INTRODUCTION

1.1.OVERVIEW

In the mining process of underground metal mines, the misjudgment 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 benets and potential safety hazards of mining enterprises. In order to realize the precise and intelligent identication of rock types, the image data of biotite, bornite, chrysocolla, malachite, muscovite, pyrite, quartz are amplied.
The experimental verification shows that the system is correct for single-type rock image recognition and the accuracy is more than 96%. In order to realize accurate and intelligent identication of the surrounding rock surface under complex lithological conditions, the multi-type rocks hybrid images are also identied. The results show that the recognition effect is great and the accuracy rate is over 80%. Therefore, this system can accurately identify rock types with similar image features, which proves that the model has strong robustness and generalization ability. It has broad application prospects in rock mass stability evaluation and rock classication in underground mining.

1.2.PURPOSE

Granularity analysis is one of the most essential issues in authenticate under microscope. To improve the efficiency and accuracy of traditional manual work, an convolutional neural network based method is proposed for granularity analysis from thin section image, which chooses and extracts features from image samples while build classifier to recognize granularity of input image samples.
The results show that the convolution neural network can classify the rock images with high reliability.

LITERATURE SURVEY

2.1 EXISTING PROBLEM

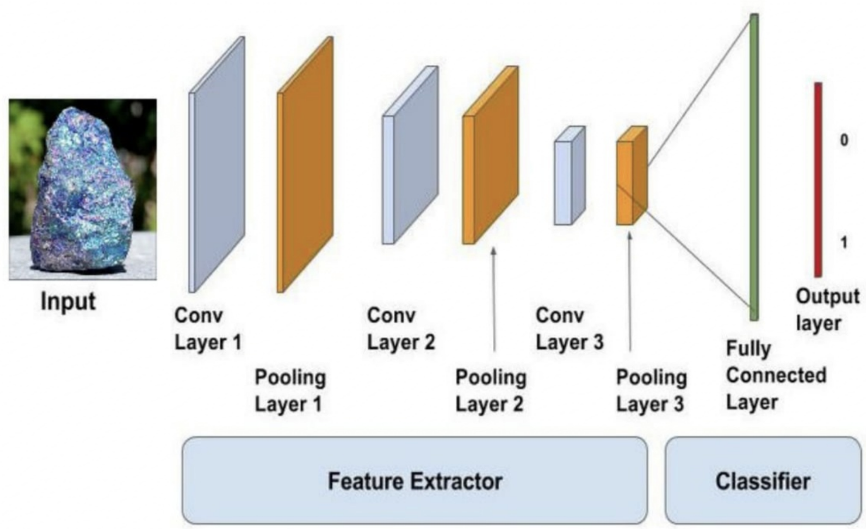
Rocks are a fundamental component of Earth. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. It is a basic part of geological surveying and research, and mineral resources exploration. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. 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.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.

2.2 PROPOSED SOLUTION

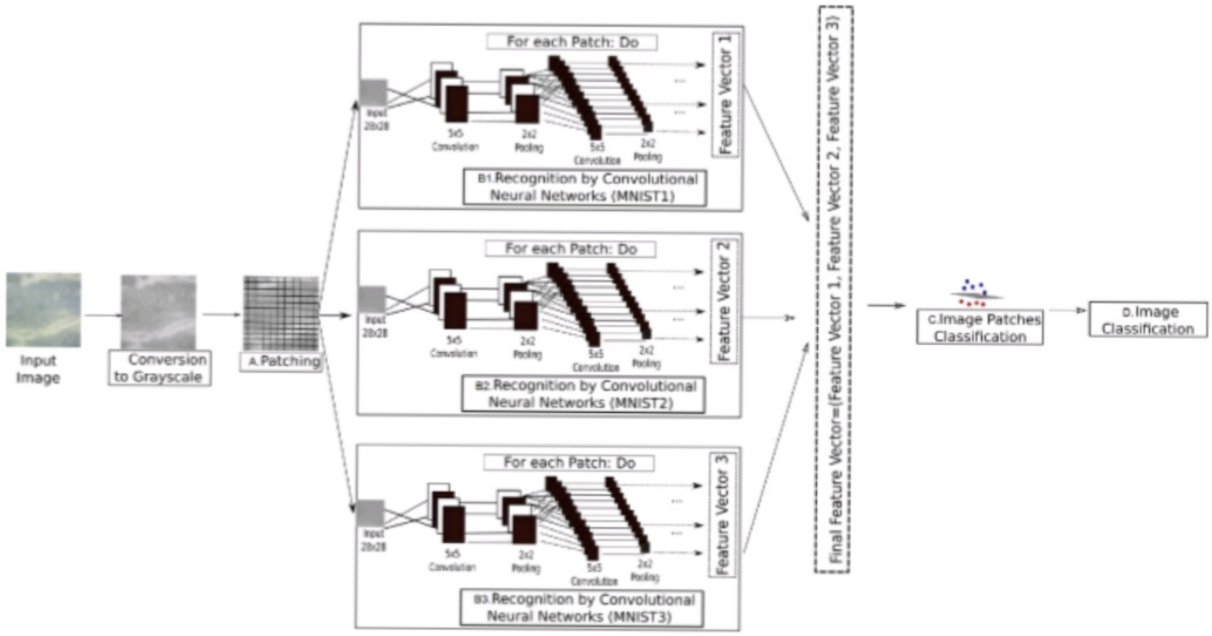
Deep learning is receiving significant research attention for pattern recognition and machine learning. Its application here has effectively identified rock types from images captured in the field. This paper proposes an accurate approach for identifying rock types in the field based on image analysis using deep convolutional neural networks. The 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.Who are experienced in the field of geological they can identify the rocks easily. But who are new to the field, it can help to identify the type of rock.

THEORITICAL ANALYSIS

3.1 BLOCK DIAGRAM



3.2 HARDWARE / SOFTWARE DESIGNING



EXPERIMENTAL INVESTIGATION

A. Data Sources

In this paper, 2000 rock images in RGB colour space are selected as experimental samples, normalize the size of them to 224*224.The images of biotite, bornite, chrysocolla, malachite, muscovite, pyrite, quartz are used.

B. The Architecture

The convolution neural network structure designed in this paper is shown in figure , which is a 6-layer structure, 4 layers are convoluted and 2 layers are fully connected. The convolution layers use ReLU as the activation function and the fully connected layers do classification by the Softmax classifier.

