's resources, such as minerals, ores, and fossil fuels. A rock geology project can help you understand the distribution and formation of these resources.

5. Enhancing Scientific Skills: Conducting a rock geology project can improve your scientific skills, including observation, data collection, analysis, and critical thinking. It also provides an opportunity for hands-on learning and fieldwork.

2 . LITERATURE SURVEY

A literature survey on rock geology identification using deep learning involves reviewing relevant studies and research articles in the field. Some key areas to explore include:

Introduction To Deep Learning In Geology: Understand how deep learning techniques, such as convolutional neural networks (CNNs), have been applied in geology and remote sensing.

Previous Rock Identification Approaches: Examine traditional methods for rock identification and classification to provide a baseline for comparing deep learning approaches.

Deep Learning Architectures: Explore various deep learning architectures used in geology image analysis, such as CNNs, recurrent neural networks (RNNs), or hybrid models.

Datasets Used in Rock Geology Studies: Investigate datasets employed for training and testing deep learning models in rock identification. Analyze their characteristics and limitations.

Feature Extraction Techniques: Review feature extraction methods specific to rock geology images, considering geological textures, mineral composition, and structural patterns.

Performance Metrics: Examine the evaluation metrics used in assessing the performance of deep learning models for rock identification. This could include accuracy, precision, recall, F1 score, etc.

Transfer Learning in Rock Geology: Explore studies employing transfer learning techniques in rock geology image analysis, leveraging pre-trained models for improved performance.

Challenges and Limitations: Identify challenges faced in applying deep learning to rock geology, such as data scarcity, interpretability, or issues related to specific geological contexts.

Integration with Remote Sensing Data: Investigate how deep learning models are integratedwith remote sensing data for a comprehensive understanding of geological features.

Recent Advances and Future Directions: Summarize the latest advancements in the field and identify potential areas for future research, addressing gaps and proposing

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innovative approaches.Remember to cite the relevant papers and studies in your literature survey to provide a comprehensive overview of the current state of deep learning applications in rock geology identification from images.

3 . SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE

Developments in deep learning technology have allowed continuous improvements to be made in the accuracy of CNNs models. Such advances have been gained by models becoming ever deeper, which has meant that such models demand increased computing resources and time. This paper proposes a RTCNNs model for identifying rock types in the field. The computing time of the RTCNNs model is much less than that of a model 10 or more layers. The hardware requirements are quite modest, with computations being carried out with commonly used device CPUs and Graphics Processing Units (GPUs). The RTCNNs model includes six layers.

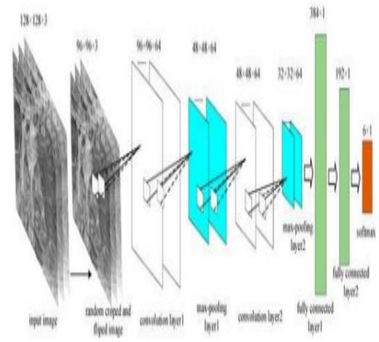

Fig 1.The Rock Types deep CNNs (RTCNNs) model for classifying rock type in the field.

Before feeding the sample images into the model, Random_Clip and Random_Flip operations are applied to the input samples. Each part of the image retains different feature of the target object. Random clipping can reserve the different features of the image. For example, partition A of the image shown in records smaller changes in grain size of mylonite, in which quartz particles do not undergo obvious deformation, while partition B records larger tensile deformation of quartz particles, and the quartz grains in the partition C are generally larger. In addition, in the proposed model, each layers of training have fixed size parameters, such as the input size of convolution layer1 is 96 × 96 × 3, while the output size of feature is 96 × 96 × 64. The input images are cropped into sub-images with given size, while the given size is less. In the proposed model, the cropped size is

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$96 \times 96 \times 3$, while the input size is $128 \times 128 \times 3$.

Through the random clipping operation of fixed size and different positions, different partitions of the same image are fed into the model during different training epochs. The flipping function can flip the image horizontally randomly. Both clipping and flipping operations are realized through the corresponding functions of TensorFlow deep learning framework. The sample images fed into the model are therefore different in each epoch, which expands the training dataset, improving the accuracy of the model and avoiding overfitting. Before performing patch-based sampling, the various features of the rock are spread all over the entire original field-captured image. The experiments described shows that a smaller convolution kernel can filter the rock features better than the bigger kernel of other models. As a consequence, the first convolutional layer is designed to be 64 kernels of size $5 \times 5 \times 3$, followed by a max-pooling layer, which can shrink the output feature map by 50%. A Rectified Linear Unit activation function is then utilized to activate the output neuron. The second convolutional layer has 64 kernels of size $5 \times 5 \times 64$ connected to the outputs of the ReLU function, and it is similarly followed by a maxpooling layer. Below this layer, two fully connected layers are designed to predict six classes of field rock, and the final layer consists of a six-way Softmax layer. Detailed parameters of the model, as obtained by experimental optimization, are listed. A convolution layer extracts the features of the input images by convolution and outputs the feature maps. It is composed of a series of fixed size filters, known as convolution kernels, which are used to perform convolution operations on image data to produce the feature maps. $hkij$ = $\sum i \in M((wk \times x)ij+bk)h$??? = ∑?∈??((??×?)??+??)(1) where k? represents the k?th layer, hh represents the value of the feature, (i, j) are coordinates of pixels, wk?? represents the convolution kernel of the current layer, and bk? is the bias. The parameters of CNNs, such as the bias (bk)(??) and convolution kernel (wk),(??), are usually trained without supervision . Experiments optimized the convolution kernel size by comparing sizes of 3×3, 5×5, and 7×7; the 5×5 size achieves the best classification accuracy. The number of convolution kernels also affects the accuracy rate, so 32, 64, 128, and 256 convolution kernels were experimentally tested here. The highest accuracy is obtained using 64 kernels. Based on these experiments, the

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RTCNNs model adopts a 5 × 5 size and 64 kernels to output feature maps.

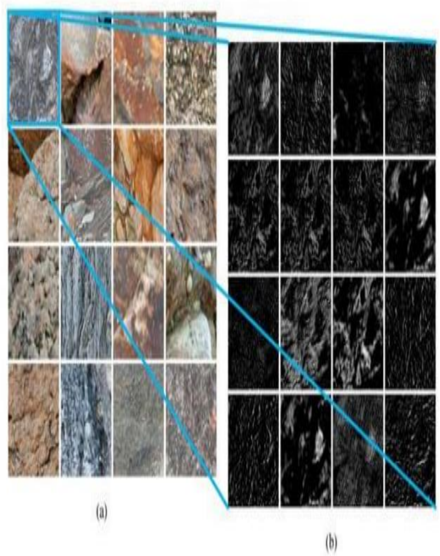

Fig 2. Learned rock features after convolution by the RTCNNs model.

(a) Input patched field rock sample images. (b) Outputted feature maps partly after the first convolution of the input image, from the upper left corner in (a) shows the feature maps outputted from the convolution of the patched field images a depicts the patch images from field photographs inputted to the proposed model during training, and shows the edge features of the sample patches learned by the model after the first layer convolution. The Figure indicates that the RTCNNs model can automatically extract the basic features of the images for learning

3.2 PROPOSED SYSTEM

The main steps for classifying field samples are acquiring images, collecting typical rock-type images, establishing databases of rock-type images, setting up deep learning neural networks, and identifying rock types.

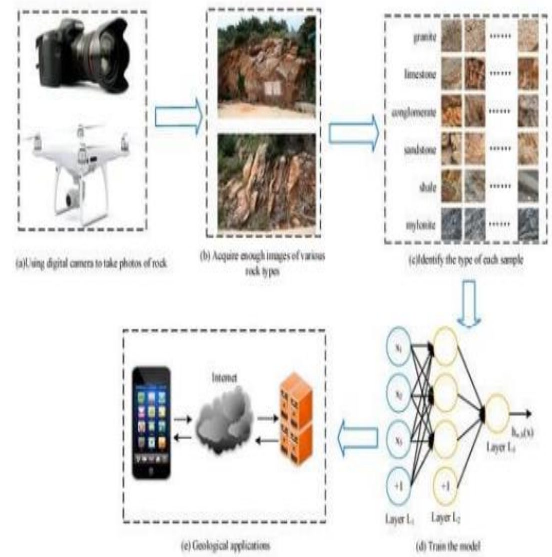

Figure 3. Whole flow chart for the automated identification of field rock types.

