PETROLEUM & MINING ENGINEERING

Mineral Identification Using Convolutional Neural Network: A Deep Learning Approach

Presented by

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Reg No: 20173360[redacted]
Session: 2017-2018

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Session: 2017-2018

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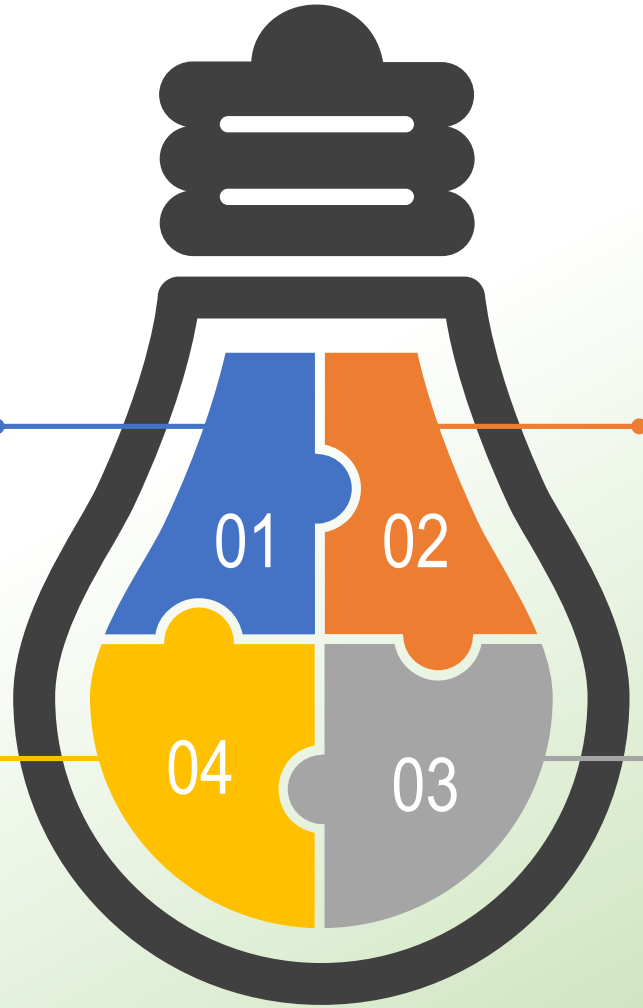
INTRODUCTION



Mineral classification

Convolutional Neural Network (CNN)

Hand specimen images

Scientific and industrial applications

OBJECTIVES

1

ACCURATE IDENTIFICATION AND CATEGORIZATION

2

ROBUST MINERAL CLASSIFICATION MODEL

3

PERFORMANCE EVALUATION

4

MANUAL LABOUR REDUCTION

3

METHODOLOGY

Methodology (Cont.)

