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A METHOD FOR CLASSIFICATION OF MINERALS MINING BASED ON DEEP LEARNING

Lakshmi K, S.Shanmugapriya, *Assistant Professors, Department of Computer Science and Data Science, Nehru Arts and Science College, Coimbatore, Tamilnadu, India.*
Dinesh Raj K, *Research Scholar, Karpagam Academy of Higher Education, Coimbatore, Tamilnadu, India.*

Abstract— **With the development of deep learning, this technology is more and more used in people's daily life, such as object classification, portrait recognition, text analysis and so on. In recent years, researchers have tried to apply machine learning to Earth Sciences, such as image recognition of geological ores. In this project, we apply the method of deep learning to the classification and recognition mineral, and propose a classification algorithm based on deep learning. we obtain the key attribute of classification, namely feature selection, through accurate data, and add a classification algorithm on this basis, so that the category can be obtained quickly when new samples are encountered. At the same time, our experiments are based on type of minerals dataset.**
Keywords—*Minerals Mining, Deep Learning, AI, Python, MobileNet.*

I. INTRODUCTION

At this stage, the exploitation and application of mineral resources have entered a new era since the inventory of their mineral resources has declined rapidly with the growth of industrial development, which raises new demands for ore mining and application technology. Recently, intelligent ore sorting has become one of the crucial factors for mineral processing and mining enterprises, which not only saves workforce and material consumption, increases mining safety factors but also lays the foundation for sustainable development.

For example, intelligent ore sorting technology can quickly realize the gangue discharge or pre-separation of underground or concentrator feed and effectively reduce the energy consumption of lump ore crushing, grinding, and other processes. To obtain chemical composition of matter, there are usually two solutions; one may choose to use more accurate, but time-consuming and more expensive methods. The second may choose less accurate, but faster and cheaper such as the micro XRF, EDS, etc. Can we find a way to use the data by fast and cheap EDS method as accurate as those by EMPA to class the chemical composition of the mineral? The development of machine learning gives such a chance. Identification or counting of mineral grains in sediments or sands is a critical task in many scientific endeavours. In environmental science, some minerals can release toxic elements such as arsenic or lead.

In some engineering projects using sand as a building material, some minerals in the sand can cause major problems in mortars. In mineral exploration geology, the abundance of mineral such as gold (Au) or chalcopyrite ($CuFeS_2$) in sediments or milled rock can indicate the proximity of a gold or copper mineral deposit. How to realize the classification and identification mineral is very important. Classification according to geologists is the first step. Heavy minerals with densities higher than 2.8 g/cm^3 generally are trace components of sand or sandstones, typically forming 1% of the weight in the samples. Although the content of heavy mineral is low, because of their stable physical and chemical properties, important information such as material composition, geotectonic, magmatic-metamorphic events, climate and environment in the sedimentary source area are retained and recorded. At present, many geologists identify and classify mineral by manual methods, and they distinguish different types of mineral according to the visual information such as colour, gray scale, texture and luster of mineral.

Manual selection is easy to be affected by subjective factors such as individual discrimination criteria, visual fatigue, thoughts and emotions, so it is difficult to ensure the consistency of primary selection criteria, and manual selection increases the time cost of scientific research work. However, the actual situation is that rocks and minerals are stable solid aggregates formed by single or multiple chemical elements in the earth's crust under various geological processes. In nature, many rocks and minerals are not a single mineral composition, but belong to many different mineral compositions.

Python is a dynamic, high level, free open source and interpreted programming language. It supports object-oriented programming as well as procedural oriented programming. In Python, we don't need to declare the type of variable because it is a dynamically typed language.
For example, x=10. Here, x can be anything such as String, int, etc. Anaconda distribution comes with over 250 packages automatically installed, and over 7,500 additional open-source packages can be installed from PyPI as well as the conda package and virtual environment manager. It also includes a GUI, Anaconda Navigator, as a graphical alternative to the command line interface (CLI). The big difference between conda and the pip package manager is in how package dependencies are managed, which is a significant challenge for Python data science and the reason conda exists. Anaconda Navigator is a desktop graphical user interface (GUI) included in Anaconda distribution that allows users to launch applications and manage conda packages, environments and channels without using command-line commands. Navigator can search for packages on Anaconda Cloud or in a local Anaconda Repository, install them in an environment, run the packages and update them. It is available for Windows, macOS and Linux.

II. PROPOSED SYSTEM

In the proposed project we have been implementing the images of minerals and training the images using deep learning method. By using Mobile Net algorithm, we are training the model to classify the images. By using this algorithm, we are gaining the values of accuracy and classification report. The following shows its benefits:

- High accuracy prediction.
- Efficient.
- Can train more dataset of images

Mobilenet Algorithm

As the name applied, the MobileNet model is designed to be used in mobile applications, and it is TensorFlow's first mobile computer vision model. MobileNet uses depthwise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks. A depthwise separable convolution is made from two operations.

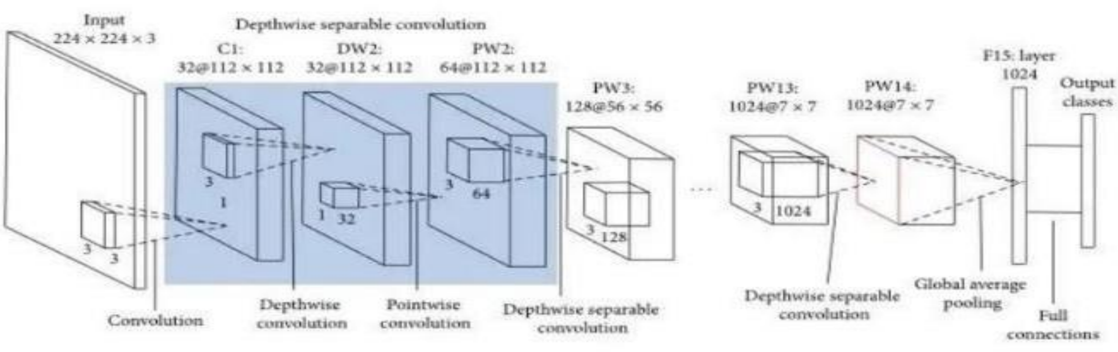
A. *MOBILENET ARCHITECTURE*

- Depthwise convolution.
- Pointwise convolution.

MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

a. DEPTHWISE SEPARABLE CONVOLUTION

This convolution originated from the idea that a filter's depth and spatial dimension can be separated thus, the name separable. Let us take the example of Sobel filter, used in image processing to detect edges.



Formula:
D – Depthwise
P – Pointwise
Dp x Dp x M
Confusion Matrix Formula:
You can separate the height and width dimensions of these filters. Gx filter can be viewed as a matrix

product of [1 2 1] transpose with [-1 0 1]. We notice that the filter had disguised itself. It shows it had nine parameters, but it has 6. This has been possible because of the separation of its height and width dimensions. The same idea applied to separate depth dimension from horizontal (width*height) gives us depth- wise separable convolution where we perform depth-wise convolution. After that, we use a 1*1 filter to cover the depth. In long-term and complex geological activities, various chemical elements and their compounds in nature promote the diversified combination of rocks and minerals in various ways. Therefore, it is not feasible for us to use manual methods.

B. ***ARCHITECTURE DIAGRAM***

In view of the challenge of manual primary selection, at present, the composition of the mineral can be measured, such as the use of electron probe micro analysis (EMPA) and energy dispersed spectrum (EDS) measurement to classify. In general, to categorize between cats and dogs, or men and women, we don't draw a line in our brains, and the position of dogs and cats is arbitrary for illustration purposes only, and it is needless to say the way we categorize between cats and dogs in our brains is much complex than drawing a red line as above.