C. Architecture Adjustment

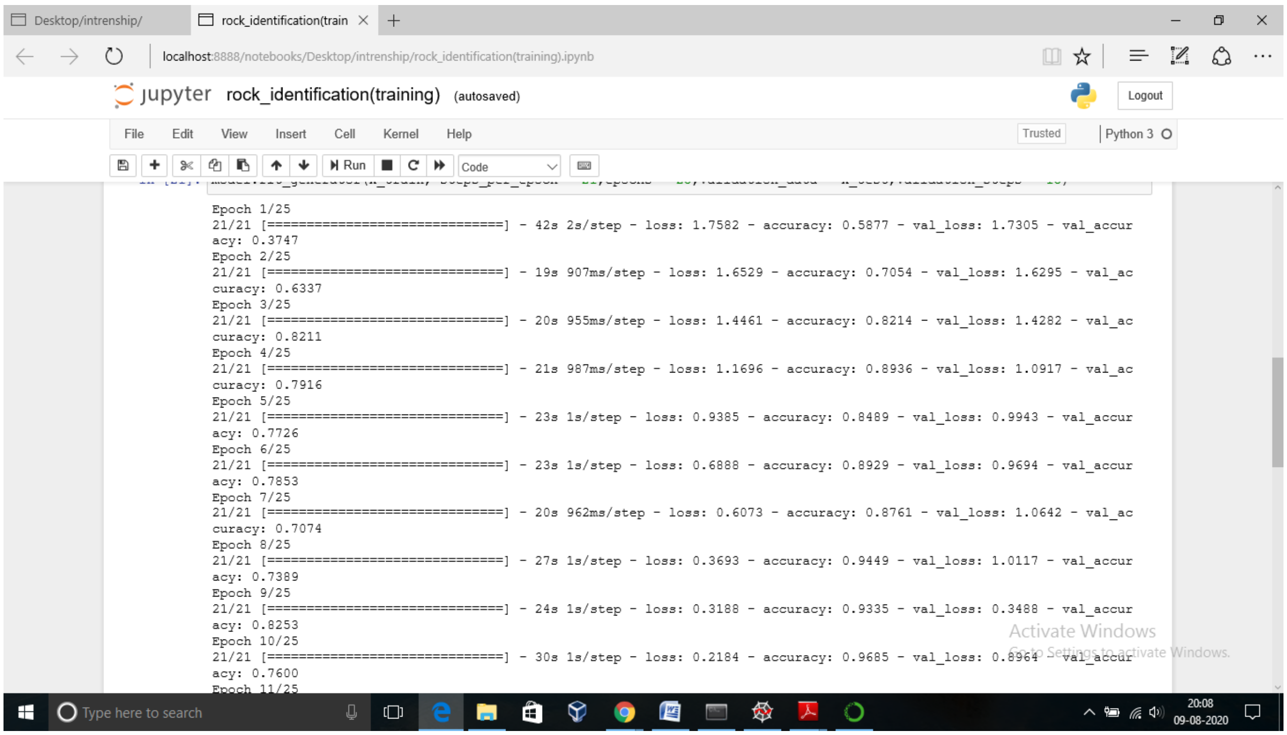
The experimental data is loaded into memory by batch whose size is 100. An iteration is performed while a batch of data is loaded, where the dropout is set to 0.5.

D. MODEL TRAINING

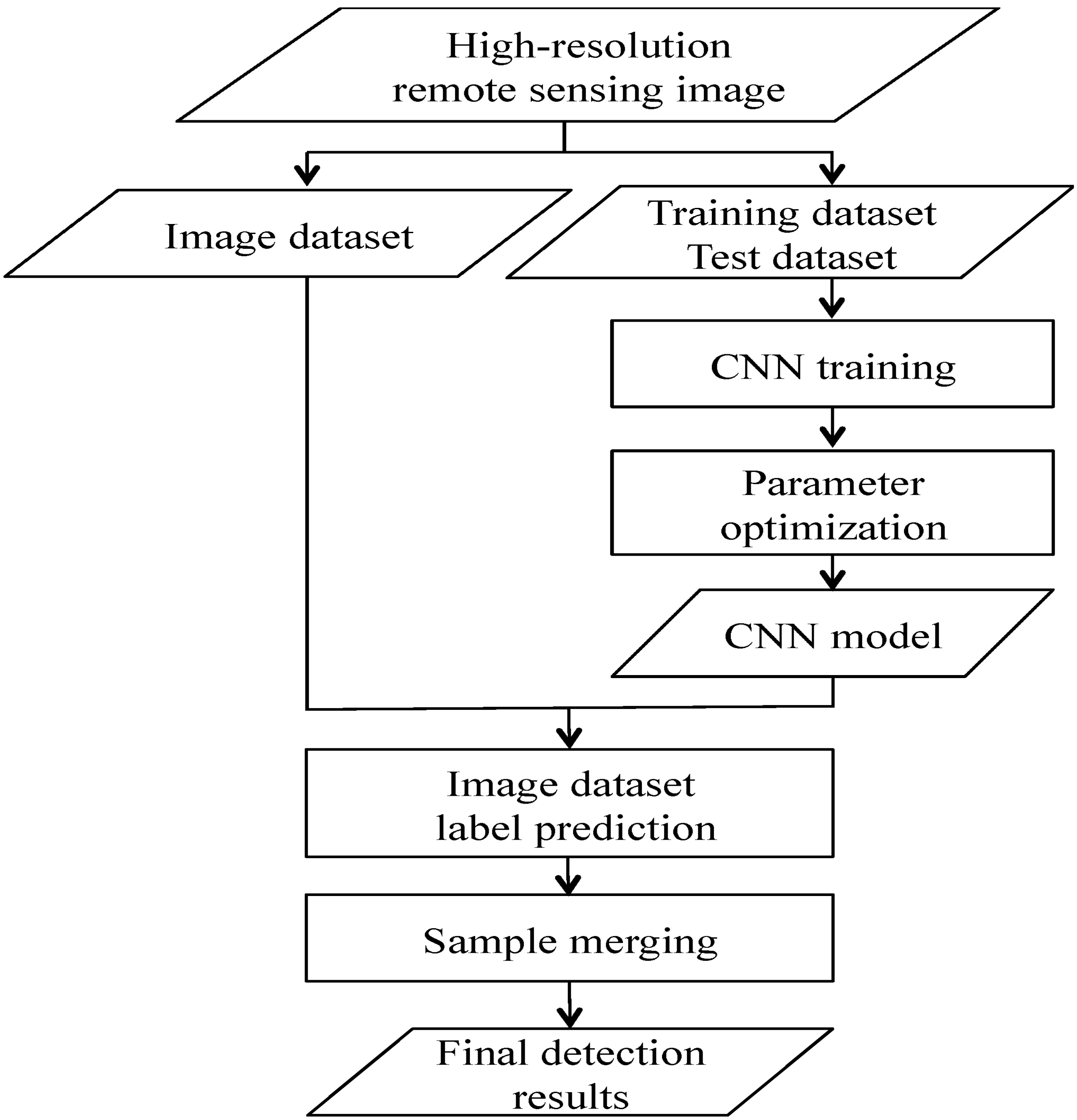
Under the Tensorfow deep learning framework, the rock type identication model was constructed by using Python programming language. Finally, the model was
trained by GPU acceleration. The iterations of the whole training process is 40,000 times, the rst 30,000 iteration learning ratio is 0.001, and the last 10,000 iteration learning ratio is 0.0001.
During the training process, the classication and regression loss curves (loss function) need to be obtained rst, and then their average value should be used to obtain the average loss (loss function). When the number of iterations is 0 ~ 5000, the value of

each loss function decreases rapidly. When the number of iterations is 40,000, the loss curve reaches a state of convergence. Therefore, the model when the number of iterations reaches 40,000 could be taken as the nal rock type identication model.

