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Centre for Doctoral Training (CDT) in Oil and Gas

INSIGHT INTO THE FUTURE

Deep Learning as Fold Geometry Classification Tool

22 OF JUNE 2021

KAUST Virtual Workshop
Intelligent Illumination of the Earth

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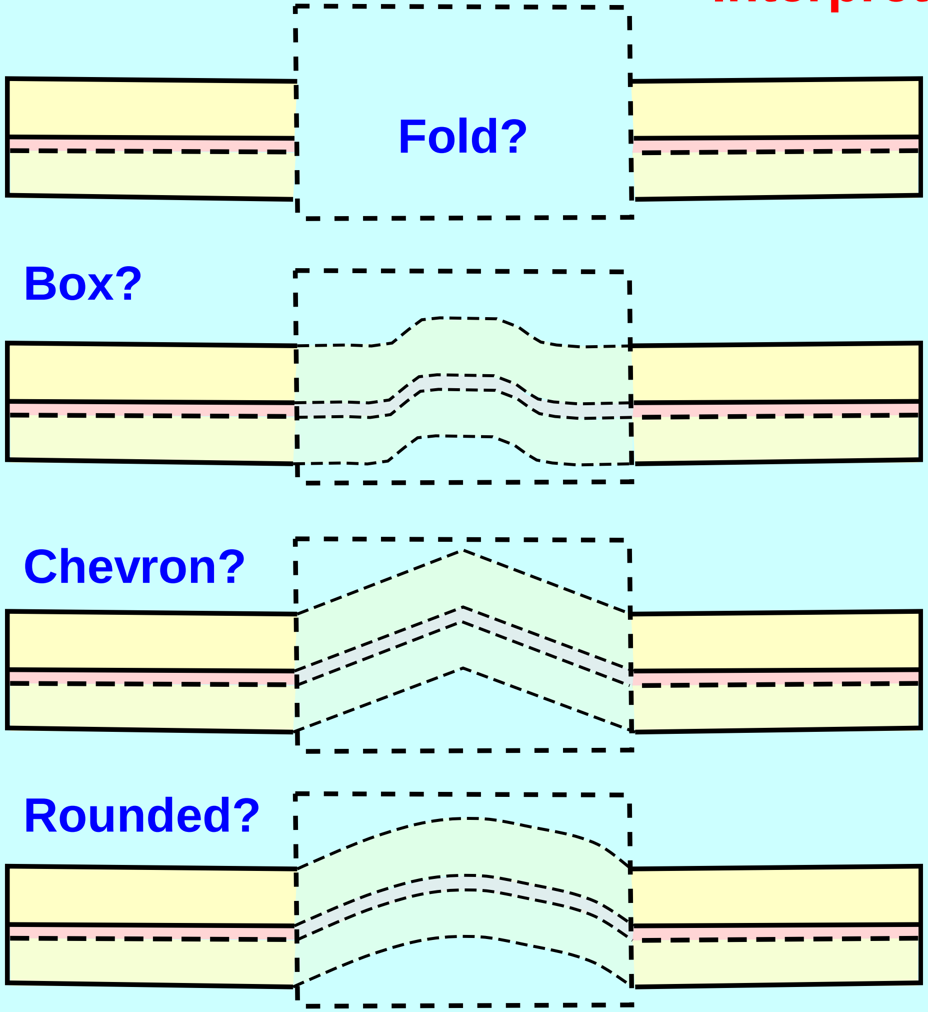
Why perform fold classification?

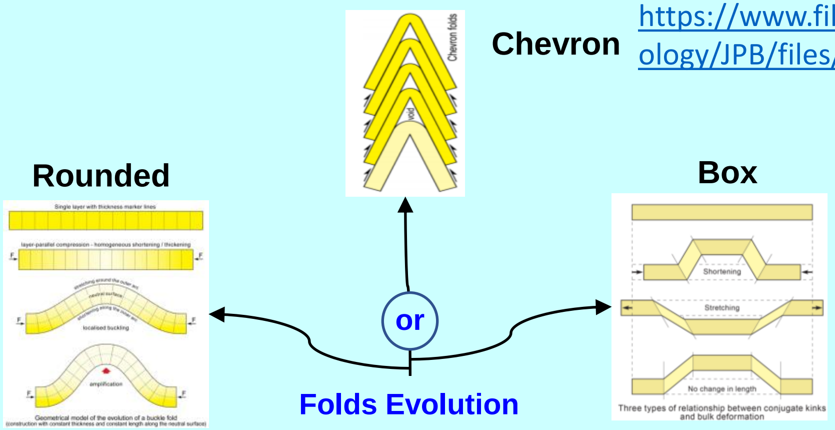
1. Provide additional information and constraints when interpreting complex structure:

Interpret this?