-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

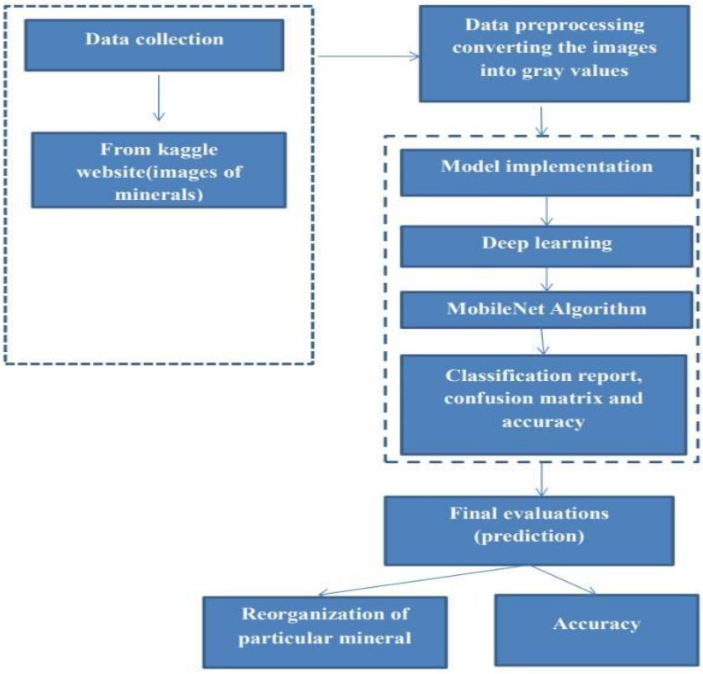
Gy

We will categorize between two things based on shapes, size, height, looks, etc., and sometimes it will be difficult to categorize with these features such as a small dog with fury and a newborn cat, so it is not a clear-cut categorization into cats and dogs. Once we are able to categorize between cats and dogs when we are children, then onwards we are able to categorize any dog or cat even we didn't see it before.

ACC – Accuracy
T – True
F – False
P – Positive
N – Negative

$$\mathbf{ACC} = \frac{\mathbf{TP+TN}}{\mathbf{P+N}}$$

$$= \frac{\mathbf{TP + TN}}{\mathbf{TP + TN + FP + FN}}$$



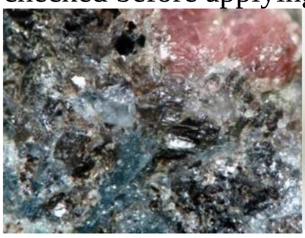
C. *DATASET COLLECTION*

Data collection is a significant barrier to efficient machine learning. Hence, data collection has recently become a hotly debated issue in the global tech community for primarily two reasons. The first reason is that as machine learning is employed more often, we are witnessing new applications that may not have enough labelled data. Second, deep learning algorithms, unlike conventional ML techniques, automatically produce features, saving on feature engineering expenses but potentially requiring more annotated data. The images were taken from the kaggle website of minerals.

Biotite	Chrysocolla
Bornite	Malachite
Quartz	Pyrite

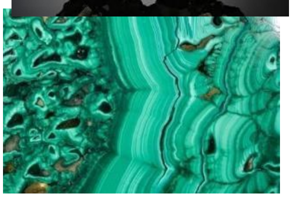
D. *PRE-PROCESSING*

Data pre-processing is the process of transforming raw data into an understandable format. It is also an important step In data mining as we cannot work with raw data. The quality of the data should be checked before applying machine learning or data mining algorithms.