DATA

Training Data : 250 Image per mineral
Validation data: 20 image per mineral

1.Agate

2. Amber

3. Biotite

4. Bornite

5. Chrysocolla

6. Galena

7. Malachite

8. Muscovite

9. Orpiment

10. Pyrite

11. Quartz

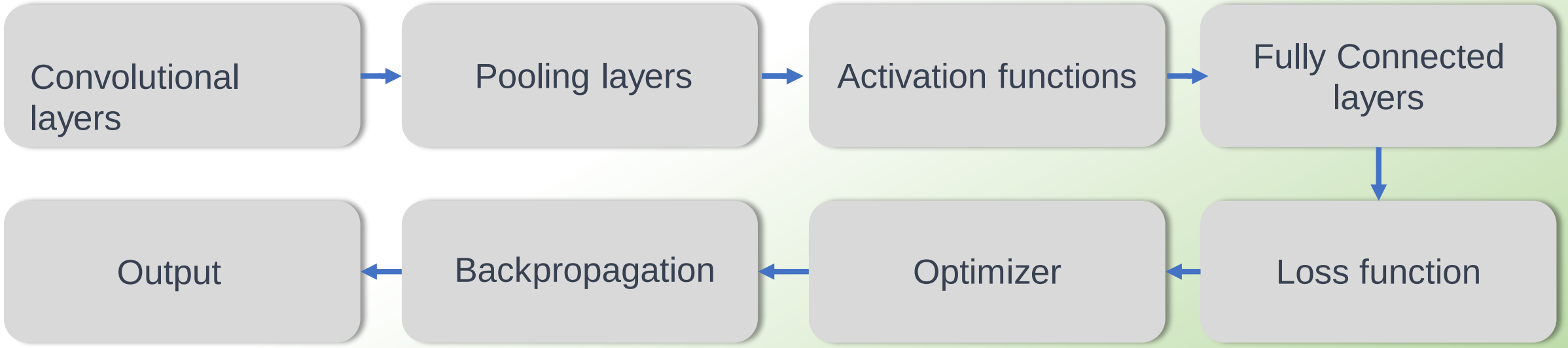
12. Rhodochrosite

13. Schrol

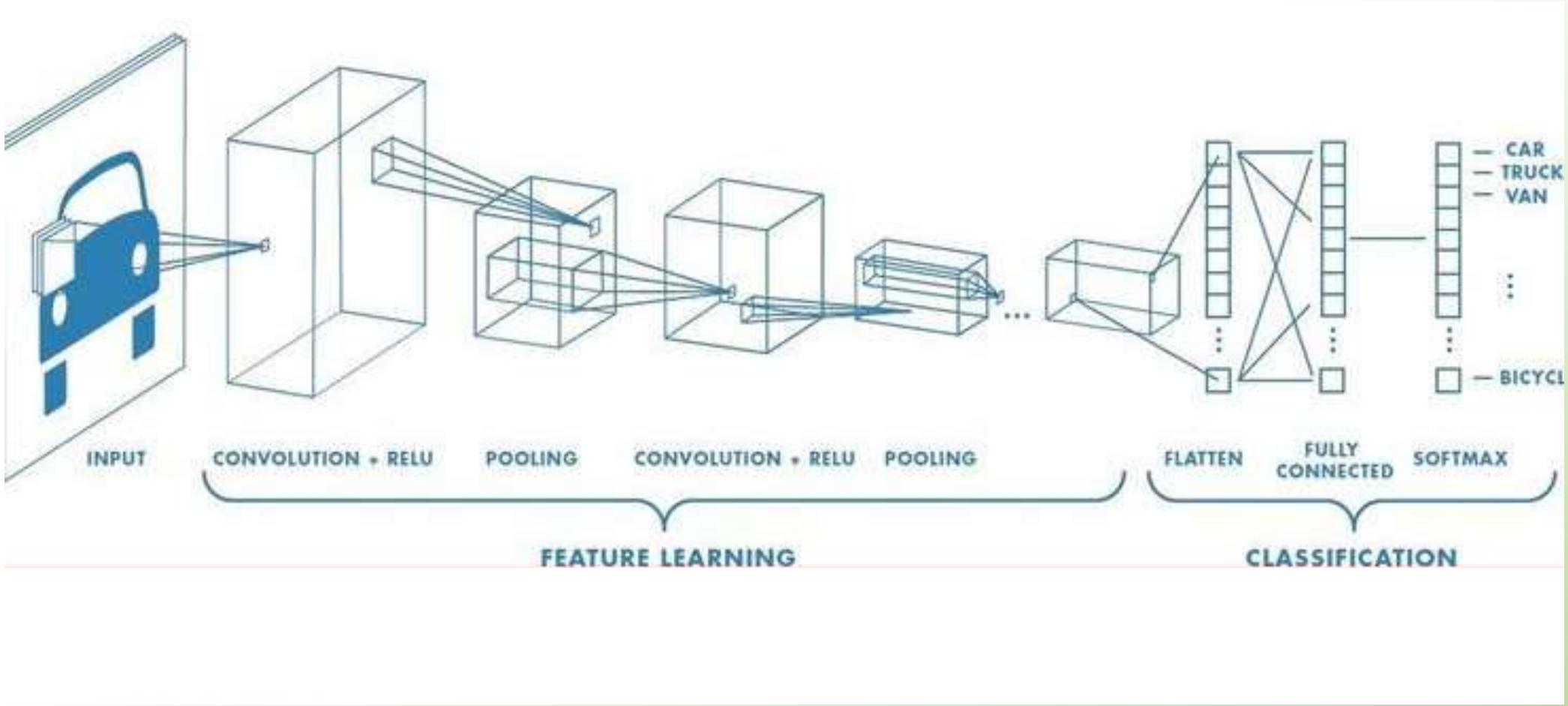
14. Sulphur

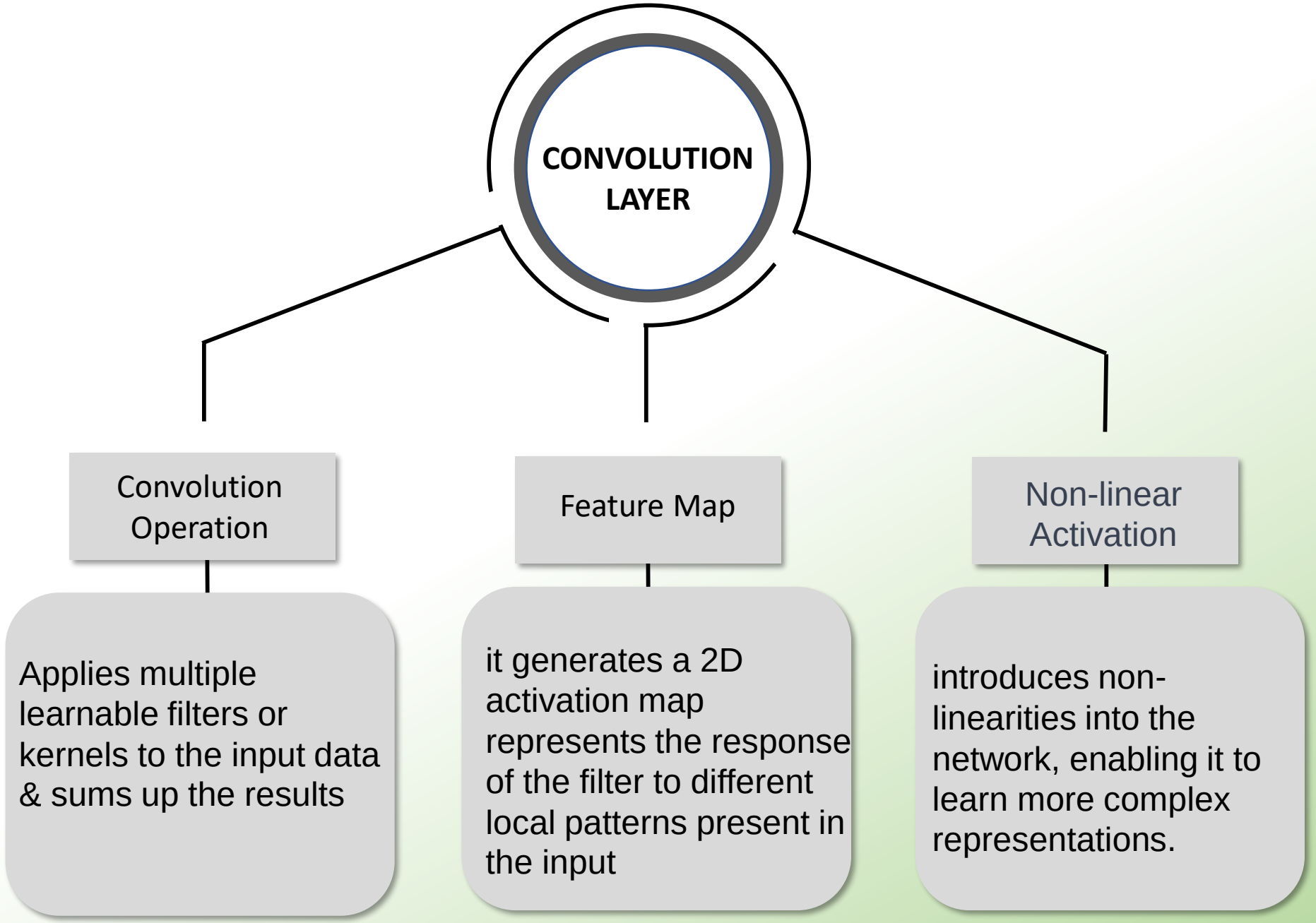
15. Torbernite

CONVOLUTIONAL NEURAL NETWORK



A CONVOLUTIONAL ARCHITECTURE




CONVOLUTION LAYER
Convolution Operation
Applies multiple learnable filters or kernels to the input data & sums up the results
Feature Map
it generates a 2D activation map represents the response of the filter to different local patterns present in the input
Non-linear Activation
introduces non-linearities into the network, enabling it to learn more complex representations.