The model training is as shown in the figure.



FLOWCHART


High-resolution
remote sensing image
Image dataset
Training dataset
Test dataset
CNN training
Parameter
optimization
CNN model
Image dataset
label prediction
Sample merging
Final detection
results

RESULTS

Training employs random initial weights. After each batch of training is complete, the learning rate changes and the weights are constantly adjusted to find the optimal value, which decreases the loss value of training. After each epoch, the trained parameters are saved in files and used to evaluate the validation dataset and obtain the identification accuracy of each epoch. After 200 epochs, the training loss gradually converged to the minimum. The trained parameters trained after 200 epochs are used to evaluate the testing dataset and obtain the identification accuracy. 10 identical experiments are established totally Figure 7 shows the average loss and accuracy curves for the training and validation datasets from the model using sample patch images of 128 × 128 pixels in the same 10 experiments. The curves show that the model has good convergence after 50 training epochs, with the loss value being below 1.0, and the training accuracy being 95.7%, validation accuracy achieved 95.4%. The highest accuracy of training and validation achieved was 98.6% and 98.2% at 197th epoch. After 200 training epochs, the final training and validation accuracy of the model reached 98.5% and 98.0% respectively. The saved parameters at 197th epoch with the highest validation accuracy was used to test the testing dataset, and the confusion matrix was gained. Finally, the testing accuracy achieved was 97.96%.

ADVANTAGES AND DISADVANTAGES

ADVANTAGES:

The rock identification method is compared with the traditional method and the method based on rock slice image processing.The model of this paper can quickly identify the types and properties of rocks on the condition that the accuracy requirements are met. The presented method can quickly get the recognition results in less than 1 second after taking photos in the field. And there is no need to make rock flakes to reduce the cost of identification. The experimental results show that the convolutional network model has obvious performance in model compression and computation. It is suitable for rapid and accurate recognition of rock lithology under field offline conditions.

DISADVANTAGES:

1. The accuracy of estimation of rock support is very difficult to evaluate.
2. In the poorer rock (Q<1) system may give erroneous design
3. The true nature of rock mass (e.g. swelling, squeezing or popping ground) is not explicitly considered in the Q- system.
4. The value is used as the only indicator to define the classes in question.
5. Requires more calculation than RMR & Q- system.
6. For special ground conditions like swelling, squeezing & fault zones, etc. the rock support should be evaluated seperatlly for each & every cases.
7. Like other empirical method, it is not possible to evaluate the accuracy of the system.

APPLICATIONS

Rock mass classification systems are used for various engineering design and stability analysis. These are based on empirical relations between rock mass parameters and engineering applications, such as tunnels, slopes, foundations, and excavatability.
Application of rock mass classification systems to rock slope stability assessment.
Rock mass classification is widely used throughout the underground mining industry in both coal and hard rock mines. Civil engineering project like mines, dam, can be constructed properly with sound and in-depth knowledge of existing nature in advance. The classification systems used today should, strictly speaking, either be described as rock mass characterization systems or empirical design methods, as long as the outcome is not organized into classes. Rock mass classification is widely used throughout the underground mining industry in both coal and hard rock mines. Rock mass classification system uses rock mass modulus for characterization of systems: RMR, Q, GSI, and others. These are based on empirical relations between rock mass parameters and engineering properties widely used as a tool in determining the stability of structure such as tunnels, slopes, foundations. In this study, uniaxial compressive strength, modulus ratio and direct shear tests have been performed in order to classify the double jointed rock mass, artificially made of POP and POP lime mix. This classification can thereafter give a probable direction of Rock engineering design concept.

CONCLUSION

Under this project convolutional neural network was used for the prediction. Then, the training data can be obtained by data amplication technology, and the GPU can be used to accelerate the training of the rock type identication model. Finally, the precise identication of the images of peridotite, basalt, marble, gneiss,conglomerate, limestone, granite and magnetite quartzite was realized. When the recognition target is a single-type rock image, the recognition probability is greater than 96%, and the rock and background can be well distinguished. When the image is a multi-type rocks hybrid image, the probability of recognition of most rocks is greater than 80%. In addition, the model can also identify the types of rocks with incomplete images and complex images, which fully proves that the lithology recognition model of this study has strong robustness and generalization ability. The research results show that the simplied convolutional network has better feature extraction effect for rock images. During the whole model training and recognition process, the training data and test data are randomly selected, and there are no articial interventions on the pixel, imaging distance and illumination intensity of the images. Moreover, the rock image features of various lithologies are automatically extracted by

the convolutional network, which fully shows that the use of this model to identify the rock types is more intelligent.The research results lay the foundation for the next step to realize the on-site intelligent identication of rock lithology in underground mine.

FUTURE SCOPE

Granularity analysis can provide authenticate researchers essential basis for determining types and structural parameters of rocks, but it is a manual work with low reliability in traditional. However, the experiment results above shows that do the rock granularity analysis using CNN is with high accuracy which could improve the reliability and efficiency.

CNN is used to identify the rock granularity. The experiments show that it has high reliability whether in HSV, YCbCr or RGB colour space. In RGB colour space, the classification accuracy achieves 98.5% with high efficiency. However, the experimental results still have deviation may be caused by the use of single polarized images. The next step of study can be committed to multi-polarized light in the rock image. In view of the high reliability of the application of CNN in rock image classification based on rock granularity, it can be considered to apply to the classification of rock components.

Several pre-trained models can be incorparated and studied for better results.

BIBILOGRAPHY

[1] D. Thompson, S. Niekum, T. Smith, and D. Wettergreen, ``Automatic detection and classication of features of geologic interest,'' in Proc. IEEE Aerosp. Conf., Feb. 2005, pp. 366 377, doi: 10.1109/aero.2005.1559329.

[2] S. Niekum, ``Reliable rock detection and classication for autonomous science,'' M.S. thesis, CMU, Pittsburgh, PA, USA, 2005.

[3] R. Marmo, S. Amodio, R. Tagliaferri, V. Ferreri, and G. Longo, ``Textural identication of carbonate rocks by image processing and neural network: Methodology proposal and examples,'' Comput. Geosci., vol. 31, no. 5, pp. 649 659, Jun. 2005, doi: 10.1016/j.cageo.2004.11.016.

[4] N. Singh, T. N. Singh, A. Tiwary, and K. M. Sarkar, ``Textural identication of basaltic rock mass using image processing and neural network,'' Comput. Geosci., vol. 14, no. 2, pp. 301 310, Mar. 2010,doi: 10.1007/s10596-009-9154-x.