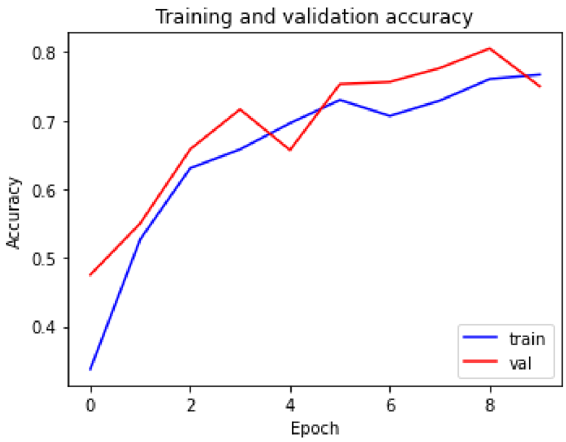






III. Model Implementation

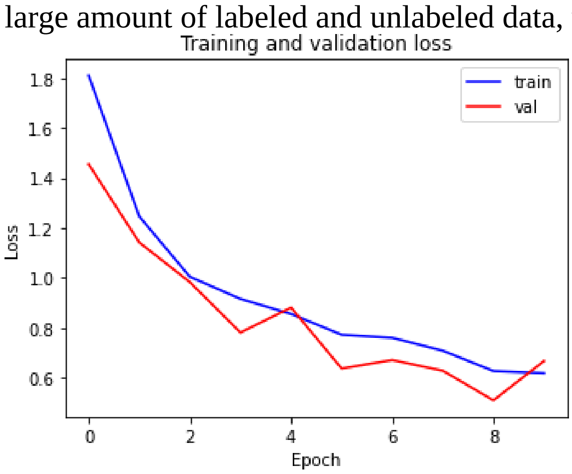
For this project we are implementing the deep learning algorithm to predict the datasets. In the deep learning algorithm, we are using Mobile Net algorithm to train the data. By training the dataset we gain the values like, Accuracy, classification report and confusion matrix. Mobile Net is a streamlined architecture that uses depth wise separable convolutions to construct lightweight deep convolutional neural networks and provides an efficient model for mobile and embedded vision applications. Mobile Net is a type of convolutional neural network designed for mobile and embedded vision applications. They are based on a streamlined architecture that uses depth wise separable convolutions to build lightweight deep neural networks that can have low latency for mobile and embedded devices.



PREDICTION

Finally, we are predicting the models using the Mobile Net algorithm to predict for a single or a particular minerals name with the accuracy values. For prediction based on the line, we draw through data points if we are able to predict where it is most likely to go upward or downward. The curve is also a prediction of fitting new data points within the range of existing data points, i.e., how close the new data point is to the curve. The data points which are in red color in the above image (right side) are examples of both within and beyond the range of existing data points, and the curve attempts to predict both.

Finally, both task categorization and prediction are ended at a similar point, i.e., drawing a curvy line from data points. If we are able to train the computer model to draw the curvy line based on data points we are done with, then we can extend this to apply in different models such as drawing a curvy line in three-dimensional planes and so on. The above thing can be achieved by training a model with a large amount of labeled and unlabeled data, which is called deep learning.



IV. Conclusion

In this project, we proposed a fast and accurate classification algorithm based on two different datasets. After feature selection, samples from different datasets are represented as vectors with the same dimension and the classification algorithm is applied on this basis to output a set of prototype vectors from the precise data. This makes it possible to get categories quickly and precisely when a new sample is encountered. At the same time, taking the heavy mineral recognition in geological science as an example, the algorithm is verified by real experimental data. A large number of test results show that our algorithm has high accuracy and can rapidly identify heavy mineral through EDS data, which also shows that our algorithm is truly effective. There are many future research directions

that can be used to improve current research problems.
A promising research direction is to explore methods that are suitable for larger dataset and have lower computational complexity than the method proposed in this project. At the same time, because this method has a certain universality, we can find more scenarios to apply our proposed algorithm, and through experiments to verify the reliability and accuracy of our algorithm, to make it play a greater value. In order to solve the problems of low classification accuracy in multi- category mineral image classification tasks and low efficiency of mineral image feature extraction in CNNs models. Now we have been used the deep learning method of mobile net algorithm to predict the values and gain the accuracy.

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