2. Helps to understand folding mechanisms and development:

https://www.files.ethz.ch/structuralgeology/JPB/files/English/7folding.pdf



3. Helps to understand distribution and heterogeneity of strain:

Heterogeneous or Inhomogeneous Strain

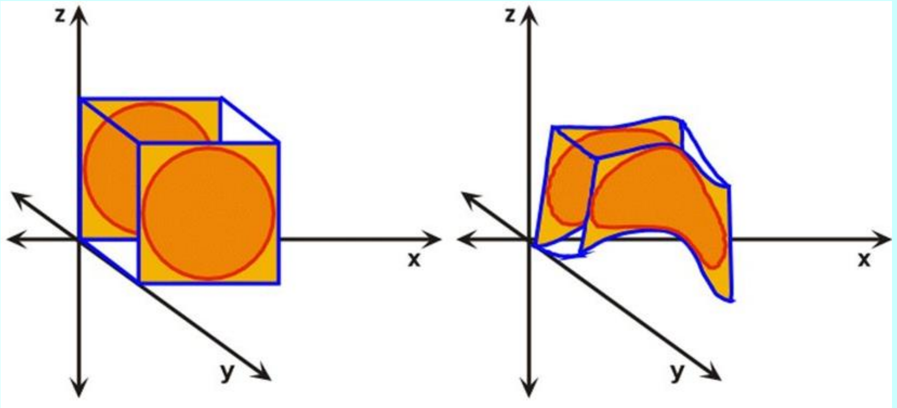
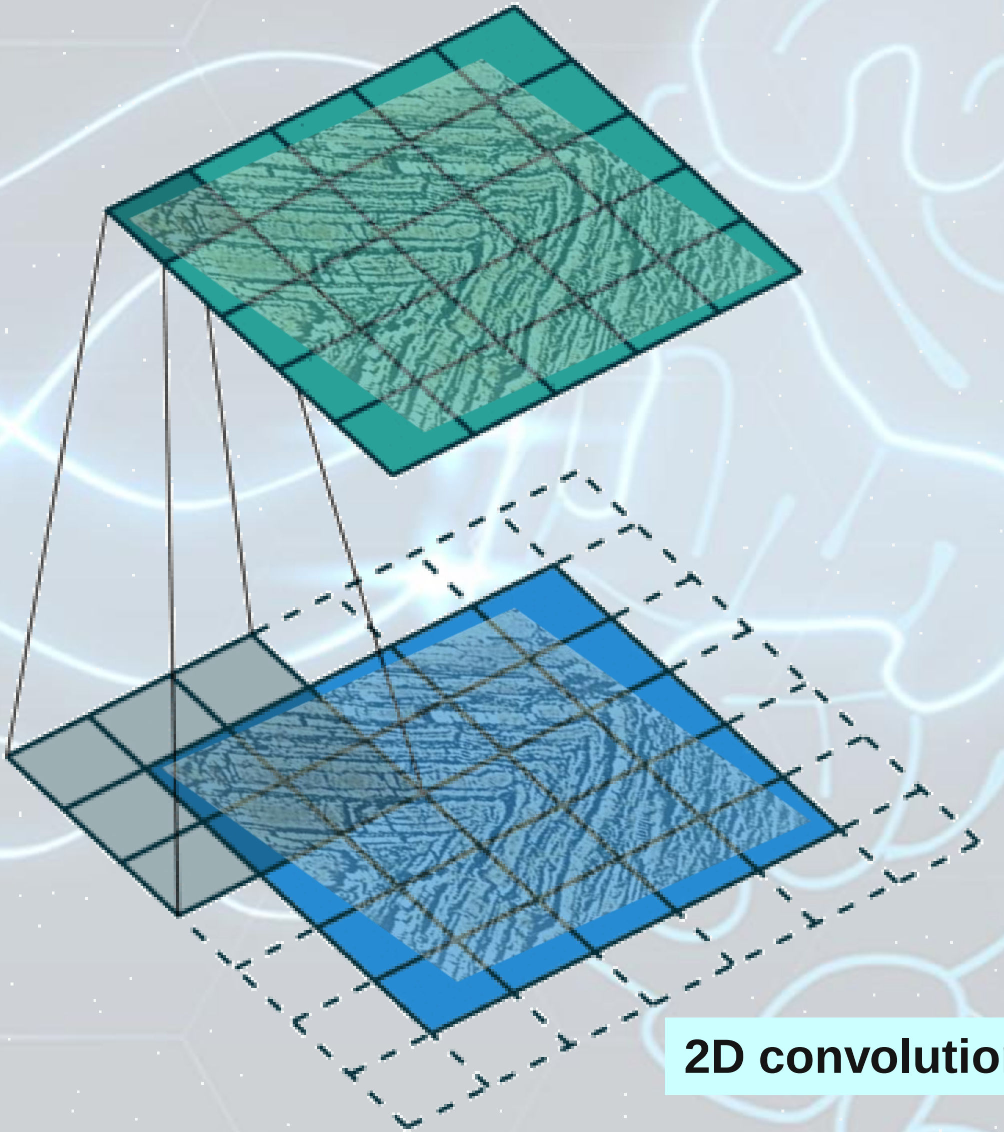