[5] G. Cheng, J. Yang, and Q. Huang, ``Rock image classication recognition based on probabilistic neural networks,'' Sci. Technol. Eng., vol. 13,pp. 9231 9235, 2013, doi: 10.3969/j.issn.1671-1815.2013.31.014.

[6] M. Mªynarczuk, A. Górszczyk, and B. lipek, ``The application of pattern recognition in the automatic classication of microscopic rock images,'' Comput. Geosci., vol. 60, pp. 126 133, Oct. 2013, doi: 10.1016/j.cageo.2013.07.015.

[7] S. Chauhan, W. Rühaak, H. Anbergen, A. Kabdenov, M. Freise, T. Wille, and I. Sass, ``Phase segmentation of X-ray computer tomography rock images using machine learning techniques: An accuracy and performance study,'' Solid Earth, vol. 7, no. 4, pp. 1125 1139, Jul. 2016, doi: 10.5194/se-7-1125-2016.

[8] H. Izadi, J. Sadri, and M. Bayati, ``An intelligent system for mineralidentication in thin sections based on a cascade approach,'' Comput.Geosci., vol. 99, pp. 37 49, Feb. 2017, doi: 10.1016/j.cageo.2016.10.010.

[9] G. Cheng, W. Guo, P. Fan, ``Study on rock image classication based on convolution neural network,'' J. Xi'an Shiyou Univ., vol. 32, pp. 116 122,Feb. 2017, doi: 10.3969/j.issn.1673-064X.2017.04.020.

[10] K. Hong, E. Han, and K. Kang, ``Determination of geological strength index of jointed rock mass based on image processing,''J. Rock Mech. Geotech. Eng., vol. 9, no. 4, pp. 702 708, Aug. 2017,doi: 10.1016/j.jrmge.2017.05.001.

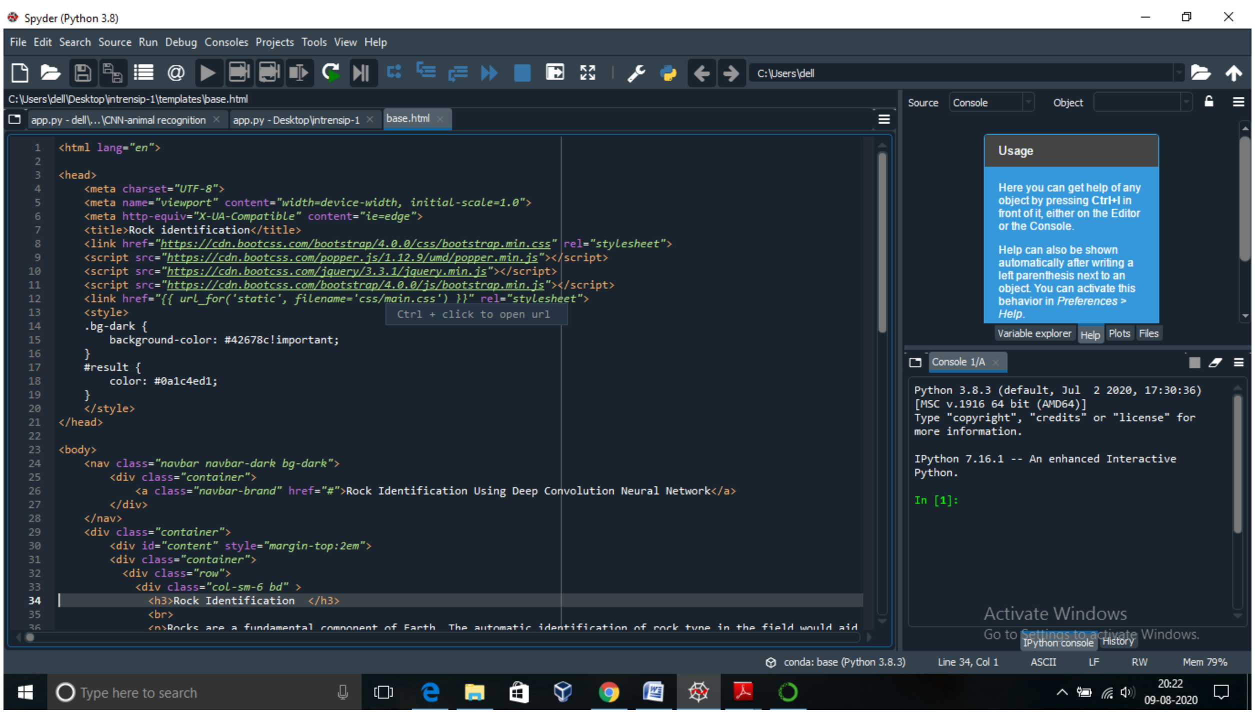
[11] L. Lepistö, I. Kunttu, and A. Visa, ``Color-based classication of natural rock images using classier combinations,'' in Proc. Image Anal.,Jun. 2005, pp. 901 909, doi: 10.1007/11499145_91.

[12] Y. Zhang, M. Li, and S. Han, ``Automatic identication and classication in lithology based on deep learning in rock images,'' Acta Petrologica Sinica,vol. 34, pp. 333 342, 2018.
[13] A. Rahman, G. Timms, M. S. Shahriar, C. Sennersten, A. Davie,C. A. Lindley, A. D. Hellicar, G. Smith, D. Biggins, and M. Coombe,``Association between imaging and XRF sensing: A machine learning approach to discover mineralogy in abandoned mine voids,'' IEEE Sensors J., vol. 16, no. 11, pp. 4555 4565, Jun. 2016, doi:10.1109/JSEN.2016.2546241.