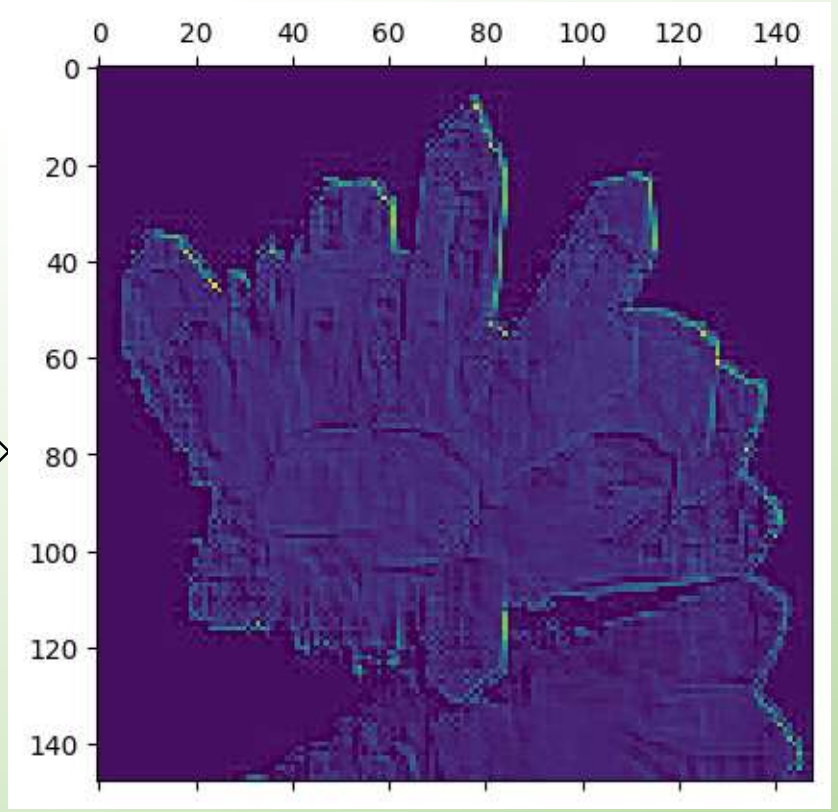
CONVOLUTION LAYER

Input image

150 X 150

1st Conv Layer

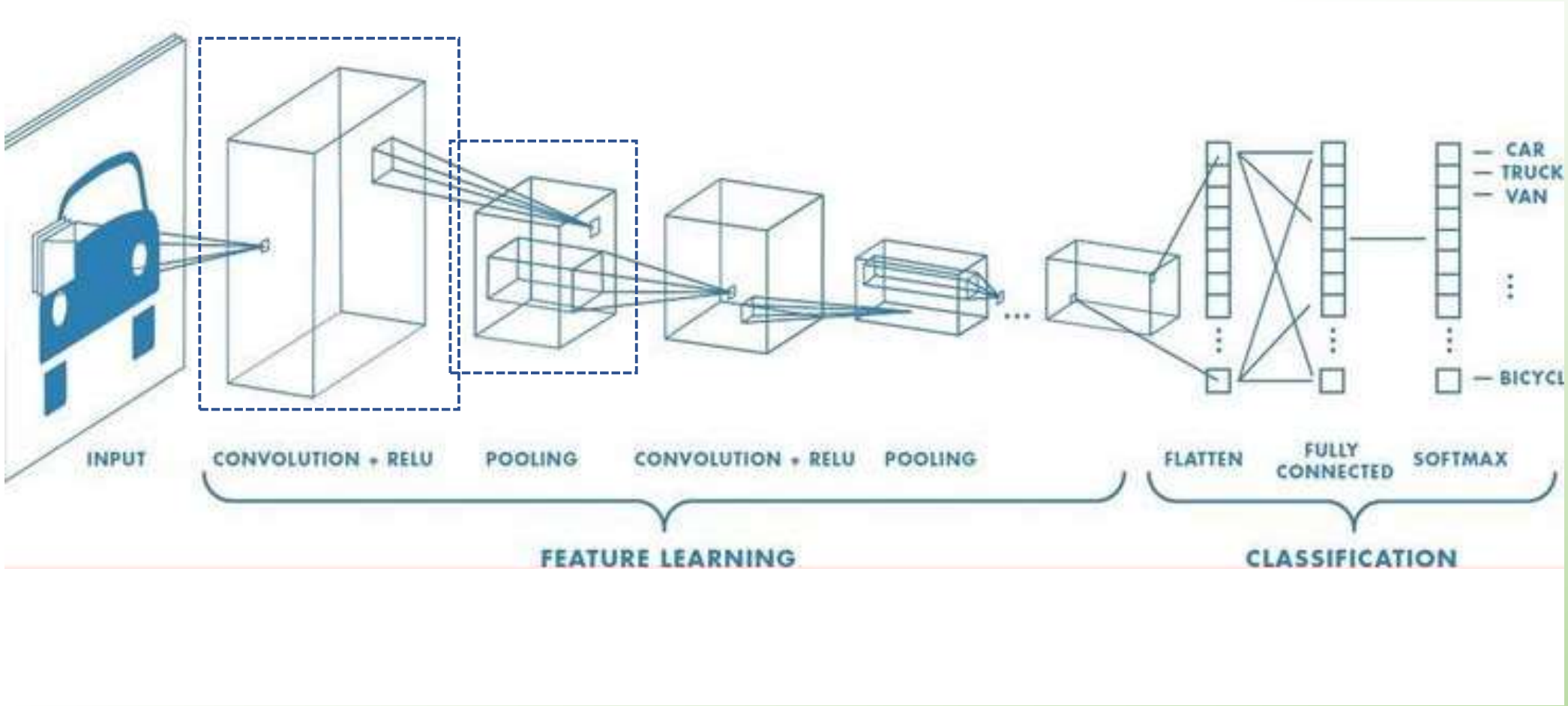
32 filter

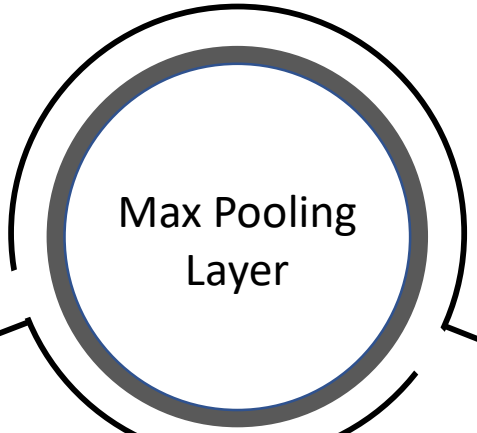


output image

148 X 148

Methodology (Cont.)





Pooling Operation

It selects the maximum value within that window and discards the rest of the values. The result is a downsampled version of the input, with reduced spatial dimensions.