Image Classification

Using 2D Convolutional Neural Networks

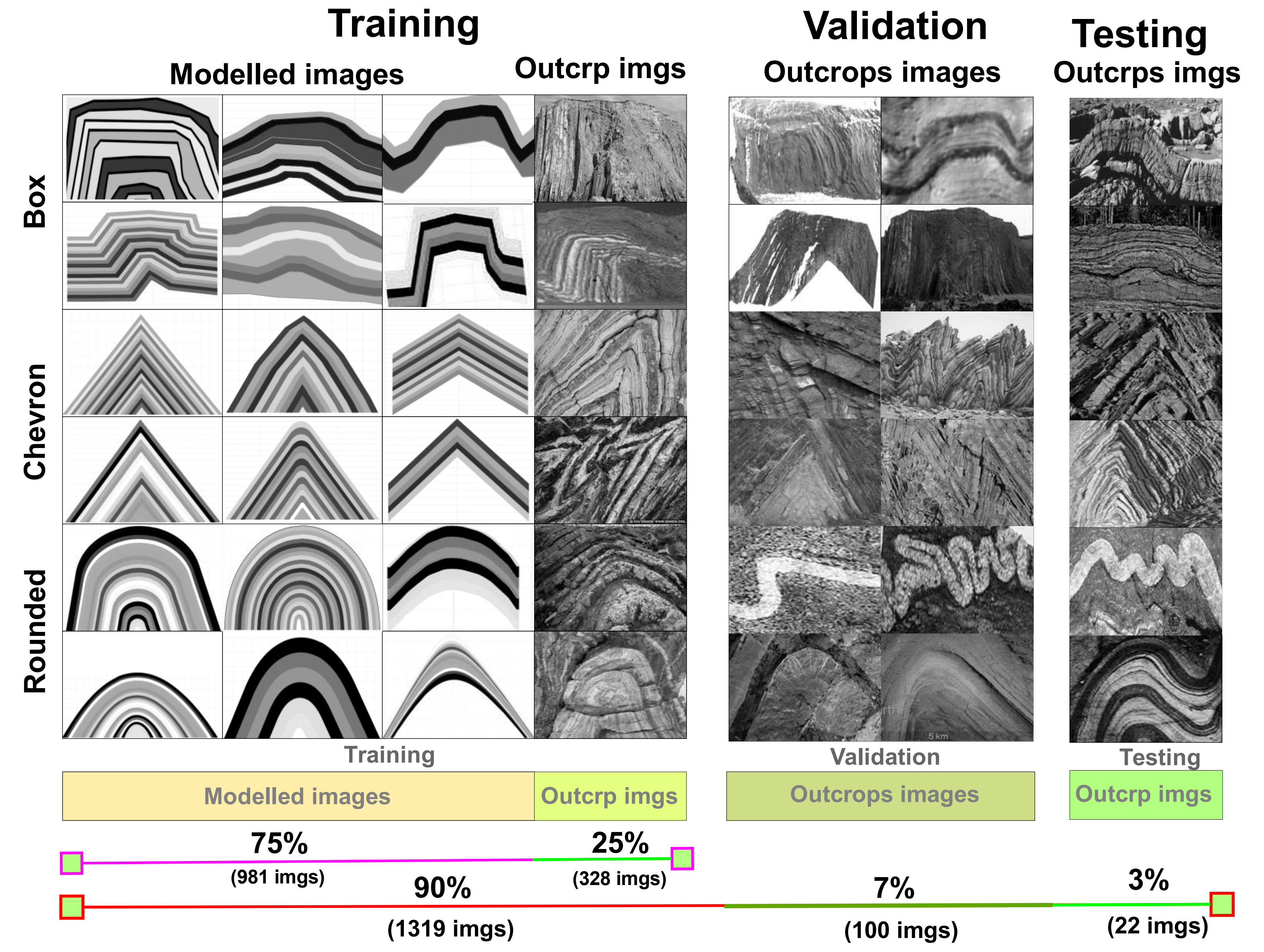
https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

- Start with a kernel, which is simply a small matrix of weights.
- This kernel “slides” over the 2D input data, performing an elementwise multiplication with the part of the input it is currently on.
- Then summing up the results into a single output pixel.

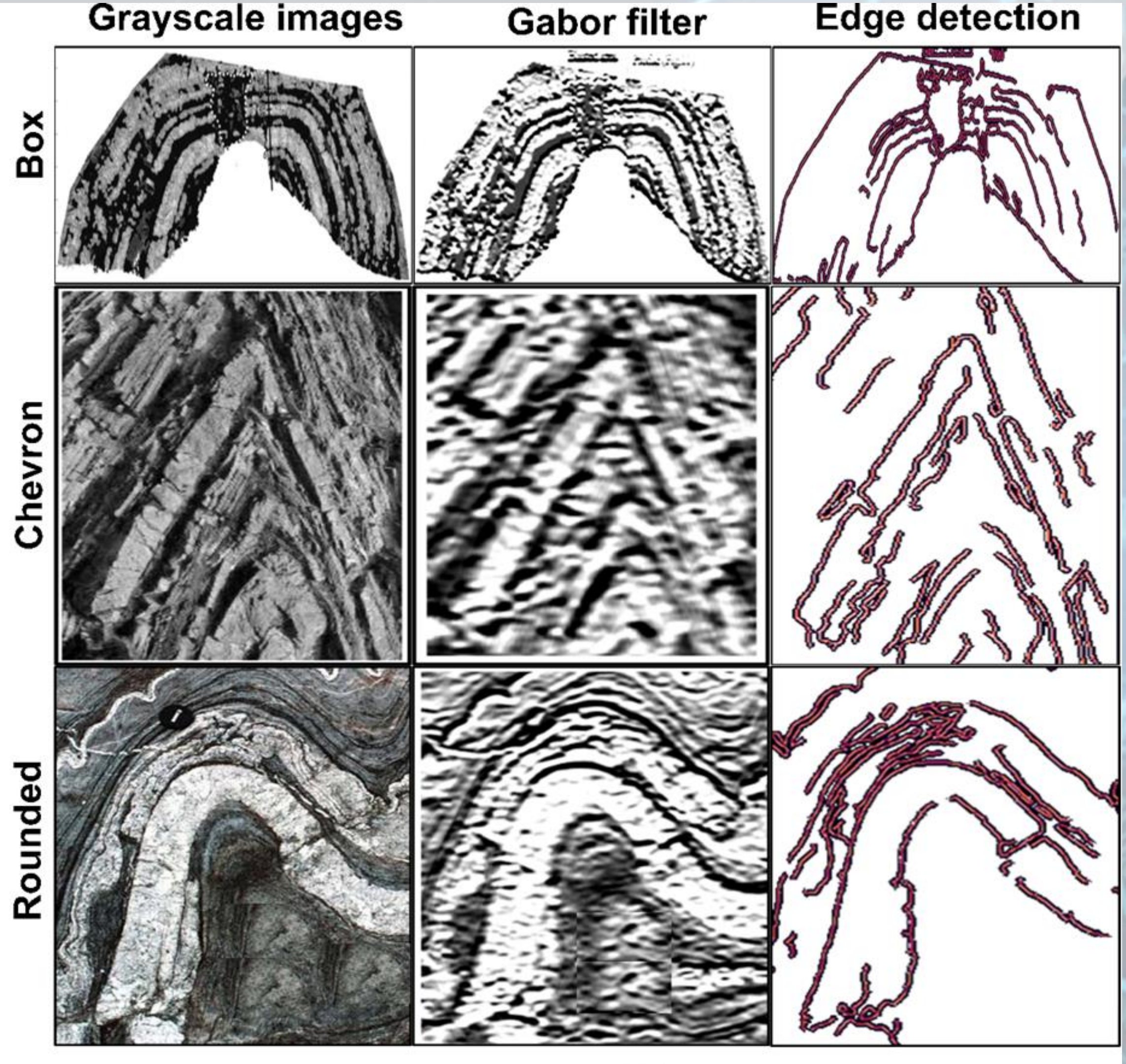


2D convolution operation

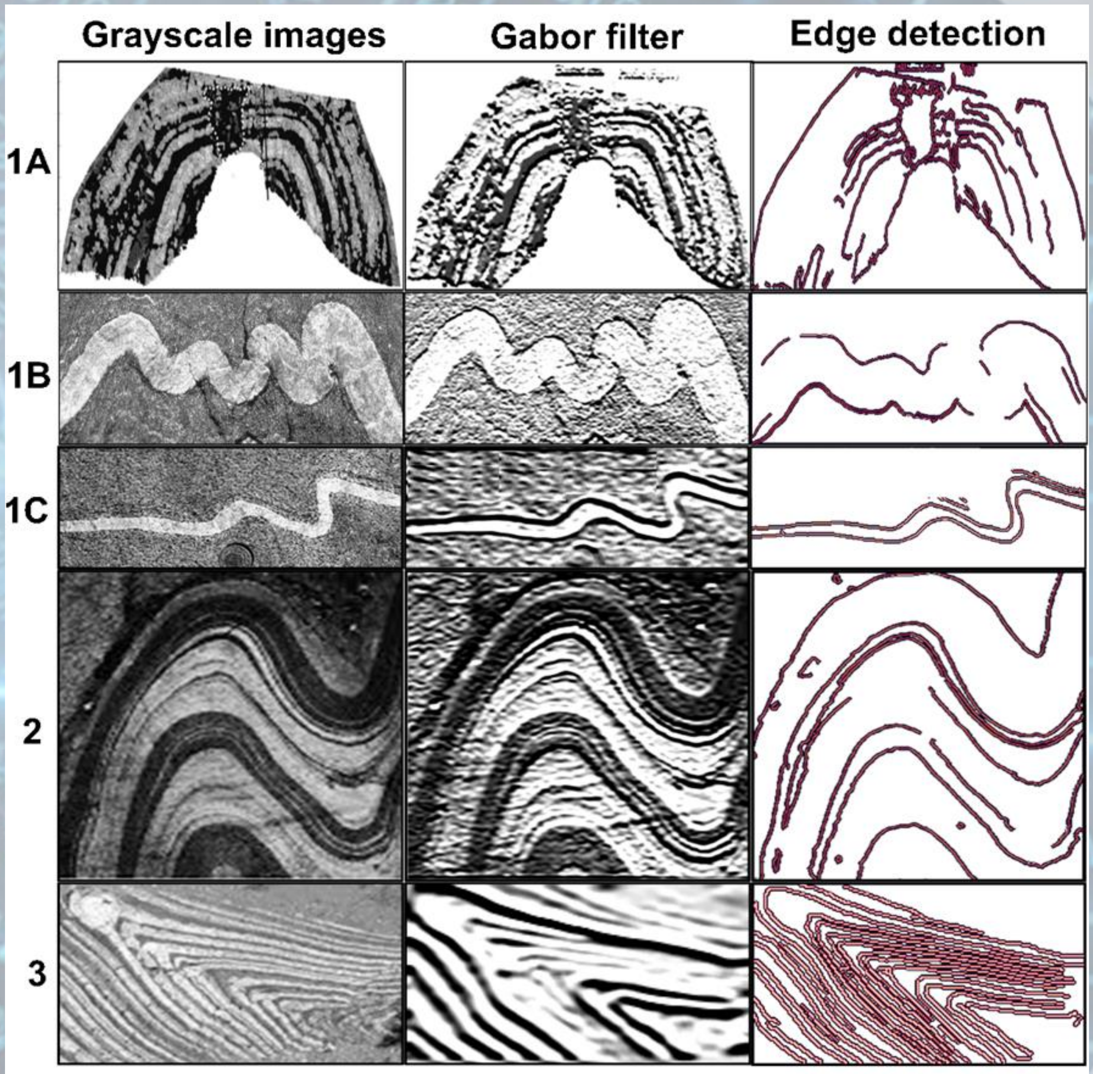
Shape of Hinges Dataset



Shallow Learning - Feature Extraction



(A)



(B)

Example of features extracted: Coloured, grayscale, original, Gabor, edge, noise, mean, std.