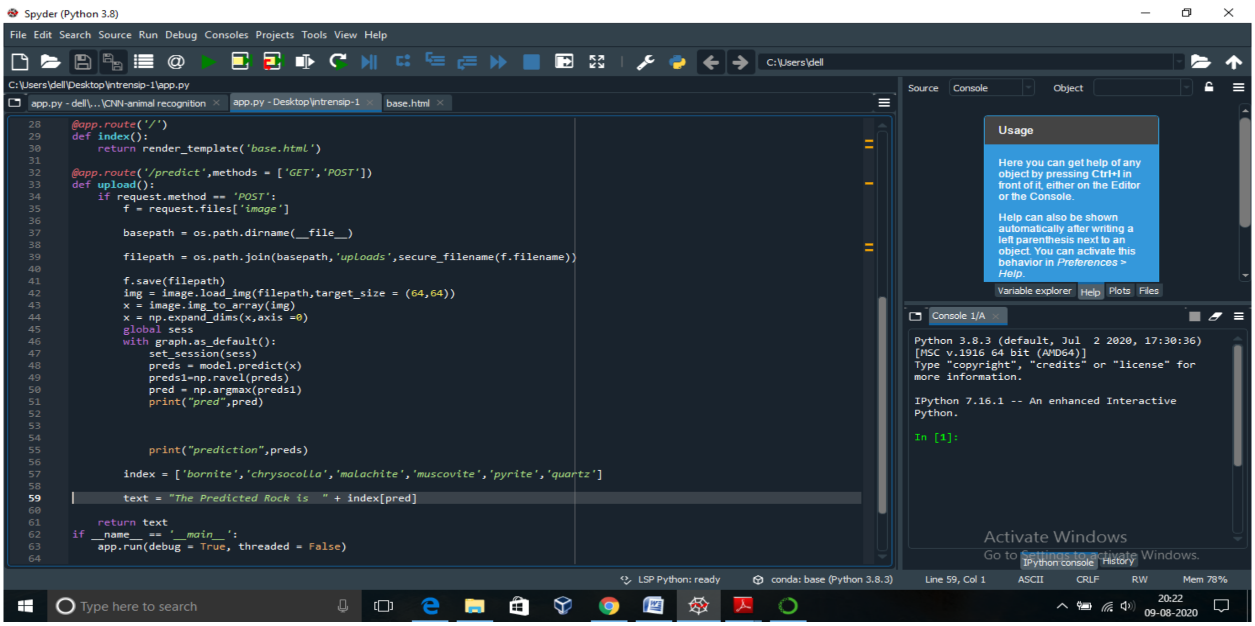
APPENDIX

A.SOURCE CODE

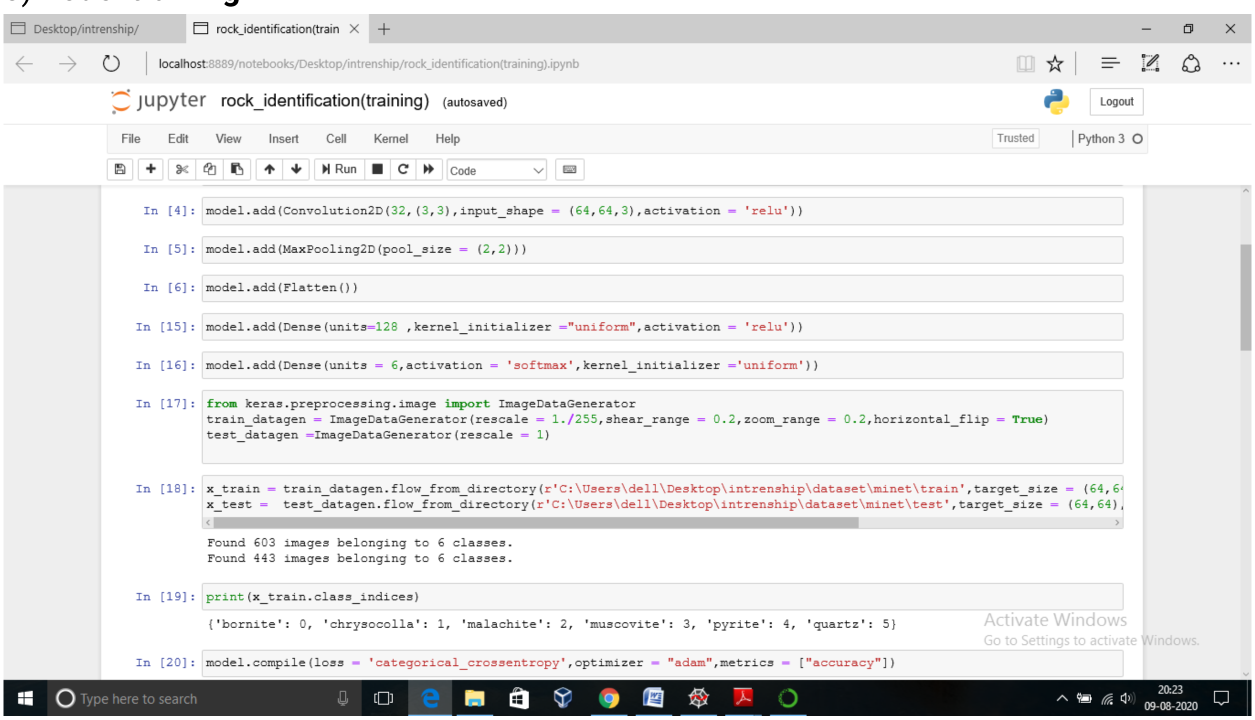
1) **base.html** for UI



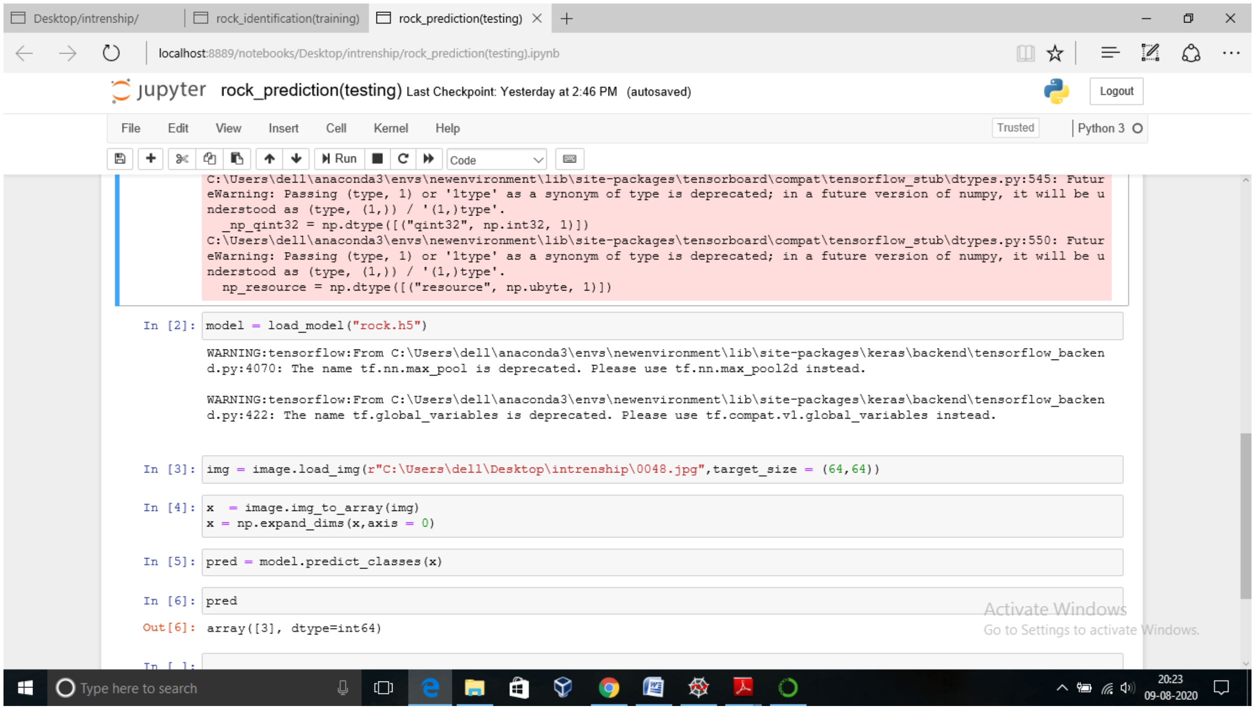
2) **app.py** for model deployment



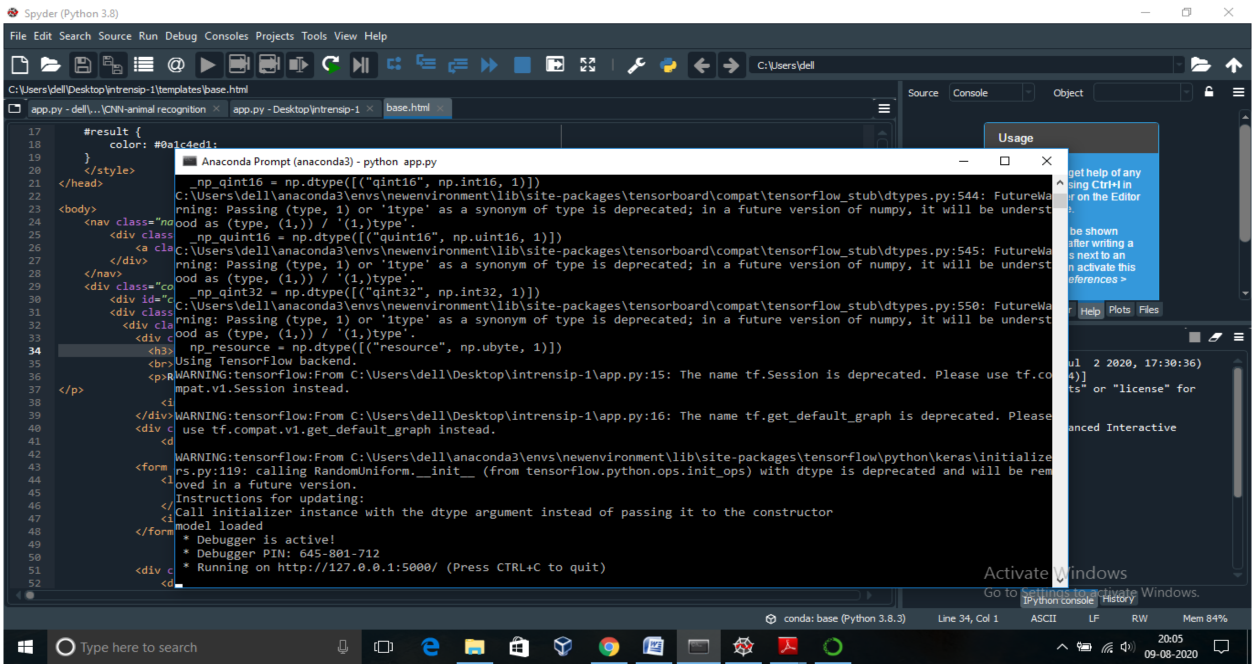
3)**model training**

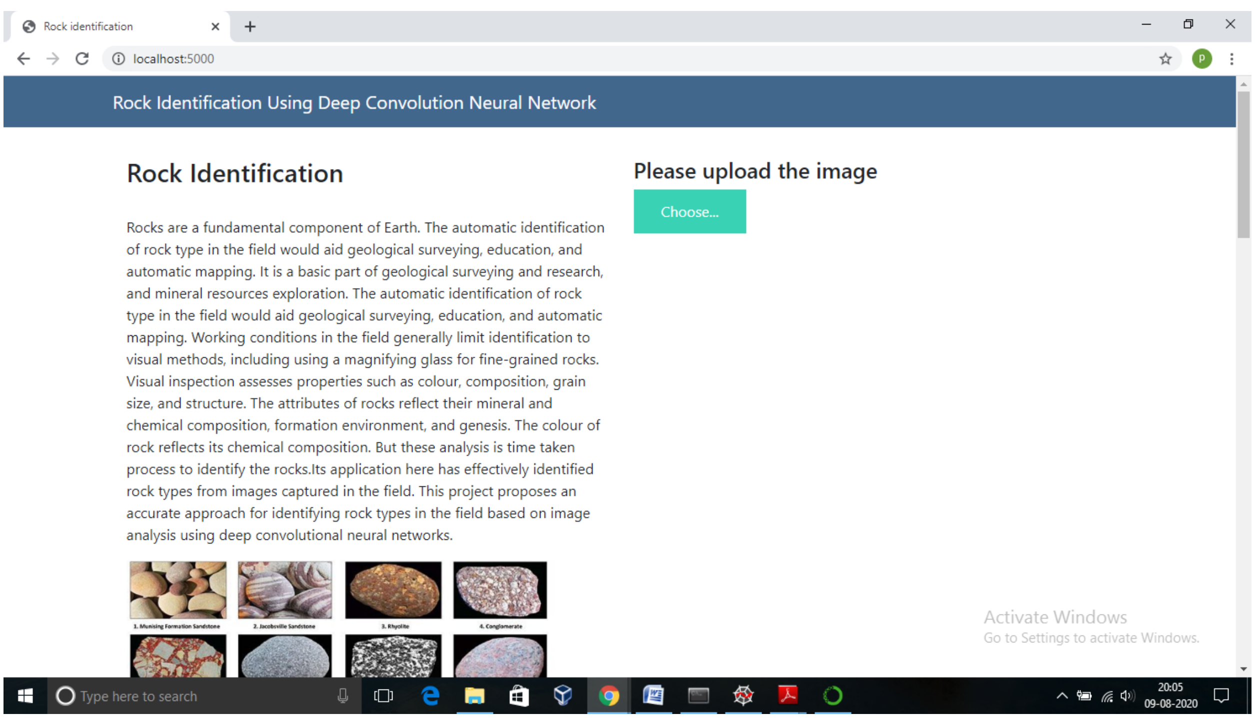


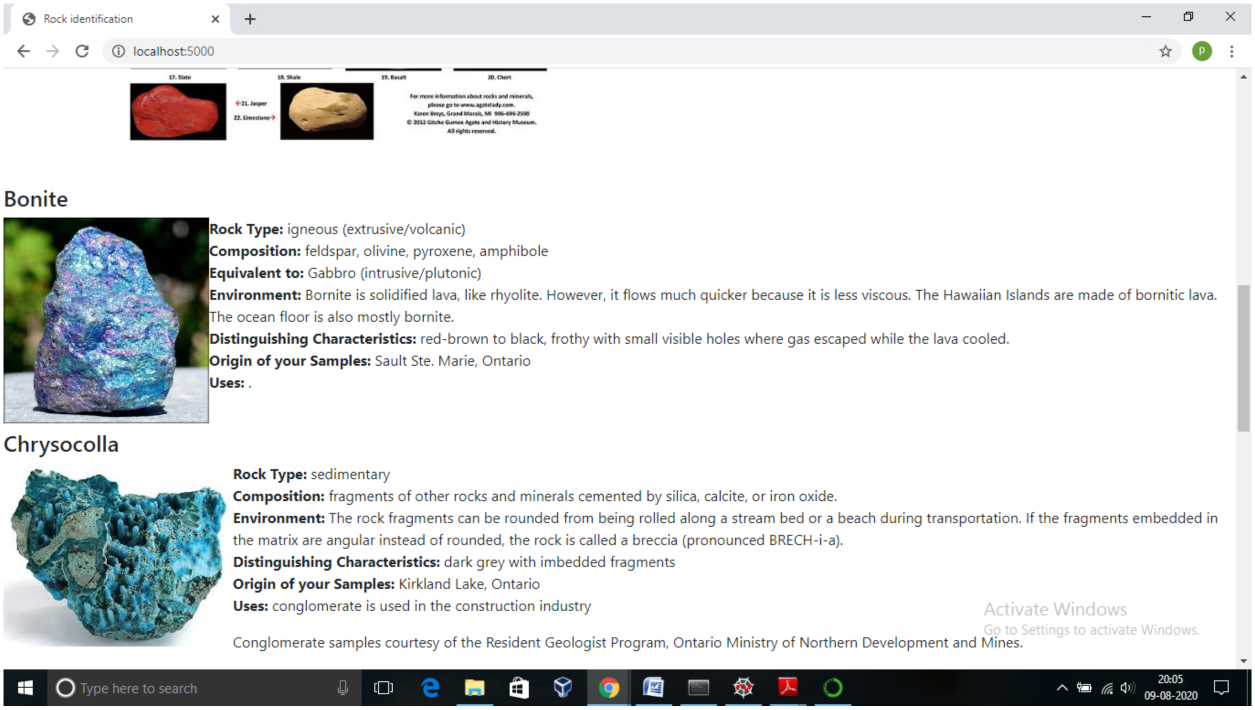
4) **model prediction**

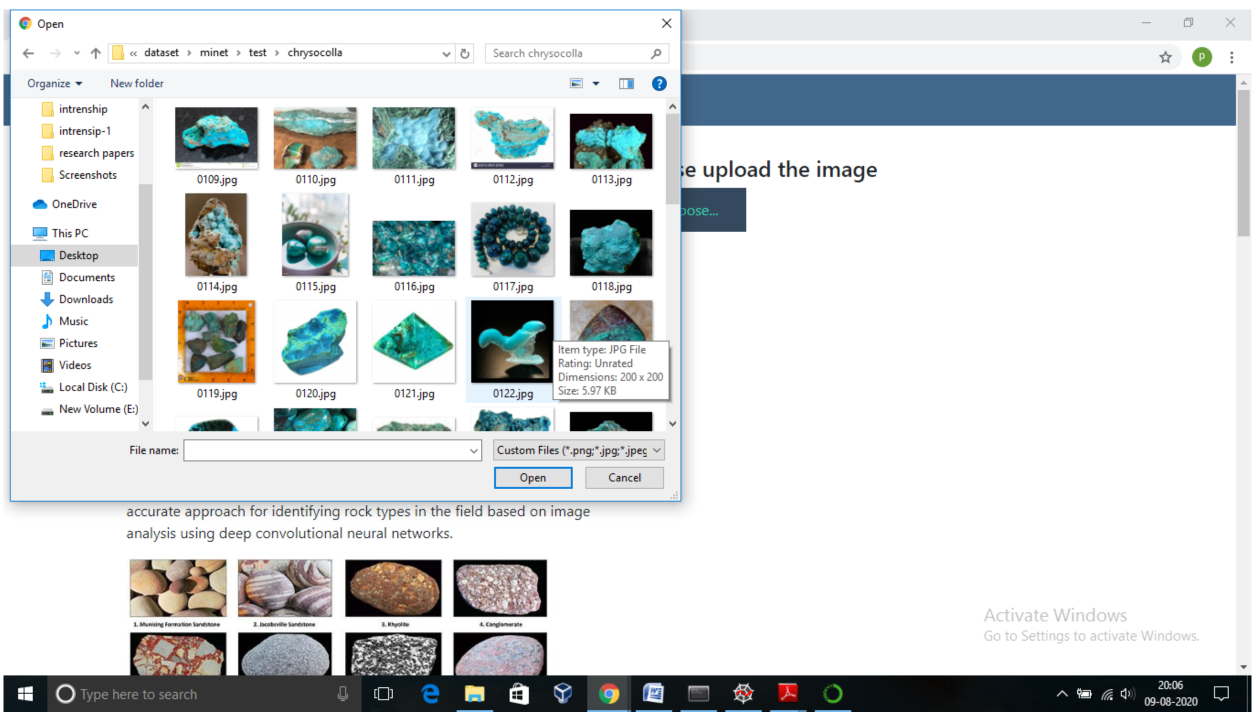


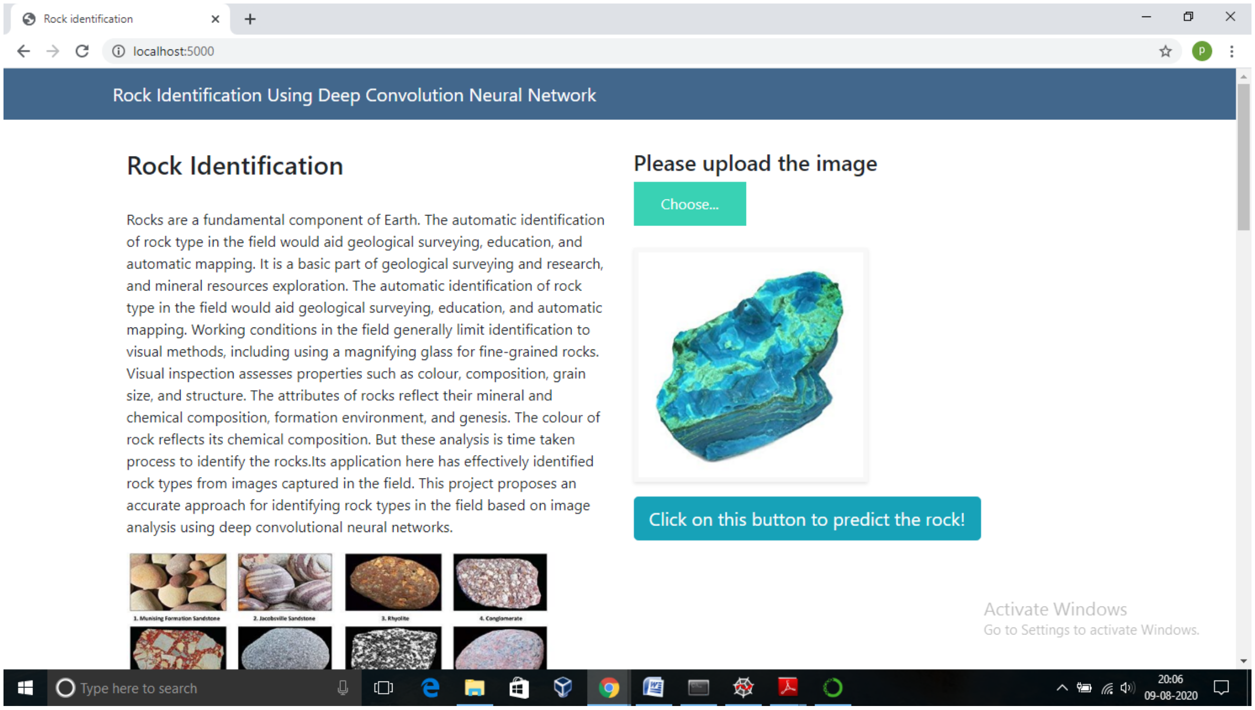
SCREENSHOTS

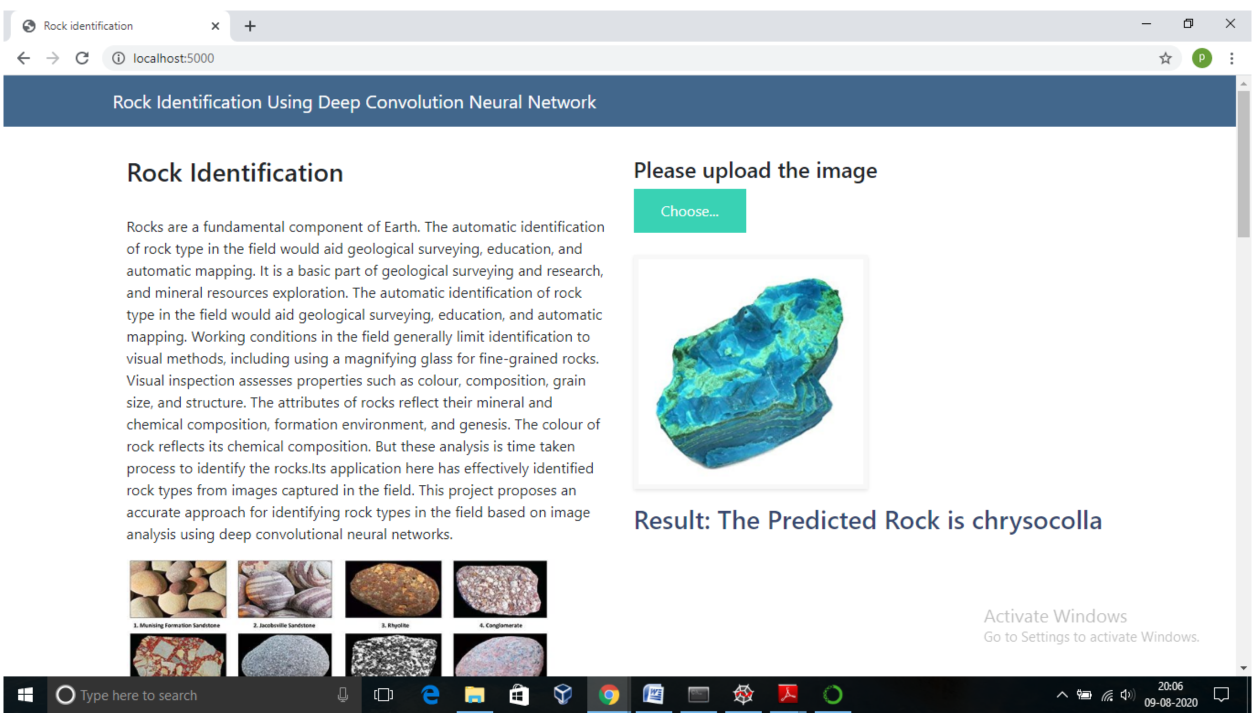





Rock identification
localhost:5000
Bonite
Rock Type: igneous (extrusive/volcanic)
Composition: feldspar, olivine, pyroxene, amphibole
Equivalent to: Gabbro (intrusive/plutonic)
Environment: Bornite is solidified lava, like rhyolite. However, it flows much quicker because it is less viscous. The Hawaiian Islands are made of bornitic lava. The ocean floor is also mostly bornite.
Distinguishing Characteristics: red-brown to black, frothy with small visible holes where gas escaped while the lava cooled.
