MINERALS CLASSIFICATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract - *Fast and reliable identification of mineral is important for various applications like geological prospecting, mineral and engineering sciences, physics and other analytical studies. Minerals can be classified in a variety of ways, such as visually under a microscope, or by chemical analysis. The main objective of the paper is to identify and categorize seven classes of minerals using computational method. In this paper, Convolutional Neural Network(CNN) model is used to classify the minerals. The VGG-16 is one of the most popular CNN models for image classification. The overall performance shows 81% of accuracy for mineral classification.*

***Key Words*: Minerals, Mining, Petrography, EfficientNet.**

1.INTRODUCTION

Minerals are all around us. Minerals are formed from natural process and are also extracted from their source materials. Their growth are controlled by various physical and chemical conditions including the mass-balance, temperature, pressure, depth or other factors of the circumstances. Minerals are naturally formed compounds, having a definite chemical composition and naturally occurring inorganic substances. Minerals are usually a specific crystal structure, that occurs naturally in pure form. Due to sophisticated improvements in geoscientific technologies, fast mineral identification is required for certain tasks such as mining, petrography and engineering geology. Minerals are used for several purposes as they provide fuel to industries like natural gas and petroleum. Minerals being a vital factor in economic growth, the necessity to improve the identification and classification of minerals is mandatory.

The image classification is a technique that categorizes images into a given number of classes. In image classification problem, where an entire image is assigned a label. It receives input images and predict the image with its label. Earlier in image classification domain, various machine learning algorithms like Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Naïve Bayes (NB), Binary Decision Tree (BDT) and Discriminant Analysis (DA)are used [6].

In recent years, Deep learning improvises the accuracy in image classification. Deep learning is a subset of machine learning in which a model learns from images to perform classification tasks. Deep learning is typically implemented using neural network architecture. The convolutional neural network gives a great success in the image classification domain in past years. Convolutional Neural Networks (CNNs) are the backbone of image classification that takes an input image and assigns it a class and a label that makes it unique. The convolutional neural network follows a hierarchical model which is learned spatial features using convolutional layers and finally gives out a fully-connected layer to classify the classes.

This paper is organized as follows. In Section 2, related work is discussed. Section 3 describes the proposed method and in Section 4 experimental results are analyzed for mineral classification. Conclusion is given in section 5.

2. RELATED WORK

This related work concentrates on the application of convolutional neural network in various fields of image classification. VGG16 based convolutional neural network[2] to classify the weld defect image tomato crop[7]. Tomato crop disease classification has been performed with the PlantVillage dataset using pretrained deep learning model viz AlexNet and VGG16 net. This analysis carried out to classify 26 different diseases in 14 crop species using 54,306 images. The accuracy of classification for AlexNet 97.49% and VGG16 net 97.23%. The pretrained VGG16 neural network is to classify batik patterns[8] . To perform batik classification VGG16 architecture for extracting feature from batik image. The classification is done using random forest as a classifier which is based on the voting method. This analysis produced 97.22% ± 2.42 of precision, 98.47% ± 1.91 of recall, 97.76% ± 2.65 of F-score, and 97.68% ± 2.71 of accuracy. VGG16 based weld defect images classification method [5]. This paper investigated with two main flaws, blow holes or solid inclusion and transversal cracks, as defects to be classified. Then pre-processed data set is divided into into train data set, validation data set and test data set with 9000, 3000 and 3000 images. Using VGG method, this analysis produced 97.6% test accuracy and 100% train accuracy on two main defects.