(a) Cameras: Canon EOS 5D Mark III (above) and a Phantum 4 Pro DJi UAV with FC300C camera (below). (b) Rock images obtained from outcrops. (c) Cutting images (512 × 512 pixels) of marked features from the originals. (d) Rock-type identification training using CNNs. (e) Application of the trained model to related geological fields.

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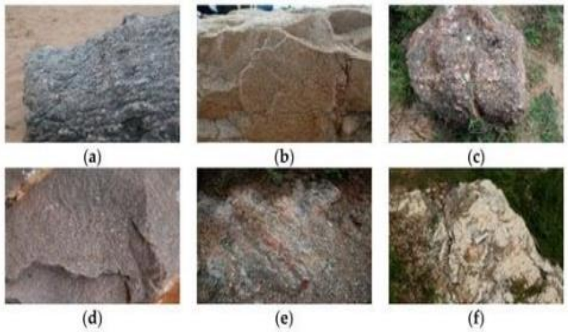

Fig 4. Types of rocks

The six types of rock in the field: (a) mylonite, (b) granite, (c) conglomerate, (d) sandstone, (e) shale, and (f) limestone.The photographic image capture used different subject distances and focal lengths for different rock types to best capture their particular features. For example, for conglomerates with large grains, the subject distance was 2.0 m, and the focal length was short (e.g., 20 mm), so that the structural characteristics of these rocks could be recorded. For sandstones with smaller grains, the subject distance was 0.8 m with a longer focal length (e.g., 50 mm), allowing the grains to be detectable. A total of 2290 images with typical rock characteristics of six rock types were obtained: 95 of mylonite, 625 of granite, 530 of conglomerate, 355 of sandstone, 210 of shale, and 475 of limestone. These six rock types include four sedimentary rocks (conglomerate, sandstone, shale, and limestone), one metamorphic rock (mylonite), and one igneous rock (granite). After every three samples, one sample was selected as the validation date, and then another sample as selected as the testing data, so 60% of the images of each rock type were selected for the training dataset, 20% for the validation dataset, and leaving 20% for the testing dataset. While training the GoogLeNet Inception V3 model, the final FC layer is trained. For VGGNet16 model, the final FC7 and FC8 layers are trained. The experimental results show that the RTCNNs model proposed in the present study achieved the highest overall accuracy (97.96%) on the testing dataset.

4 . OUTPUT SCREENS

Test case -1:

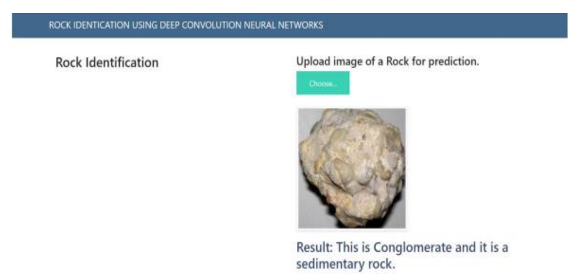

Fig 5. Uploading image and getting result

Sedimentary rocks are types of rock that are formed by the accumulation or deposition of mineral or organic particles at Earth's surface, followed by cementation.