Feature Map Reduction

It reduces the size of each feature map, resulting in a downsampled feature map. The reduction in spatial dimensions helps to make the network more robust to translation or small shifts in the input data

MAX POOLING LAYER

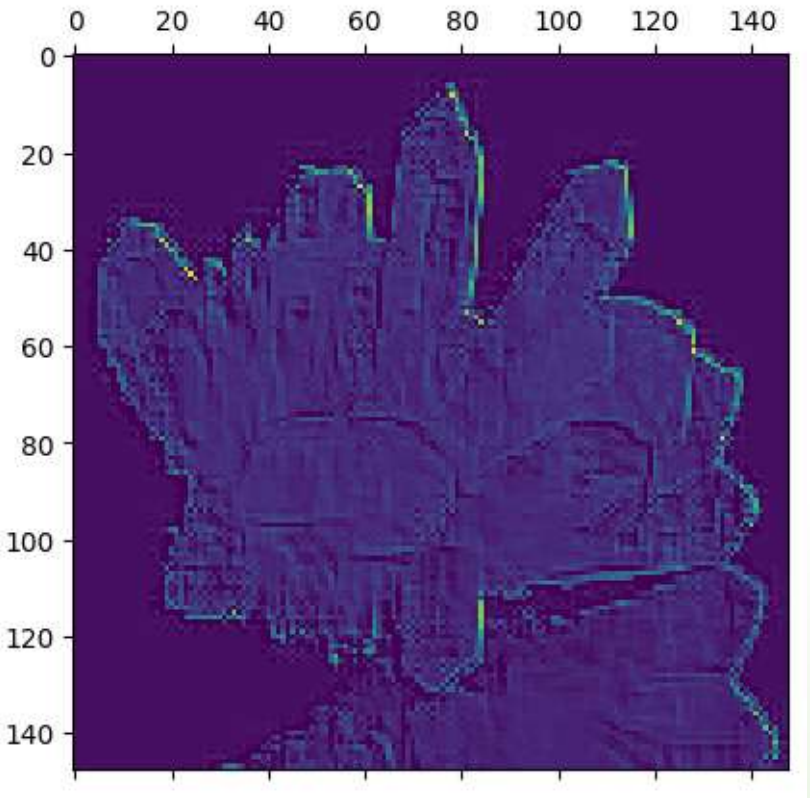


Image after 1st convulation

148 X 148

1st maxpooling

32 filter

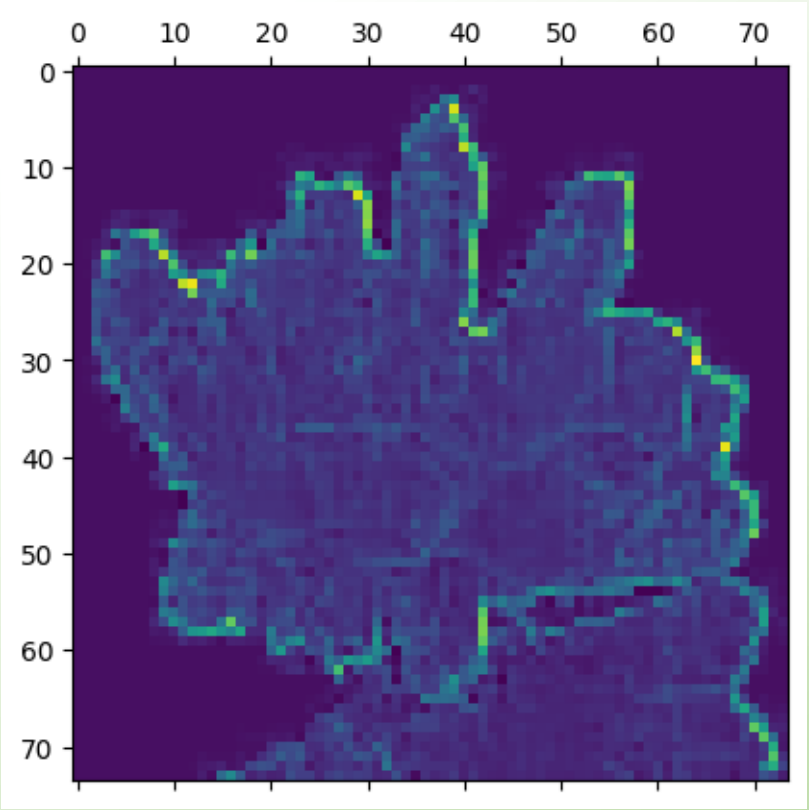
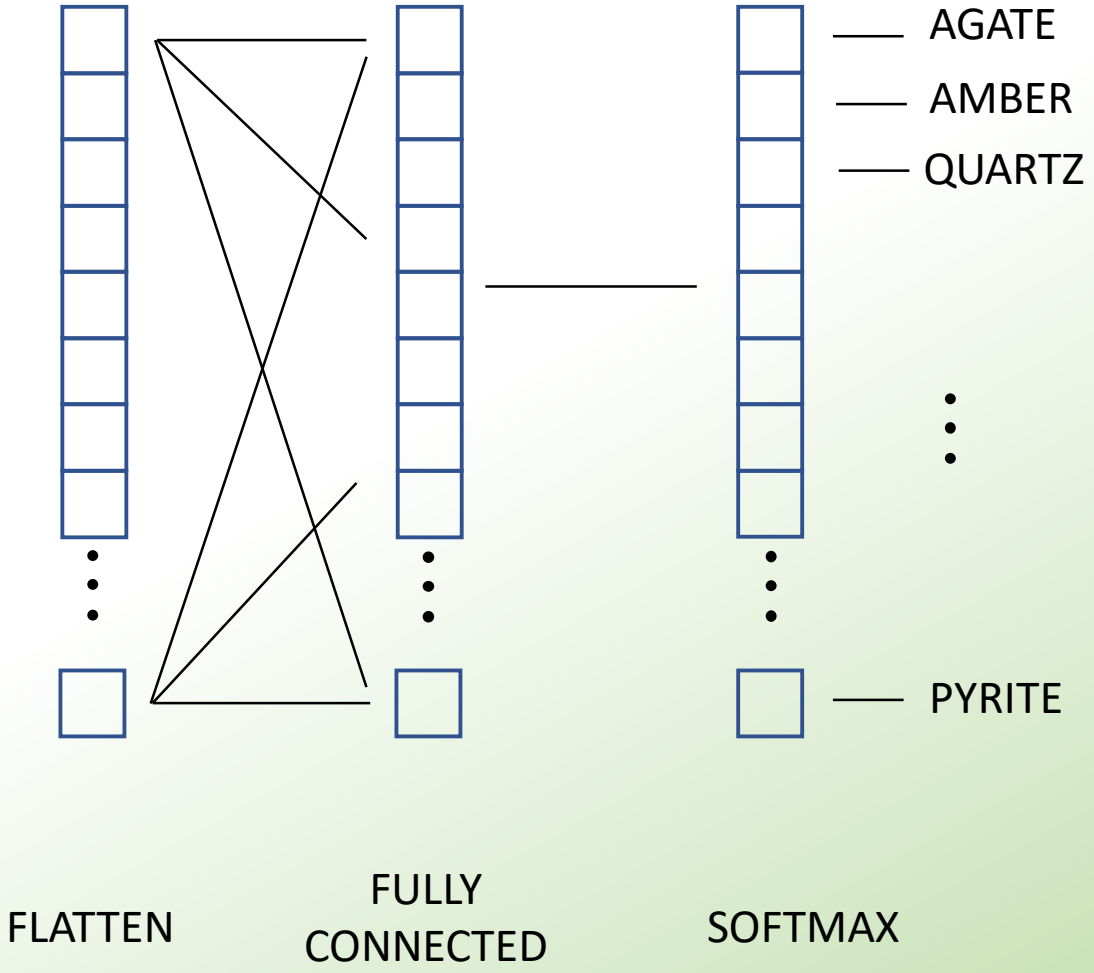


