Project Report on ROCK IDENTIFICATION using DEEP CONVOLUTION NEURAL NETWORKS

Prepared by, B.Jagadeesh

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Introduction:

In the mining process of underground metal mines, the misjudgement of rock types by on-site technicians will have a serious negative impact on the stability evaluation of rock mass and the formulation of support schemes, which will result in the loss of economic benefits and potential safety hazards of mining enterprises. In order to realize the precise and intelligent identification of rock types, the image data of peridotite, basalt, marble, gneiss, conglomerate, limestone, granite, magnetite quartzite are amplified.

Overview:

A tremendous interest in deep learning has emerged in recent years . The most established algorithm among various deep learning models is convolutional neural network (CNN), a class of artificial neural networks that has been a dominant method in computer vision tasks since the astonishing results were shared on the object recognition. Geological research is no exception, as CNN has achieved expert-level performances in various fields Needless to say, there has been a surge of interest in the potential of CNN among geological researchers, and several studies have already been published in areas such as mineral detection using satellite images, classification of geographical terrains , image reconstruction of ocean bed and unreachable places, etc. Familiarity and utilization of this methodology would help not only researchers who apply CNN to their tasks in geology, but also the common men and farmers to identify and understand the local geology , as deep learning may influence their practice in the near future. This article focuses on the creating a rock classifier using the concepts of CNN.

• Purpose:

The automated interpretation of rock structure can improve the efficiency, accuracy, and consistency of the geological risk assessment and better utilization of resources. Because of the high uncertainties in the geological images as a result of different regional rock types, as well as in-situ conditions (e.g., temperature, humidity, and construction procedure), previous automated methods have limited performance in classification of rock. This project presents a framework for classifying multiple rock structures based on the geological images of tunnel face using convolutional neural networks (CNN). A prototype recognition system is implemented to classify 13 types of rock structures including 'Basalt', 'Conglomerate', 'Dolostone', 'Gabbro', 'Gneiss', 'Granite', 'Limestone', 'Marble', 'Quartzite', 'Rhyolite', 'Sandstone', 'Shale' and 'Slate'. These are the major rock types found in Indian Subcontinent.

Meanwhile, the model trained by a large database can obtain the rock features more comprehensively, leading to higher accuracy. Compared with the original classification method, the image classification method is closer to the reality considering both the accuracy and the perspective of error divergence.

The experimental results reveal that the proposed method is optimal and efficient for automated classification of rock structure using the geological images of the rocks.

Literature Survey:

• Existing Problem:

Generally, people working at mines, identify the type of rocks by observing their configurations or testing them. It takes a lot of time. Only , a very experienced person can identify the type of rocks by seeing it.

• Proposed Solution:

This problem is overcame by creating a model for Rock Identification using CNN. Then , by training that model with with tets and tarin sets will make a person easy to identify the type of rock by simply uploading that image of the rock to the application. It saves a lot of time and effors too.

Theoretical Analysis:

• Hardware / Software designing

Python, Python Web Frame Works, Python for Data Analysis, Python For Data Visualization, Data Pre-processing Techniques, Machine Learning, Regression Algorithms

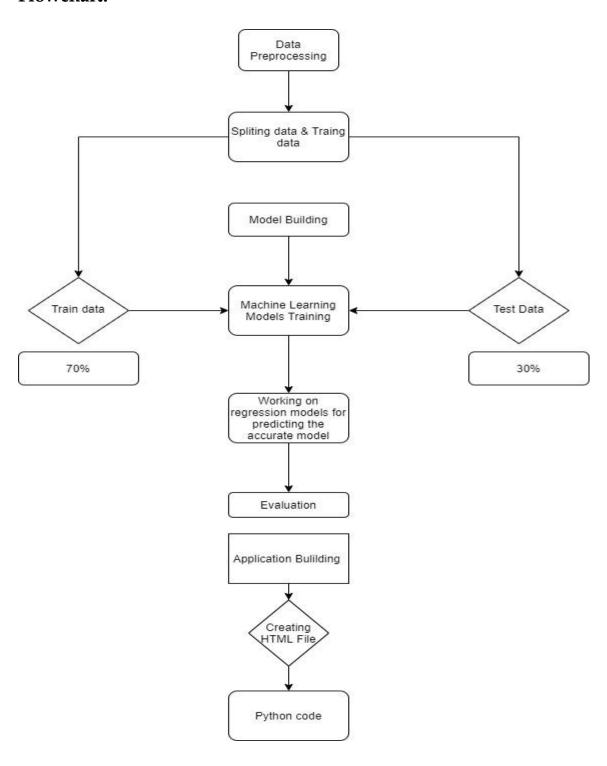
Experimental Investigation:

The rocks are classified into 13 major types. They are:

- Basalt
- Conglomerate
- Dolostone
- Gabbro
- Gneiss
- Granite
- Limestone
- Marble
- Quartzite
- Rhyolite
- Sandstone

- Shale
- Slate

Flowchart:



Result:

We have analysed the types of rock images and used Deep CNN to predict the type of rock.

Advantages and Disadvantages:

Advantages:

Using Convolutional Neural Network to predict the type of rock will save more time and more accuracy in predicting the approximately close type can be done easily. Its more trust worthy and cost effective .It also reduces the man power for doing the experiments to find the type of rock in different unknown situations.

Disadvantages:

There is a small percent chances that the outcome will not predict the approximate value in that situation it can be troublesome.

Applications:

- Can be used to identify type of rocks in mines
- Implementable on the website

Conclusion:

In this study, a prediction model of rock identification was established by Convolutional Neual 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.

Future Scope:

This model can predict the outcome with many different inputs within seconds. The model will save a lot of time of the construction companies. Experiment cost is also reduced with creates a bigger opportunity for mining companies in cost effectiveness work.

Bibliography:

Books

Hastie, Friedman, and Tibshirani, The Elements of Statistical Learning, 2001 Bishop, Pattern Recognition and Machine Learning, 2006 Ripley, Pattern Recognition and Neural Networks, 1996 Duda, Hart, and Stork, Pattern Classification, 2nd Ed., 2002 Tan, Steinbach, and Kumar, Introduction to Data Mining, Addison-Wesley, 2005.

Appendix:

Source Code:

1. Import Libraries

from keras.models import Sequential from keras.layers import Dense from keras.layers import Convolution2D from keras.layers import MaxPooling2D from keras.layers import Flatten

2. Initialize The Model

model = Sequential()

3. Add Convolution Layer

model.add(Convolution2D(32,(3,3), input_shape=(64,64,3), activation='relu'))

4. Add maxpooling Layer

model.add(MaxPooling2D(pool_size=(2,2)))

5. Add flattening Layer

model.add(Flatten())

6. Add Hidden Layers

```
model.add(Dense(units=128, init='uniform', activation='relu')) model.add(Dense(units=128, init='uniform', activation='relu')) model.add(Dense(units=128, init='uniform', activation='relu')) model.add(Dense(units=128, init='uniform', activation='relu'))
```

7. Add Output Layer

model.add(Dense(units=13, init="uniform", activation="softmax"))

8. Preprocessing Using Data Generator

from keras.preprocessing.image import ImageDataGenerator train_datagen=ImageDataGenerator(rescale=1./255, shear_range=0.2, zoom_range=0.2, horizontal_flip=True) test_datagen=ImageDataGenerator(rescale=1./255)

9. Load Dataset and Apply image generator class preprocessing techniques to dataset

 $x_train=train_datagen.flow_from_directory(r'F:\Projects\Rock Datasets\dataset\train',target_size=(64,64),batch_size=32,class_mode='cate gorical') \\ x_test=test_datagen.flow_from_directory(r'F:\Projects\Rock Datasets\dataset\test',target_size=(64,64),batch_size=32,class_mode='categ orical') \\$

10. Labels in the dataset

x_train.class_indices

11. Compiling and optimization for our model

model.compile(optimizer="adam", loss='categorical_crossentropy',
metrics=["accuracy"])

12. Training the Machine

model.fit_generator(x_train, steps_per_epoch=500, epochs=25, validation_data=x_test, validation_steps=50)

13. Saving the Model

model.save("trained_model.h5")

UI Output:

