

PROJECT REPORT
On
ROCK IDENTIFICATION
Using
DEEP CONVOLUTIONAL NEURAL NETWORK

Submitted By:

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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 three common rock types with an overall classification accuracy over 60 %. 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.

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.

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time taken process to identify the rocks. 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.

1.1 Overview:

Rock identification using traditional method is time taken process to identify the rocks. Using deep convolutional neural networks we can accurately identify the rock types based on image analysis. In this project, we construct a new convolution neural network for rock classification collecting different rock images.

This project is capable of classifying images based on the type of rock. A convolutional neural network (CNN) convolves an input image which identifies the type of rock. There will be a web application through which user can give their input image then they can check the predicted output and this application is integrated with trained CNN model.

1.2 Purpose:

Its application here has effectively identified rock types from images captured in the field. This project proposes an accurate approach for identifying rock types in the field based on image analysis using deep convolutional neural networks.

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2. LITERATURE SURVEY

2.1 Existing Problem

Working conditions in the field generally limit identification to visual methods, including using a magnifying glass for fine-grained rocks. Visual inspection assesses properties such as colour, composition, grain size, and structure. The attributes of rocks reflect their mineral and chemical composition, formation environment, and genesis. The colour of rock reflects its chemical composition. But these analysis is time taken process to identify the rocks.

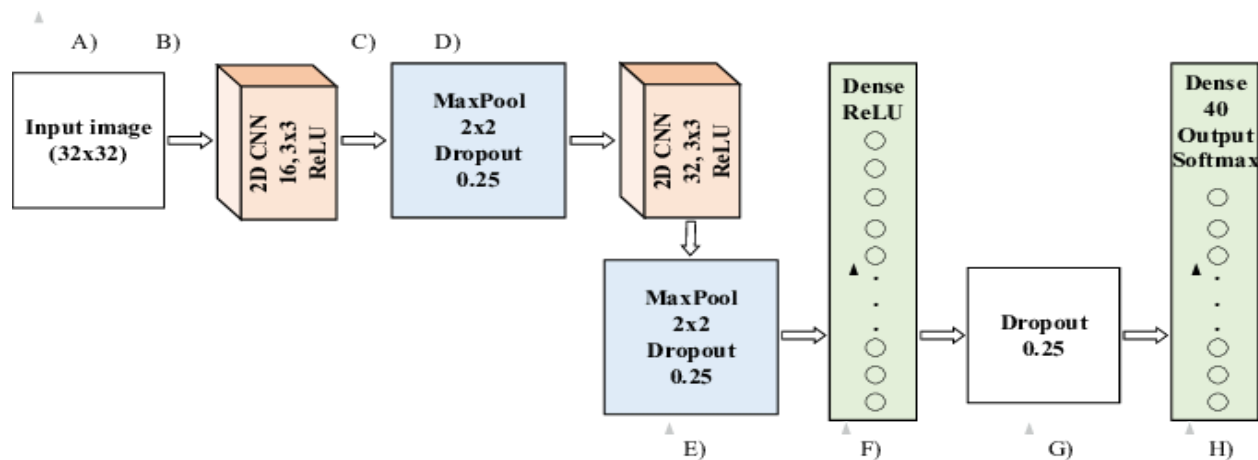
2.2 Proposed Solution:

The identification of rock type by the naked eye is effectively an image recognition task based on knowledge of rock classification. The rapid development of image acquisition and computer image pattern recognition technology has thus allowed the development of automatic systems to identify rocks from images taken in the field. These systems will greatly assist geologists by improving identification accuracy and efficiency and will also help student and newly qualified geologists practice rock-type identification.

First module is optimization model from which the maxima and minima pixel values are selected and is gives to next module. Second module is similarity measures from where the pixel similarity calculated based on location or color. Third module is computational complexity from which data and time complexity measured. Fourth one is the application to collection of images in which we not only taking single image segmentation, our method implements to multiple images. Fifth module is deep learning neural network (DLNN) which provides complete tuning of image and predicting the type of rock. In this module training the image with labeled data and un labeled data because of Deep learning could satisfies to both supervised segmentation and un-supervised segmentation. Last module is the performance evaluation from this module CPU performance time for running each image and accuracy is calculated.

3.THEORITICAL ANALYSIS

3.1 Block Diagram



3.2 Hardware / Software designing:

For hardware we would need ICT tools such as digital camera. Here we used both Digital Camera for capturing the rock image and collected the images from internet which is given as input to the web page.

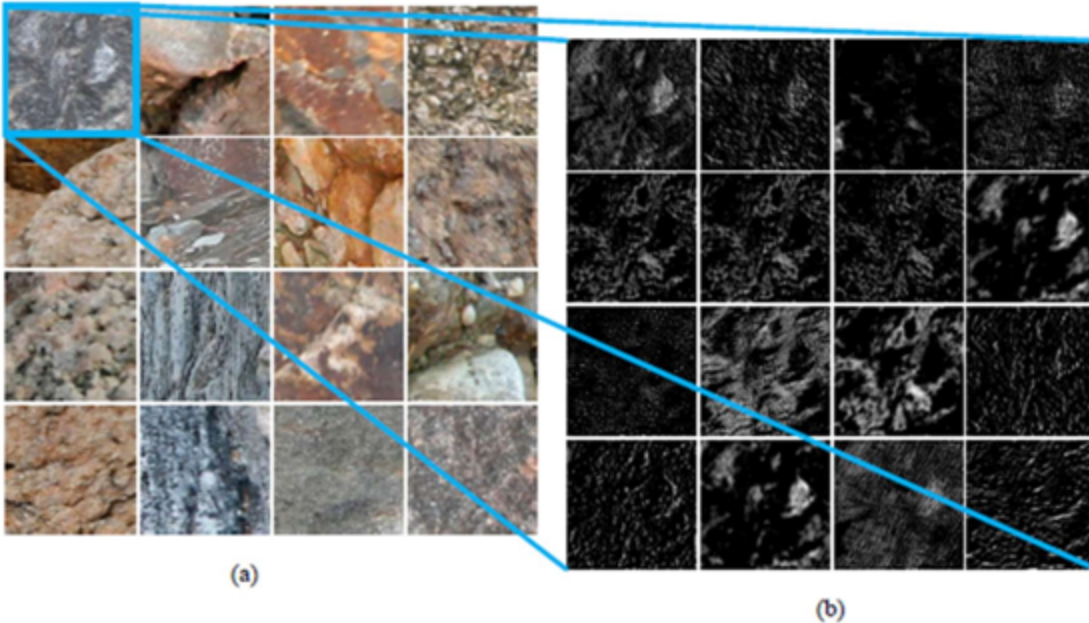
For software we would need a compatible operating system for python, java script and HTML.

Software needed are:

1. Tensorflow
2. OpenCV
3. Keras
4. Flask

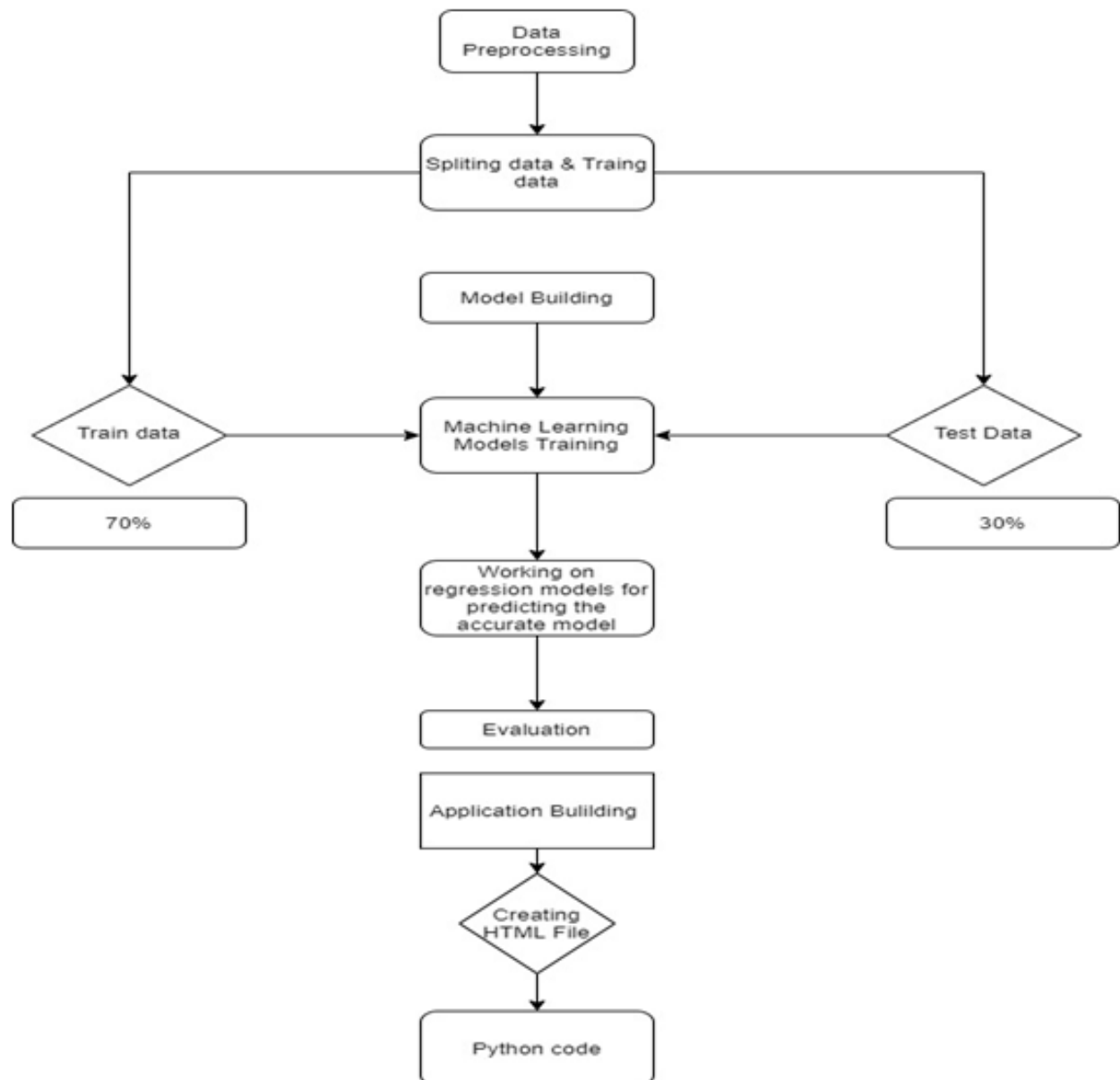
4. EXPERIMENTAL INVESTIGATION

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.



(a) Input patched field rock sample images. (b) Outputted feature maps partly after the first convolution of the input image

5. FLOWCHAT



6. RESULT

We got an accuracy of over 60 % which is good measure for a Convolution Neural Network. The Model predicts the type of rock with good efficiency.

7. ADVANTAGES & DISADVANTAGES

Advantages:

- Effective and predicts accurately.
- Predicts the type of rock using color, shape and size.
- Efficiency is maintained by updating the dataset frequently.

Disadvantages:

- The input image must have clarity to predict the correct output.
- Cost of the digital camera is high.
- High computational cost.

8. APPLICATIONS

The traditional method for rock classification is a manual work with many problems such as time-consuming and low accuracy. Hence we use this project to predict the type of rock quickly and accurately.