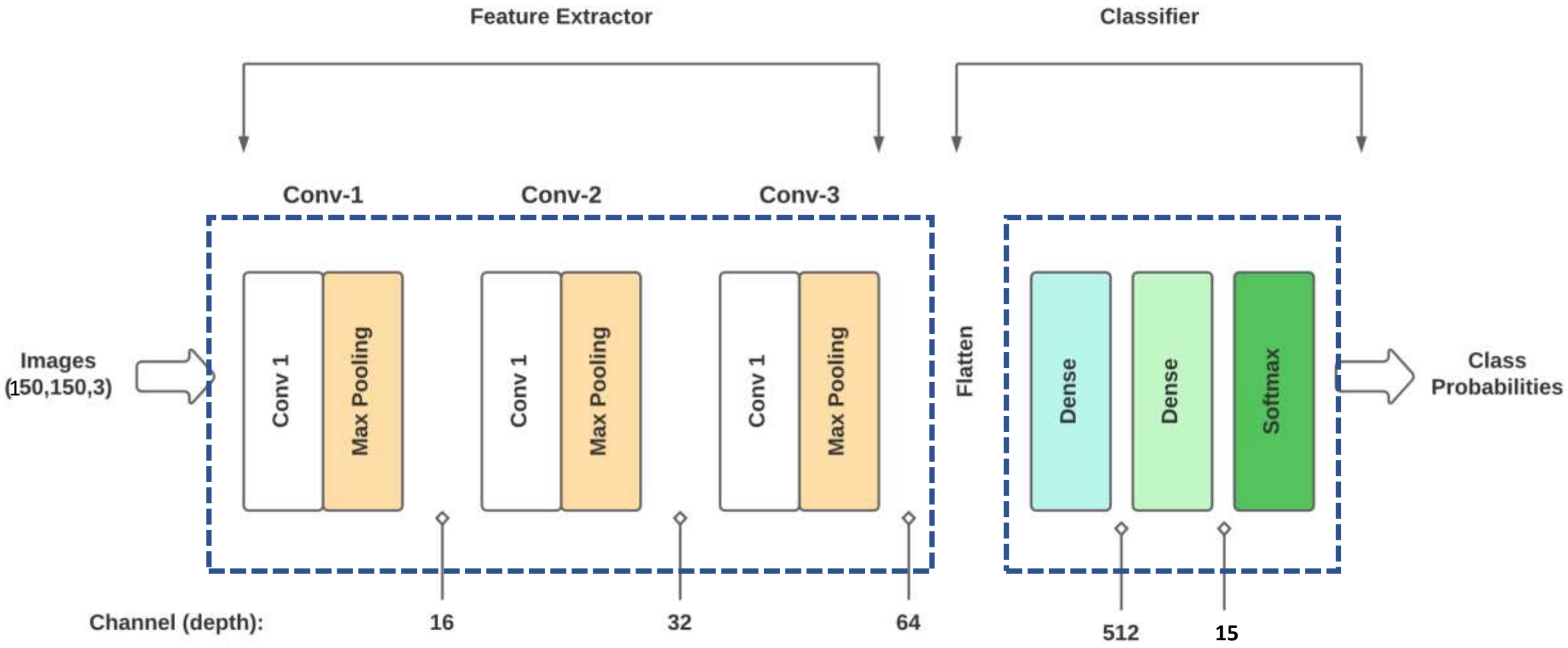
Image after 1st max pooling

74X74

FLATTEN & DENSE



OUR PROPOSED MODEL



RESULTS