This related work describes the minerals classification based on mohs hardness and it also investigate the rock classification in petrographic thin sections. Concatenated convolutional neural network (Con-CNN) method is used for classifying the geologic rock type based on petrographic thin sections [11]. This analysis have 13 types of 92 rock samples, 196 petrographic thin sections, 588 images, and 63504 image patches for the training and validation. The five-folds cross validation provides an overall accuracy of 89.97%. R-CNN method to find out the rock type using 8 kinds of rocks images (1034 images) [9] . In R-CNN method, VGG16 model was used to extract and train the rock images. The experiment result reveals that the classification with VGG16 model has 80% of accuracy and also it provides strong robustness and generalization ability. The petrographic thin section image dataset for rock forming mineral identification using Mask R-CNN [10]. In Mask R-CNN algorithm, ResNet-50 and ResNet-101 model were selected to estimate the mineral classification. Also, the analysis was carried out based on data with and without affected by lighting on polarizing microscope. The result reveals that the ResNet-101 has higher precision value of 58 % than ResNet-50 model. The mineral images and the Mohs hardness in the deep neural networks to identify the minerals using EfficientNet-b4 [12]. EfficientNet-b4 extracts image features automatically classify the minerals. The experimental results showed that the method can reach 94.0% Top-1 accuracy and 99.9% Top-5 accuracy for 28 types of minerals. The 8 kinds of rocks images (1034 images) were classified based on R-CNN method[10]. In R-CNN method, VGG16 model was used to extract and train the rock images. This paper verified that the rock classification using VGG16 model was correctly identify the single type of rock classification and was more than 90 % of accuracy. The experiment result reveals that the classification with VGG16 model has 80 % of accuracy and also it provides strong robustness and generalization ability. The intelligent system for mineral identification in thin sections is proposed based on RGB and HSI color spaces[4] . The proposed system has two phases. In first phase the segmentation is done and the second phase produced mineral clusters are identified based on a cascade approach. Finally, The proposed system yields a over all accuracy 93.81%. The colored and colorless images using Artificial Neural Network (ANN) to identifying mineral type [1]. In this system 12 parameters were used in RGB and HSV analysis. The experiment on HSV data images reveals that, the Artificial Neural Network (ANN) failed to find some feature because of same color. The experiment result of Artificial Neural Network algorithm rely on the quality and quantity of trained data. The result reveals that the mineral identification using Artificial Neural Network has accuracy of more than 90 %. Also the texture parameters and fuzzy logic classifier were suggested to be used for better and improved accuracy.

3.PROPOSED SYSTEM

The proposed system was implemented using VGG16 model to classify the minerals. The steps involved in the proposed system is given in Fig 1.The proposed system has five modules. Viz Data collection, Data Pre-processing, Data Modeling, Train and Test the model and Performance Analysis.

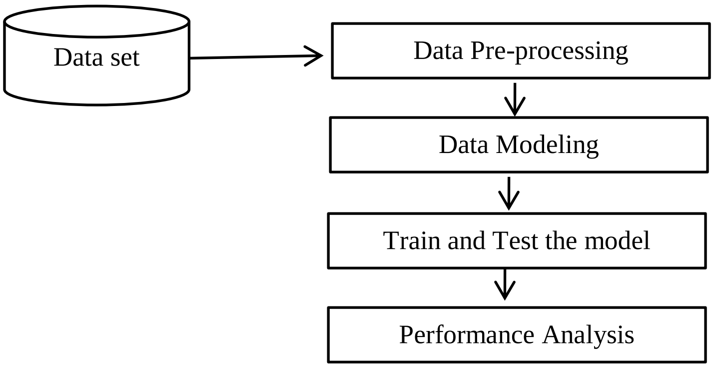

Fig -1: Proposed system

3.1 Data Collection

Minerals identification dataset [13] was used in analysis of minerals classification. This mineral image dataset created by Albert Klu from the Geological engineering department of the University of Mines and Technology, Tarkwa. The data set have seven classes of minerals. The seven classes are Biotite, Bornite, chrysocolla, Malachite, Muscovite, Pyrite and Quartz.

3.2 Data pre-processing

The purpose of pre-processing is to improve the present features of image and reduce the noise and distortions. Data augmentation like resize, rotation, cropping and flipping are applied to the input images to make them convenient for further processing. The VGG16 network accepts an input image of size 224x224 and the images are converted to tensor and normalized to the range [1,-1].

3.3 Data Modeling

In this paper mineral classification is implemented using Convolutional neural network with VGG16 model.