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Sedimentation is the collective name for processes that cause these particles to settle in place. The particles that form a sedimentary rock are called sediment, and may be composed of geological detritus (minerals) or biological detritus (organic matter). The geological detritus originated from weathering and erosion of existing rocks, or from the solidification of molten lava blobs erupted by volcanoes. The geological detritus is transported to the place of deposition by water, wind, ice or mass movement, which are called agents of denudation. Biological detritus was formed by bodies and parts (mainly shells) of dead aquatic organisms, as well as their fecal mass, suspended in water and slowly piling up on the floor of water bodies (marine snow). Sedimentation may also occur as dissolved minerals precipitate from water solution

Fig 6. Uploading image and getting result

Metamorphic rocks started out as some other type of rock, but have been substantially changed from their original igneous, sedimentary, or earlier metamorphic form. Metamorphic rocks form when rocks are subjected to high heat, high pressure, hot mineral-rich fluids or, more commonly, some combination of these factors. Conditions like these are found deep within the Earth or where tectonic plates meet.

Test case -2:

Test case -3:

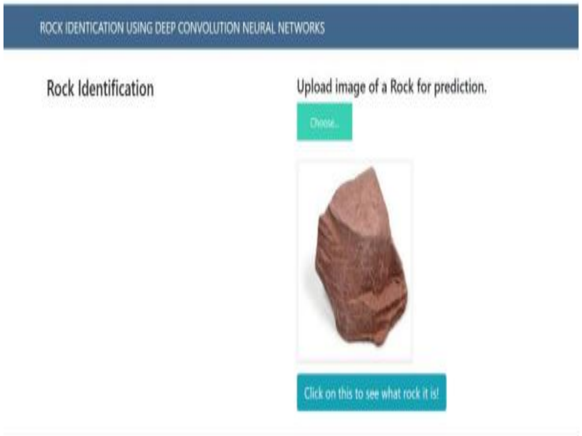

fig 7. Uploading Image

5 . CONCLUSION

In this study, a prediction model of rock identification was established by Convolutional Neural Network. A total of 500 sample data collected from the experimental test were used to develop the CNN model for predicting the type of rock. The CNN was first calibrated and then verified using the experimental data from rock images. So, to wrap it up, the study of rock geology involves using various testing methods like visual inspection, petrographic analysis, X-ray diffraction, X-ray fluorescence, spectroscopy, and field observations. These techniques help us understand the type of rocks, their mineral composition, and the overall geological context. By combining these methods, we can gain a comprehensive understanding of rock formations. In conclusion, the identification of rock geology involves a systematic analysis of various characteristics such as mineral composition, texture, color, and structural features. By combining field observations with laboratory tests, geologists can accurately classify and interpret rocks, providing valuable insights into Earth's geological history and processes.

6 . FUTURE ENHANCEMENT

To enhance rock geology identification in the future, incorporating advanced machine learning algorithms could improve accuracy. Integration of real-time geological data, such as seismic and geochemical information, might also enhance the precision of rock identification systems. Additionally, incorporating portable spectroscopy or imaging devices for field analysis could provide more comprehensive data for accurate geologic classification. When it comes to future enhancements for the identification of rock geology in detail, there are a few exciting possibilities to consider:

ADVANCED IMAGING TECHNIQUES: Developments in imaging

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technologies, such as hyper spectral imaging or 3D scanning, can provide more detailed and accurate information about the rocks' textures, mineralogy, and structures.

MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE: Implementing machine learning algorithms and AI models can help automate the identification process by analyzing large datasets of rock samples and identifying patterns that humans might miss. This can speed up the identification process and improve accuracy.

PORTABLE FIELD INSTRUMENTS: The development of portable and handheld instruments, such as XRF or Raman spectrometers, can enable real-time analysis of rock samples in the field. This allows geologists to gather data on-site and make quick decisions during fieldwork.

INTEGRATION OF GEOGRAPHIC INFORMATION SYSTEMS (GIS): By combining rock geology data with GIS technology, geologists can create detailed maps and models that provide a comprehensive understanding of rock formations, their distribution, and their geological history.

COLLABORATION AND DATA SHARING: Enhancing collaboration among geologists and creating platforms for data sharing can help build a larger and more diverse dataset for rock geology. This can lead to more accurate identifications and a deeper understanding of geological processes. These are just a few potential future enhancements in the field of rock geology identification.

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