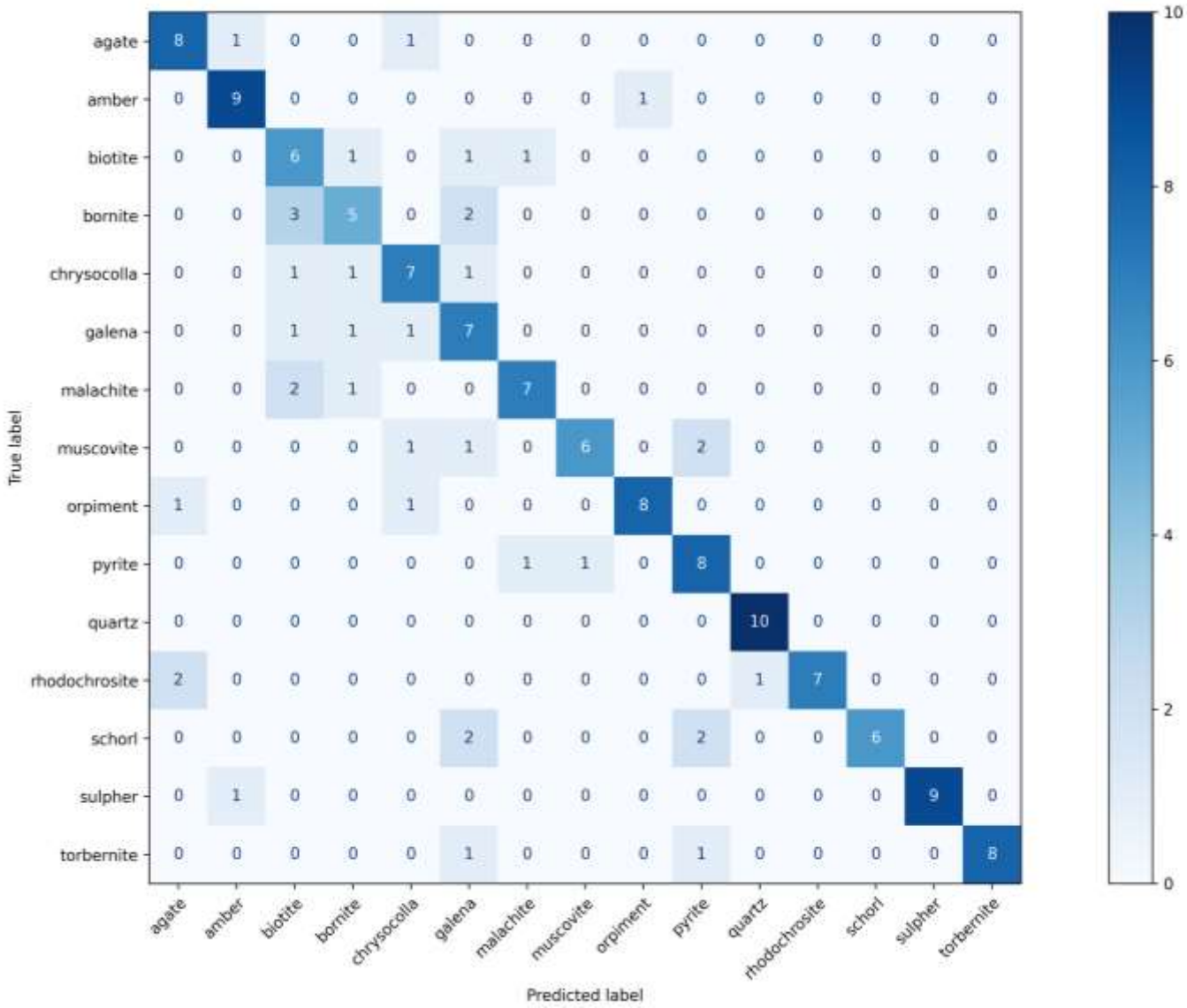
EVALUATION MATRICES

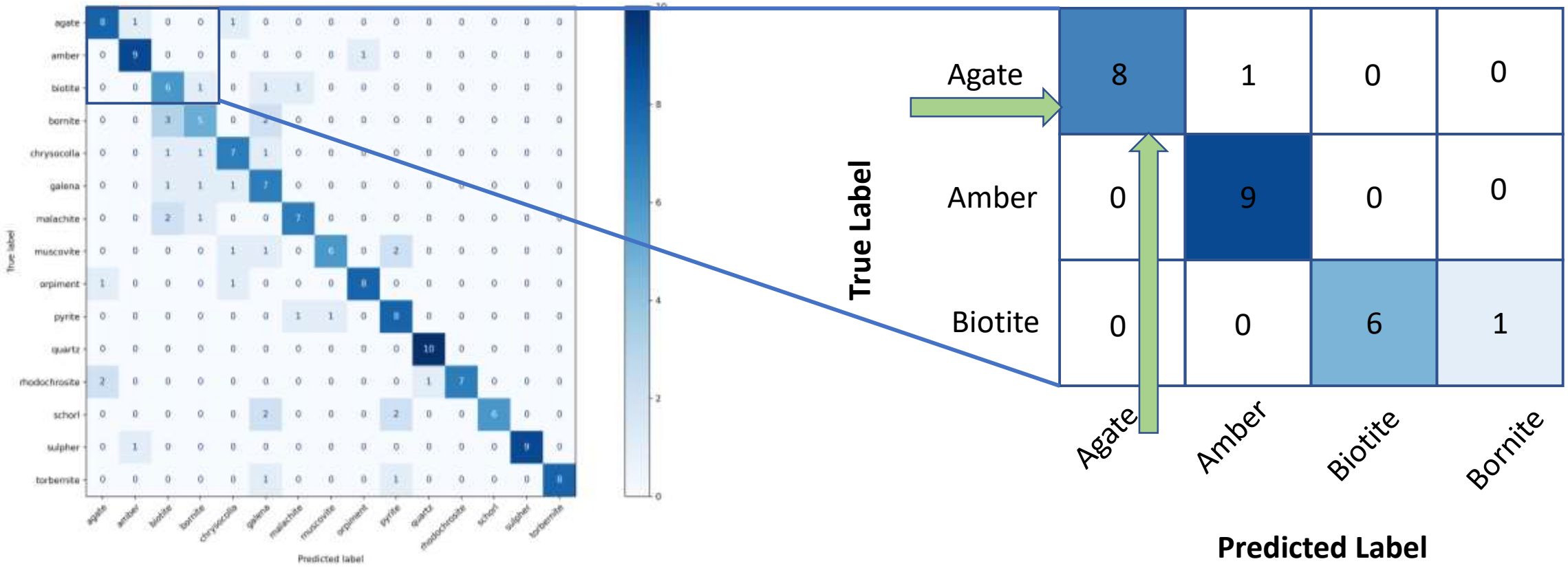
- ACCURACY
- CONFUSION MATRIX
- PRECISION
- RECALL

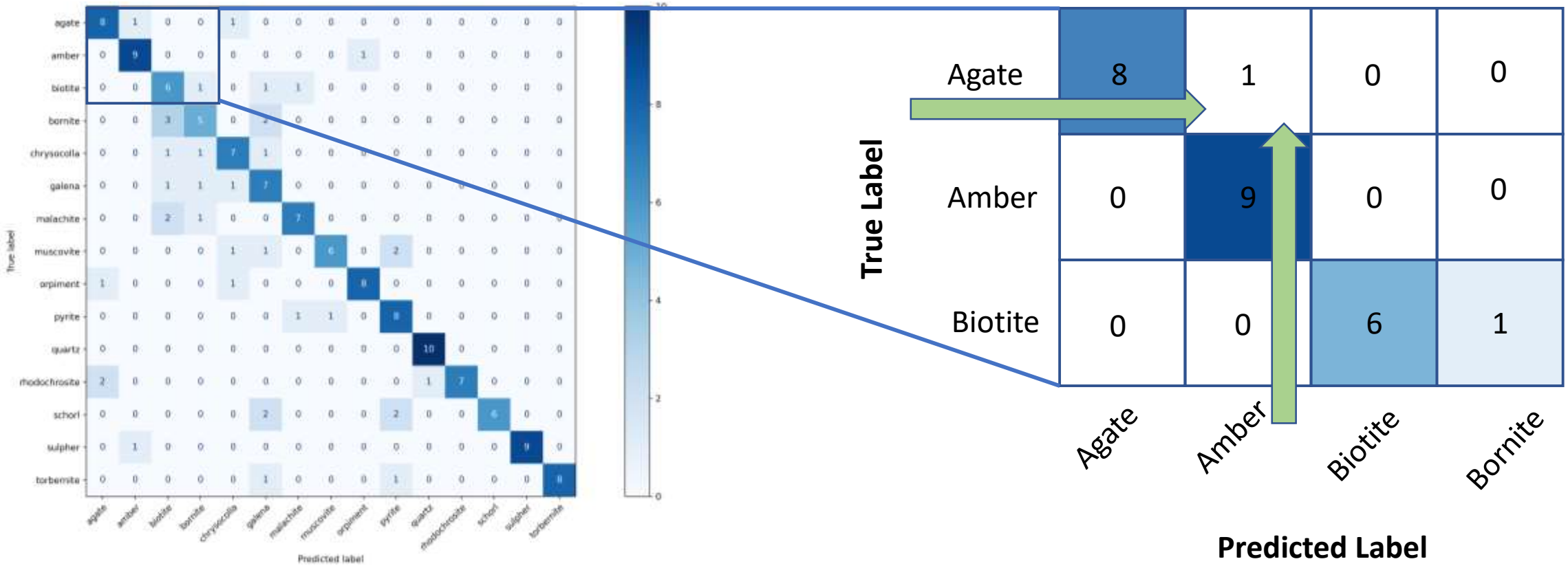
ACCURACY

Training Accuracy	90%
Validation Accuracy	80%

CONFUSION MATRIX




agate
amber
biotite
bornite
chrysocolla
galena
malachite
muscovite
orpiment
pyrite
quartz
rhodochrosite
schorl
sulpher
torbernite
True label
Predicted label
Agate
Amber
Biotite
Bornite
8 1 0 0
0 9 0 0
0 0 6 1
True Label
Predicted Label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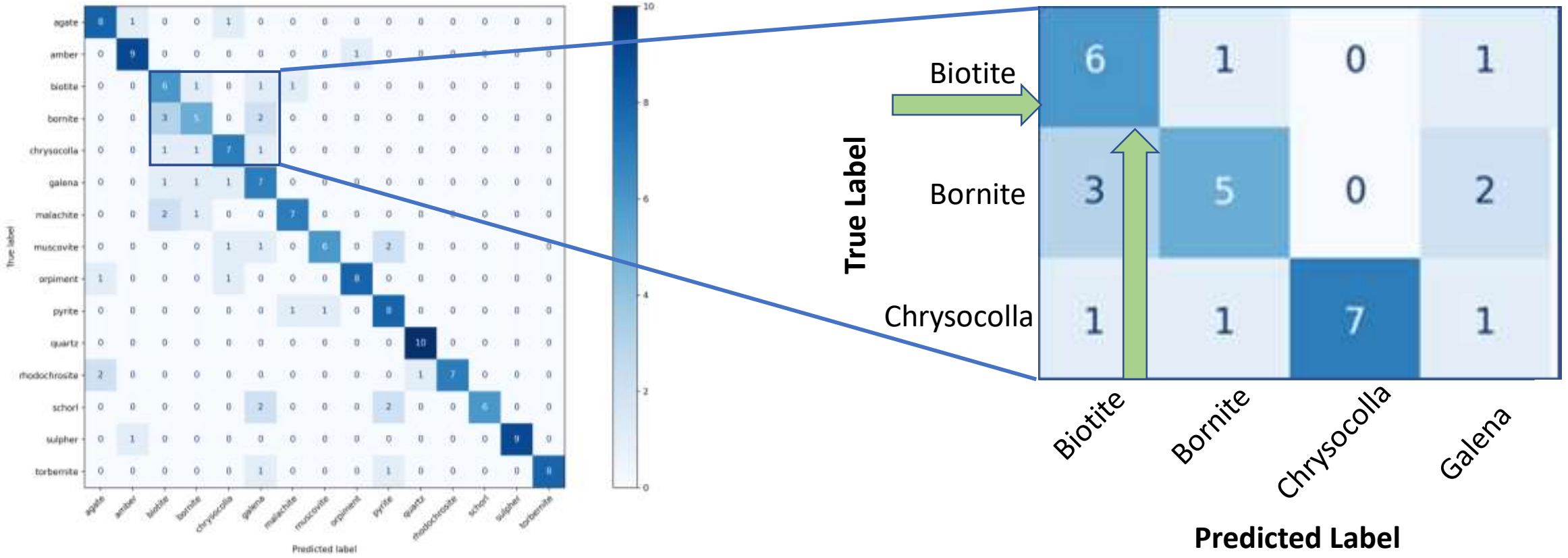
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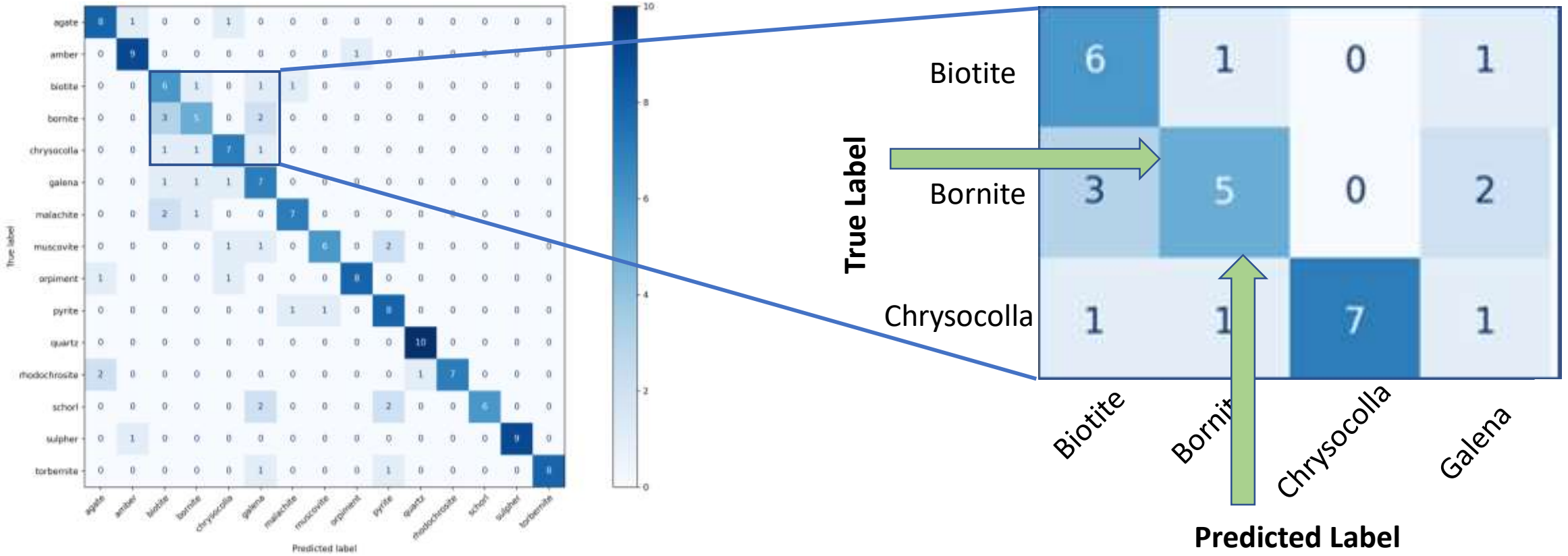
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torbernite
True label
Predicted label
Biotite
Bornite
Chrysocolla
Galena
True Label
Predicted Label

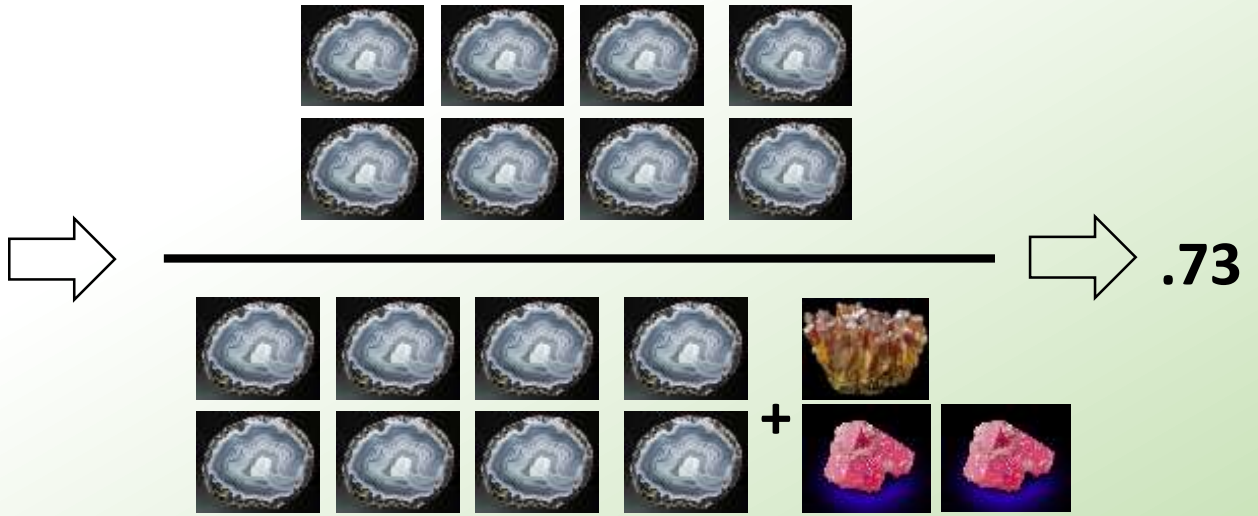
Biotite

Bornite

PRECISION

Precision is out of all true prediction how many we got it right

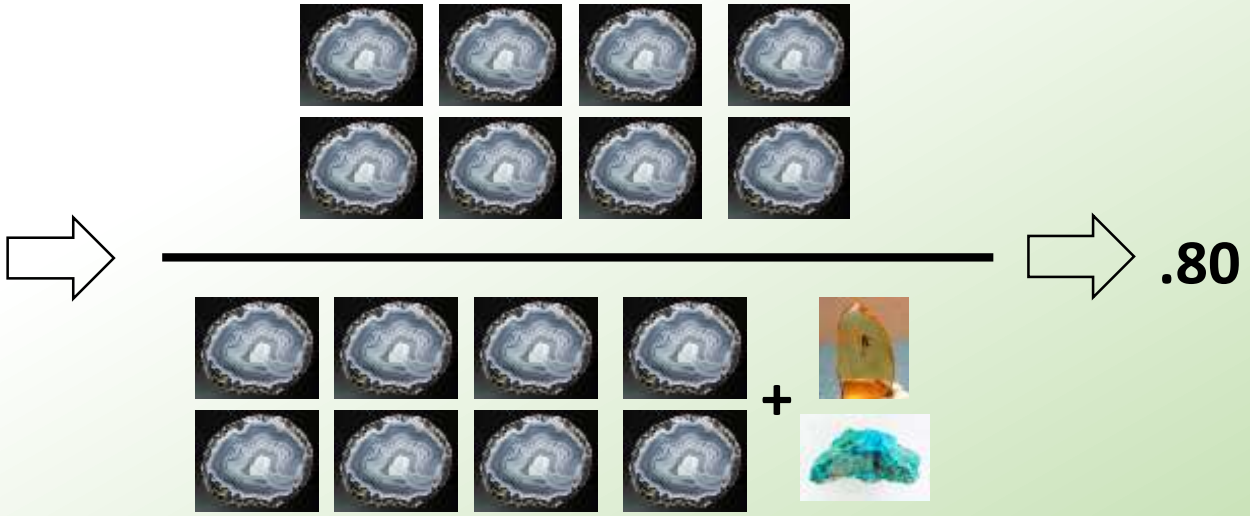
$$precision = \frac{true\ posotive}{true\ posotive + false\ posotive}$$



RECALL

Recall is out of all truth value how many we got it right?

$$recall = \frac{true\ posotive}{true\ posotive + false\ negative}$$



Precision, Recall of the individual classes

Mineral	Precision	Recall
agate	0.73	0.80
amber	0.82	0.90
biotite	0.46	0.67
bornite	0.56	0.50
chrysocolla	0.64	0.70
galena	0.47	0.70
malachite	0.78	0.70
muscovite	0.86	0.60
orpiment	0.89	0.80
pyrite	0.62	0.80
quartz	0.91	1.00
rhodochrosite	1.00	0.70
schorl	1.00	0.60
sulpher	1.00	0.90
torbernite	1.00	0.80

CONCLUSION

- ✓ Single-label image classification model
- ✓ DenseNet architecture
- ✓ Effective feature extraction capabilities
- ✓ Repository

FUTURE RESEARCH SCOPE

- ✓ Hyperspectral Imagery
- ✓ Hybrid Model
- ✓ Architecture Enhancement

THANK YOU