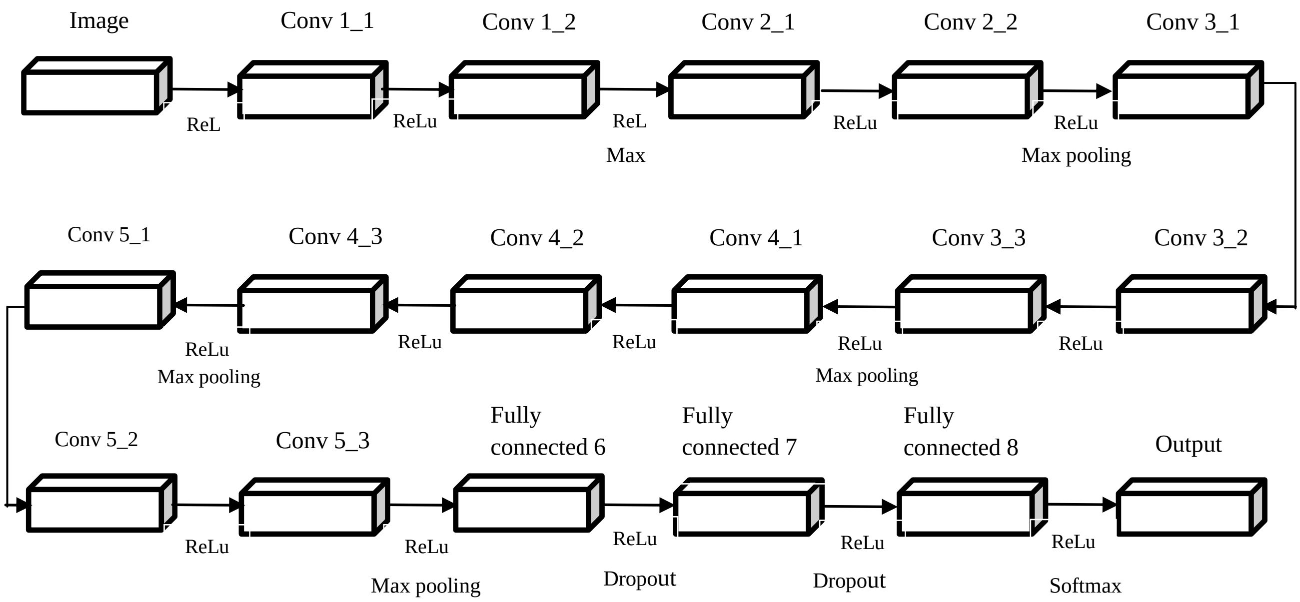

Fig -2: VGG16 model

The VGG16neural network model consists of 13 convolutional layers, which are followed by maximum pooling layers and then 3 fully-connected layers and finally softmax classifier to predict the mineral images.

3.2.1 Layers Description

The input image is a 224x224x3 RGB image, which passes through first convolutional layer. First and second convolutional layers with 64 filters and stride of 1. Results are applied with maximum pooling layer with stride of 2. The resulting mineral image size will be reduced to 112x112x64. The third and fourth layers are the convolutional layers with 128 filters having size 3×3 and a stride of 1. Then there is again a maximum pooling layer with stride of 2. So the output mineral image size will be reduced to 56x56x128. The fifth and sixth layers are convolutional layers with 256 filters, the size 3×3 and a stride of 1. Then again a maximum pooling layer with filter size 3×3, a stride of 2. The output image size reduced to 28x28x256. Next, there are two sets of 3 convolutional layers followed by a maximum pooling layer. All convolutional layers have 512 filters of size 3×3 and a stride of 1. The max pooling layers have 512 filters and a stride of 2. The final output size will be reduced to 7x7x512. Next is the fully connected layer with 25088 feature maps each of size 1×1. Again there are two fully connected layers each of with 4096 units. The final outputs from the network are log probabilities for each of the 7 classes in the mineral dataset.