Origin of your Samples: Sault Ste. Marie, Ontario
Uses: .
Chrysocolla
Rock Type: sedimentary
Composition: fragments of other rocks and minerals cemented by silica, calcite, or iron oxide.
Environment: The rock fragments can be rounded from being rolled along a stream bed or a beach during transportation. If the fragments embedded in the matrix are angular instead of rounded, the rock is called a breccia (pronounced BRECH-i-a).
Distinguishing Characteristics: dark grey with imbedded fragments
Origin of your Samples: Kirkland Lake, Ontario
Uses: conglomerate is used in the construction industry
Conglomerate samples courtesy of the Resident Geologist Program, Ontario Ministry of Northern Development and Mines.
Activate Windows
Go to Settings to activate Windows.
Type here to search
20:05
09-08-2020


Open
dataset › minet › test › chrysocolla
Search chrysocolla
Organize
New folder
intrenship
intrensip-1
research papers
Screenshots
OneDrive
This PC
Desktop
Documents
Downloads
Music
Pictures
Videos
Local Disk (C:)
New Volume (E:)
0109.jpg
0110.jpg
0111.jpg
0112.jpg
0113.jpg
0114.jpg
0115.jpg
0116.jpg
0117.jpg
0118.jpg
0119.jpg
0120.jpg
0121.jpg
0122.jpg
Item type: JPG File
Rating: Unrated
Dimensions: 200 x 200
Size: 5.97 KB
File name:
Custom Files (*.png;*.jpg;*.jpeg
Open
Cancel
e upload the image
accurate approach for identifying rock types in the field based on image analysis using deep convolutional neural networks.
Activate Windows
Go to Settings to activate Windows.
Type here to search
20:06
09-08-2020


Rock identification
localhost:5000
Rock Identification Using Deep Convolution Neural Network
Rock Identification
Rocks are a fundamental component of Earth. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. It is a basic part of geological surveying and research, and mineral resources exploration. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. 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.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.
Please upload the image
Choose...
Click on this button to predict the rock!
Activate Windows
Go to Settings to activate Windows.
Type here to search
20:06
09-08-2020


Rock identification
localhost:5000
Rock Identification Using Deep Convolution Neural Network
Rock Identification
Rocks are a fundamental component of Earth. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. It is a basic part of geological surveying and research, and mineral resources exploration. The automatic identification of rock type in the field would aid geological surveying, education, and automatic mapping. 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.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.
Please upload the image
Choose...
Result: The Predicted Rock is chrysocolla
Activate Windows
Go to Settings to activate Windows.
Type here to search
20:06
09-08-2020