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

9. CONCLUSION

The continuing development of CNNs has made them suitable for application in many fields. A deep CNNs model with optimized parameters is proposed here for the accurate identification of rock types from images taken in the field. Novelty, we sliced and patched the original obtained photographic images to increase their suitability for training the model. The sliced samples clearly retain the relevant features of the rock and augment the training dataset. Finally, the proposed deep CNNs model was trained and tested using many sample rock images belonging to 3 classes and achieved an overall accuracy of over 60%. , thereby signifying that the model represents an advance in the automated identification of rock types in the field. The identification of rock type using a deep CNN is quick and easily applied in the field, making this approach useful for geological surveying and for students of geoscience. Meanwhile, the method of identifying rock types proposed in the paper can

be applied to the identification of other textures after retraining the corresponding parameters, such as rock thin section images, sporopollen fossil images and so on.

10. FUTURE SCOPE

Although CNNs have helped to identify and classify rock types in the field, some challenges remain. First, the recognition accuracy still needs to be improved. The model attained relatively low identification accuracy for Igneous rock type, which is attributed to the small grain size and similar colors of these rocks. Furthermore, only a narrow range of sample types (Three rock types overall) was considered in this study. The three main rock groups (igneous, sedimentary, and metamorphic) can be divided into hundreds of types (and subtypes) according to mineral composition. Therefore, our future work will combine the deep learning model with a knowledge library, containing more rock knowledge and relationships among different rock types, to classify more rock types and improve both the accuracy and the range of rock-type identification in the field. In addition, each field photograph often contains more than one rock type, but the proposed model can classify each image into only one category, stressing the importance of the quality of the original image capture.

11. BIBLIOGRAPHY

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12. APPENDIX

A. Source Code

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Flatten

model=Sequential()

model.add(Conv2D(32,3,3,input_shape=(64,64,3),activation='relu'))
model.add(MaxPooling2D(pool_size=(2,2)))
model.add(Flatten())

model.add(Dense(output_dim=128,activation='relu',init='random_uniform'))

model.add(Dense(output_dim=3,activation='softmax',init='random_uniform'))

from keras.preprocessing.image import ImageDataGenerator

train_datagen=ImageDataGenerator(rescale=1./255,shear_range=0.2,
zoom_range=0.2,horizontal_flip=True,vertical_flip=True,fill_mode='nearest')
test_datagen=ImageDataGenerator(rescale=1./255)

x_train=train_datagen.flow_from_directory(r'Trainset',target_size=(64,64),
batch_size=8,class_mode='categorical')
x_test=train_datagen.flow_from_directory(r'Testset',target_size=(64,64),
batch_size=8,class_mode='categorical')

print(x_train.class_indices)

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

model.fit_generator(x_train,samples_per_epoch=210,epochs=40,
validation_data=x_test,validation_steps=90)

model.save('mymodel.h5')
```



```

import numpy as np
import os
from keras.models import load_model
from keras.preprocessing import image
import tensorflow as tf
global graph
graph = tf.get_default_graph()
from flask import Flask , request, render_template
from werkzeug.utils import secure_filename
from event.pywsgi import WSGIServer

app = Flask(__name__)
#model = load_model("mymodel.h5")
model_filepath = './mymodel.h5'

model = tf.keras.models.load_model(
    model_filepath,
    custom_objects=None,
    compile=False
)
global text

@app.route('/')
def index():
    return render_template('base.html')

@app.route('/predict',methods = ['GET','POST'])
def upload():
    if request.method == 'POST':
        f = request.files['image']
        print("current path")
        basepath = os.path.dirname(__file__)
        print("current path", basepath)
        filepath = os.path.join(basepath,'uploads',f.filename)
        print("upload folder is ", filepath)
        f.save(filepath)

        img = image.load_img(filepath,target_size = (64,64))
        x = image.img_to_array(img)
        x = np.expand_dims(x,axis =0)

        with graph.as_default():
            preds = model.predict_classes(x)
            print("prediction",preds)
            index = ['Igneous','Metamorphic','Sedimentary',]
            text = "the predicted rock is : " + str(index[preds[0]])

    return text
if __name__ == '__main__':
    app.run()

```

B. UI Output Screenshot