3.4 Training And Test The Model

The mineral classification model have 850 images for training, 48 images for validation and 45 images for testing. In this paper the last output layer is set to 7 i.e for each type of mineral. The global learning rate of the model is set as 0.0001. The learning rate of the initial layers as it is already a pre-trained network which has been fine-tuned for classifying ImageNet dataset. The weights are updated using stochastic gradient descent with momentum which utilizes an exponential weighted average of the gradients [5]. Batch size was set to 128 and the number of epochs was fixed to 30. The main loop iterates over a number of epochs and on each epoch, then iterate through the train Dataloader. The Dataloader hold one batch of data and targets which are pass through the model.After each training batch, the loss of training and test set can be calculated and then update the parameters with the optimizer. Then continue the iteration through the data until reach a given number of epochs.

3.5 Performance Analysis

A Classification report is used to measure the predictions of classification algorithm. This shows classification metrics precision, recall on a per-class basis. The classification accuracy is one of the performance metric used in mineral classification. These performance metrics are calculated by using true and false positives, true and false negatives.

Precision is a metric that quantifies the number of correct positive mineral image predictions made.

$$Precision = TP / TP + FP.$$

Recall is a metric that quantifies the number of correct positive mineral image predictions made out of all positive mineral image predictions made.

$$Recall = TP / TP + FN.$$

Accuracy is the number of correct mineral image predictions made divided by the total number of mineral images predictions made.

$$Accuracy = (TP+TN)/(TP+TN+FP+FN).$$

Where,

True Positive (TP) is the number of true mineral images which are correctly extracted,

True negatives(TN) is the number of true mineral images which are incorrectly identified,

False Positive (FP) is the number of false mineral images correctly identified,

False Negative (FN) is the number of false mineral images incorrectly identified.

4. RESULT AND DISCUSSION

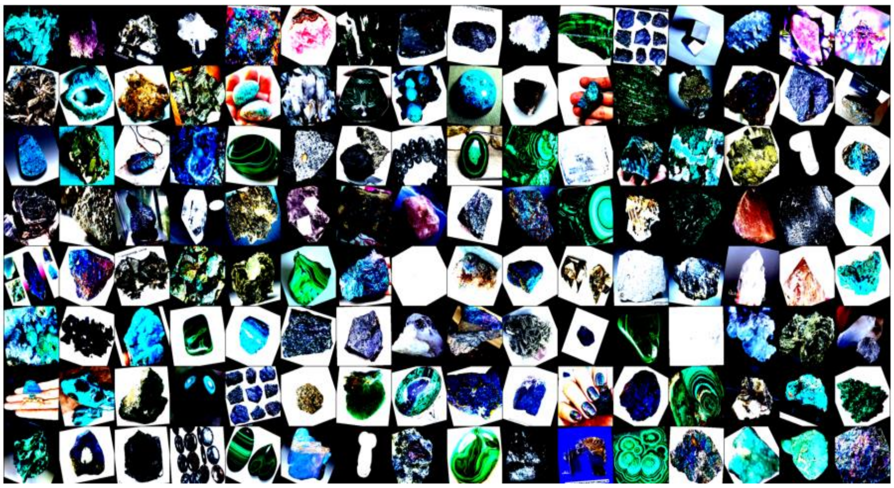

Fig -3: Pre-processed output

Fig 2. shows the pre-processed results with 224x224x3 size images.

Table 1 gives the Performance Analysis of VGG16 model for mineral classification task. The classwise precision, recall and Accuracy is given in the table. The overall classification accuracy is 81%.

Table -1: Performance Analysis

Class	Precision %	Recall %	Accuracy %
0	067	0.67	0.67
1	0.70	0.88	0.78
2	0.71	0.62	0.67

3	0.89	0.73	0.80
4	1.00	1.00	1.00
5	0.80	0.80	0.80
6	0.86	1.00	0.92
Overall Accuracy			0.81

5. CONCLUSIONS

The analysis was carried out on Mineral identification dataset. The mineral classification is done using VGG16 model with pytorch, and performance of the model was analyzed. The classification report shows the precision, recall and f-score values per class basis. The proposed model yields the average precision of 80% and average recall of 81%. The overall performance shows 80% of accuracy for mineral classification using VGG16 model. In the future, improvement in the accuracy of classification by using a larger dataset that consists of more number of mineral classes may be considered.

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