Shallow Learning - Results

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Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
RandomForestClassifier	0.64	0.64	None	0.64	3.30
ExtraTreesClassifier	0.64	0.64	None	0.64	1.16
LabelSpreading	0.60	0.60	None	0.60	2.19
LabelPropagation	0.60	0.60	None	0.60	1.82
LGBMClassifier	0.60	0.60	None	0.60	1.87
BaggingClassifier	0.59	0.59	None	0.59	2.15
XGBClassifier	0.59	0.59	None	0.59	4.14
ExtraTreeClassifier	0.56	0.56	None	0.56	0.07
KNeighborsClassifier	0.50	0.50	None	0.50	0.27
SGDClassifier	0.49	0.49	None	0.46	0.29
DecisionTreeClassifier	0.49	0.49	None	0.49	0.41
NuSVC	0.48	0.48	None	0.48	2.78
CalibratedClassifierCV	0.48	0.48	None	0.48	10.73
SVC	0.47	0.47	None	0.47	1.62
Perceptron	0.47	0.47	None	0.46	0.08
RidgeClassifier	0.47	0.47	None	0.47	0.09
LinearDiscriminantAnalysis	0.46	0.46	None	0.46	0.16
RidgeClassifierCV	0.46	0.46	None	0.46	0.12
LinearSVC	0.46	0.46	None	0.46	2.94
LogisticRegression	0.45	0.45	None	0.45	0.41
AdaBoostClassifier	0.40	0.40	None	0.40	2.63
QuadraticDiscriminantAnalysis	0.39	0.39	None	0.39	0.14
PassiveAggressiveClassifier	0.38	0.38	None	0.32	0.14
GaussianNB	0.34	0.34	None	0.28	0.05
NearestCentroid	0.33	0.33	None	0.20	0.05
BernoulliNB	0.31	0.31	None	0.17	0.06
DummyClassifier	0.30	0.30	None	0.30	0.05

- **Validation dataset**

- **Maximum Accuracy of 64%**

Model	Accuracy	Balanced Accuracy	ROC AUC	F1 Score	Time Taken
XGBClassifier	0.63	0.63	None	0.63	4.02
LGBMClassifier	0.59	0.58	None	0.56	2.08
ExtraTreesClassifier	0.57	0.57	None	0.56	1.00
RandomForestClassifier	0.57	0.57	None	0.55	3.31
DecisionTreeClassifier	0.53	0.53	None	0.52	0.40
BaggingClassifier	0.53	0.53	None	0.50	2.28
CalibratedClassifierCV	0.53	0.52	None	0.52	11.40
LinearSVC	0.53	0.52	None	0.50	2.88
LogisticRegression	0.51	0.51	None	0.50	0.40
SGDClassifier	0.49	0.49	None	0.45	0.32
NuSVC	0.49	0.48	None	0.45	2.69
LinearDiscriminantAnalysis	0.49	0.48	None	0.46	0.12
RidgeClassifierCV	0.49	0.48	None	0.46	0.12
RidgeClassifier	0.49	0.47	None	0.45	0.08
KNeighborsClassifier	0.47	0.47	None	0.47	0.13
QuadraticDiscriminantAnalysis	0.47	0.47	None	0.47	0.11
LabelPropagation	0.47	0.47	None	0.46	1.56
LabelSpreading	0.47	0.47	None	0.46	2.12
PassiveAggressiveClassifier	0.46	0.46	None	0.42	0.12
Perceptron	0.47	0.46	None	0.43	0.08
ExtraTreeClassifier	0.46	0.45	None	0.44	0.06
AdaBoostClassifier	0.38	0.39	None	0.38	2.68
SVC	0.37	0.37	None	0.34	1.57
NearestCentroid	0.32	0.33	None	0.18	0.05
BernoulliNB	0.31	0.32	None	0.15	0.07
DummyClassifier	0.31	0.31	None	0.30	0.05
GaussianNB	0.29	0.30	None	0.25	0.04

- **Testing dataset**

Deep Learning - Results

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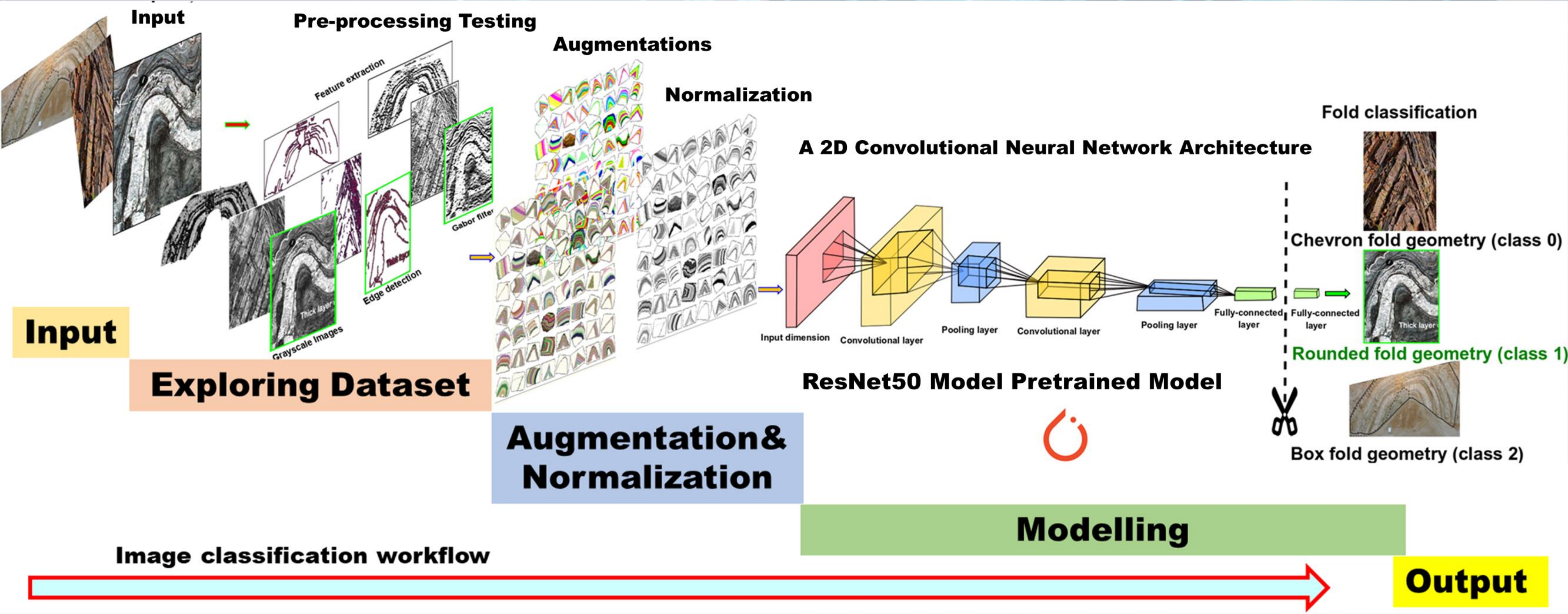
ResNet50 Pretrained Model Accuracy over 70%

Learning	Model	Training	Types of Data	Accuracy (%)	Drive (CPU) - time	Colud (GPU) - time
Shallow	RandomForest	Untrained	Test	57	13min 3s	-
			Val	64		
Deep	ResNet9	Untrained Greyscale	Test	61.7	2h 12min 43s	20min 35s
			Val	55.7		
		Untrained Coloured	Test	69	2h 2min 14s	22min 45s
			Val	60		
Transfer	ResNet34	Untrained	Test	42.6	2h 4min 54s	25min 15s
			Val	45		
		Pretrained	Test	63	2h 7min 25s	25min 9s
			Val	60		
	ResNet50	Untrained	Test	33.8	3h 52min 48s	31min 16s
			Val	45		
		Pretrained	Test	**75**	3h 14min 58s	27min 43s
			Val	**70**		
	ResNet101	Untrained	Test	39.7	3h 8min 15s	32min 11s
			Val	38.9		
		Pretrained	Test	61.7	4h 58min 34s	44min 9s
			Val	61		
	ResNet152	Untrained	Test	33.8	3h 33min 1s	34min 7s
			Val	36.7		
		Pretrained	Test	66.2	6h 1min 48s	58min 6s
			Val	61.3		

Transfer Learning workflow



Model Evaluation

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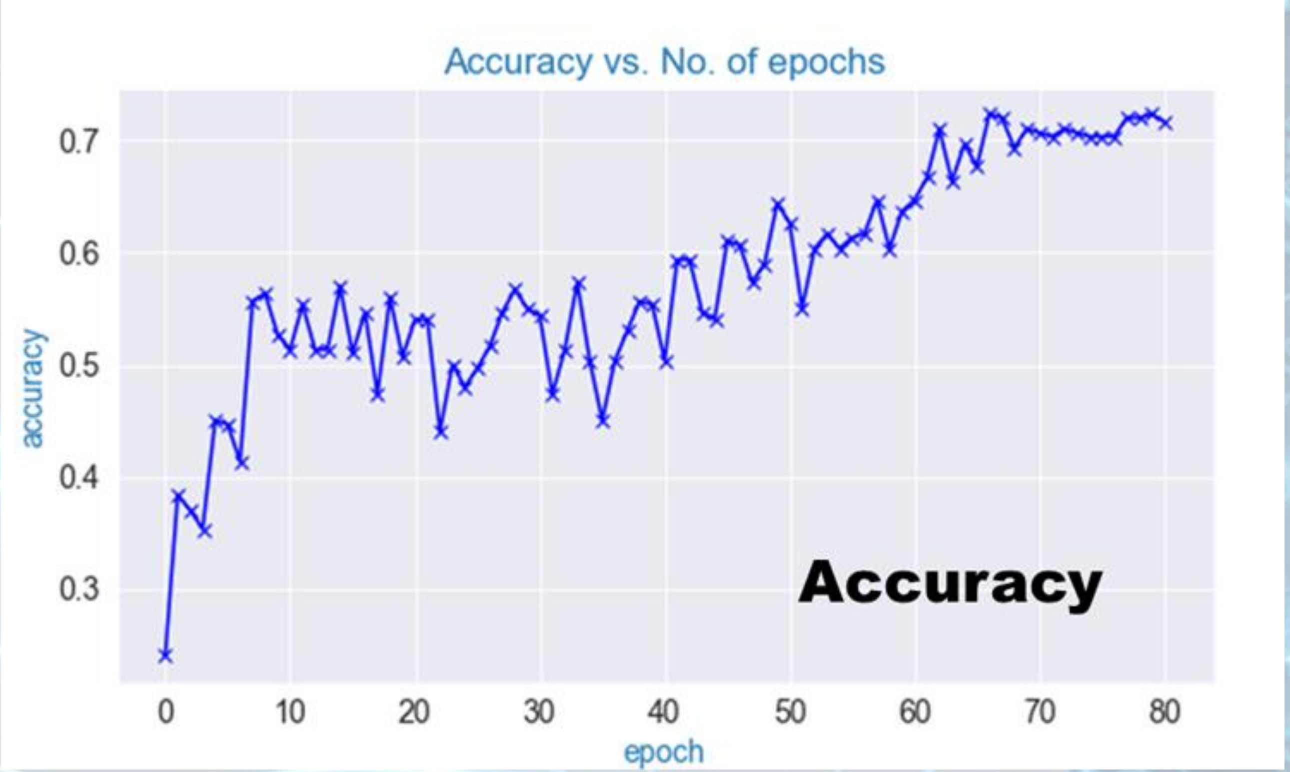
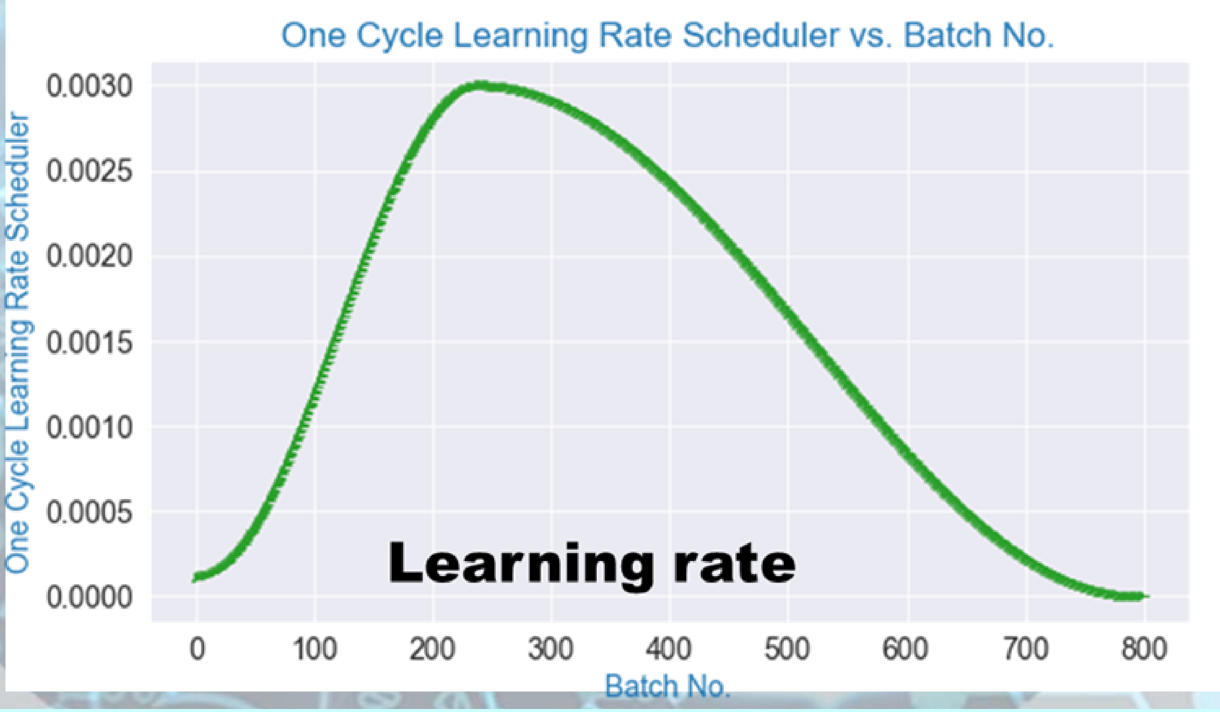
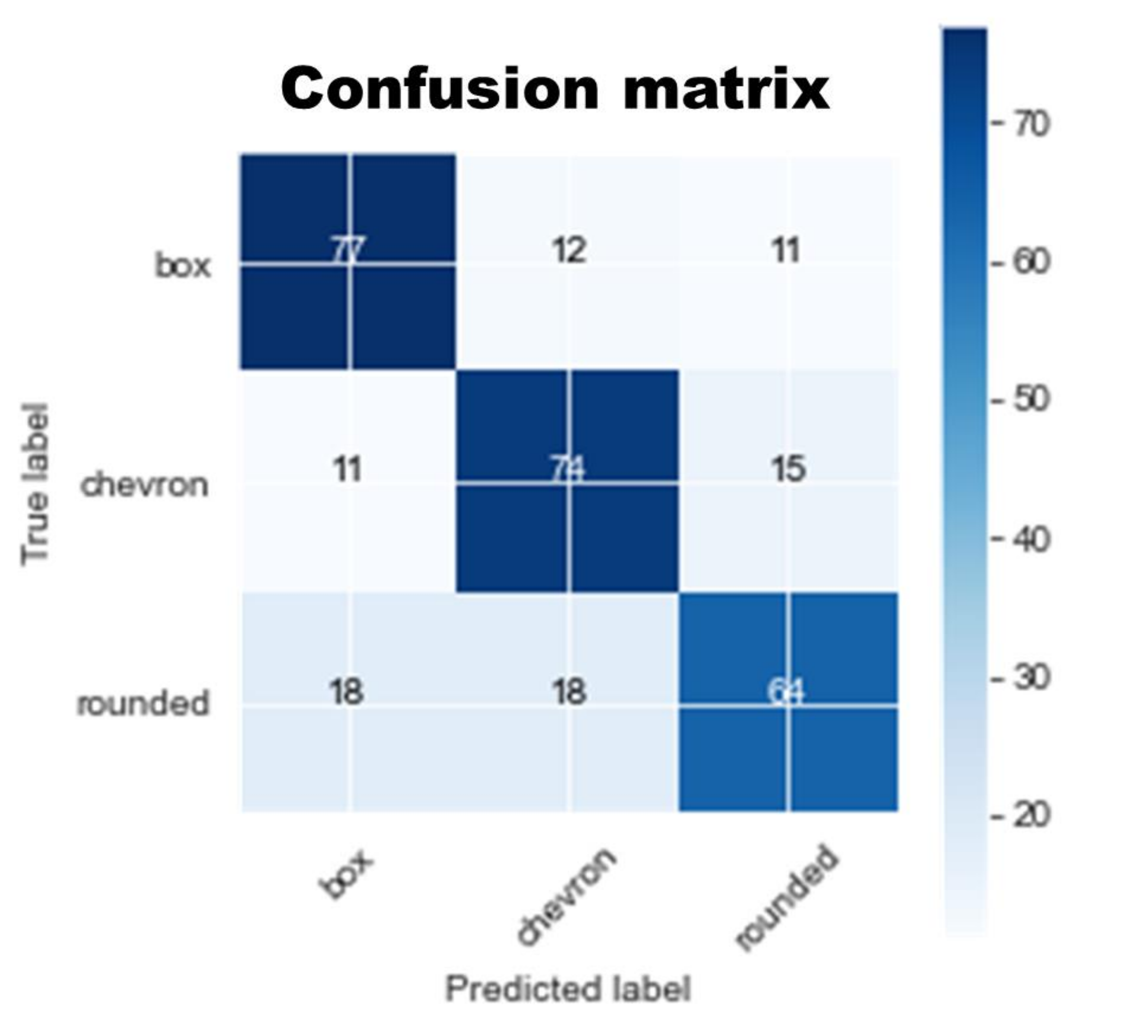
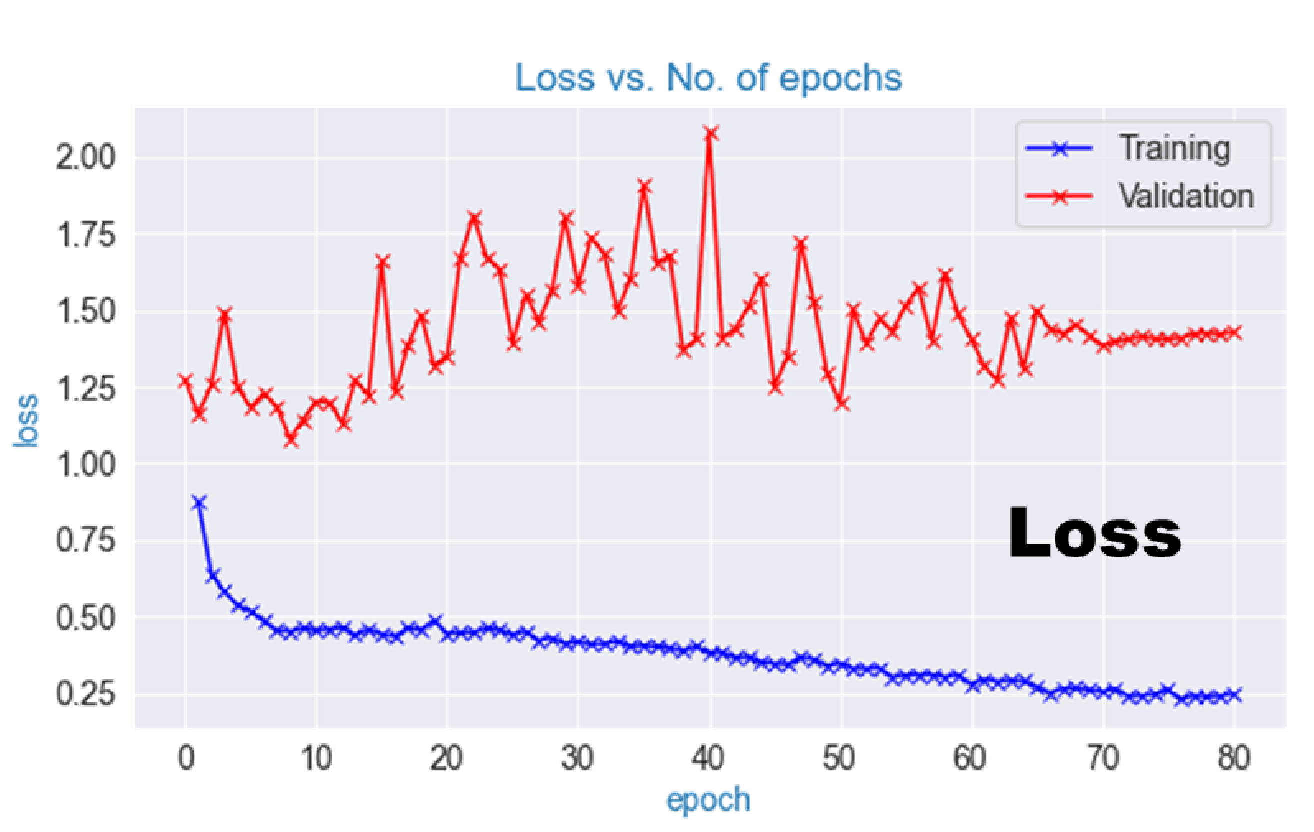


Validation Dataset

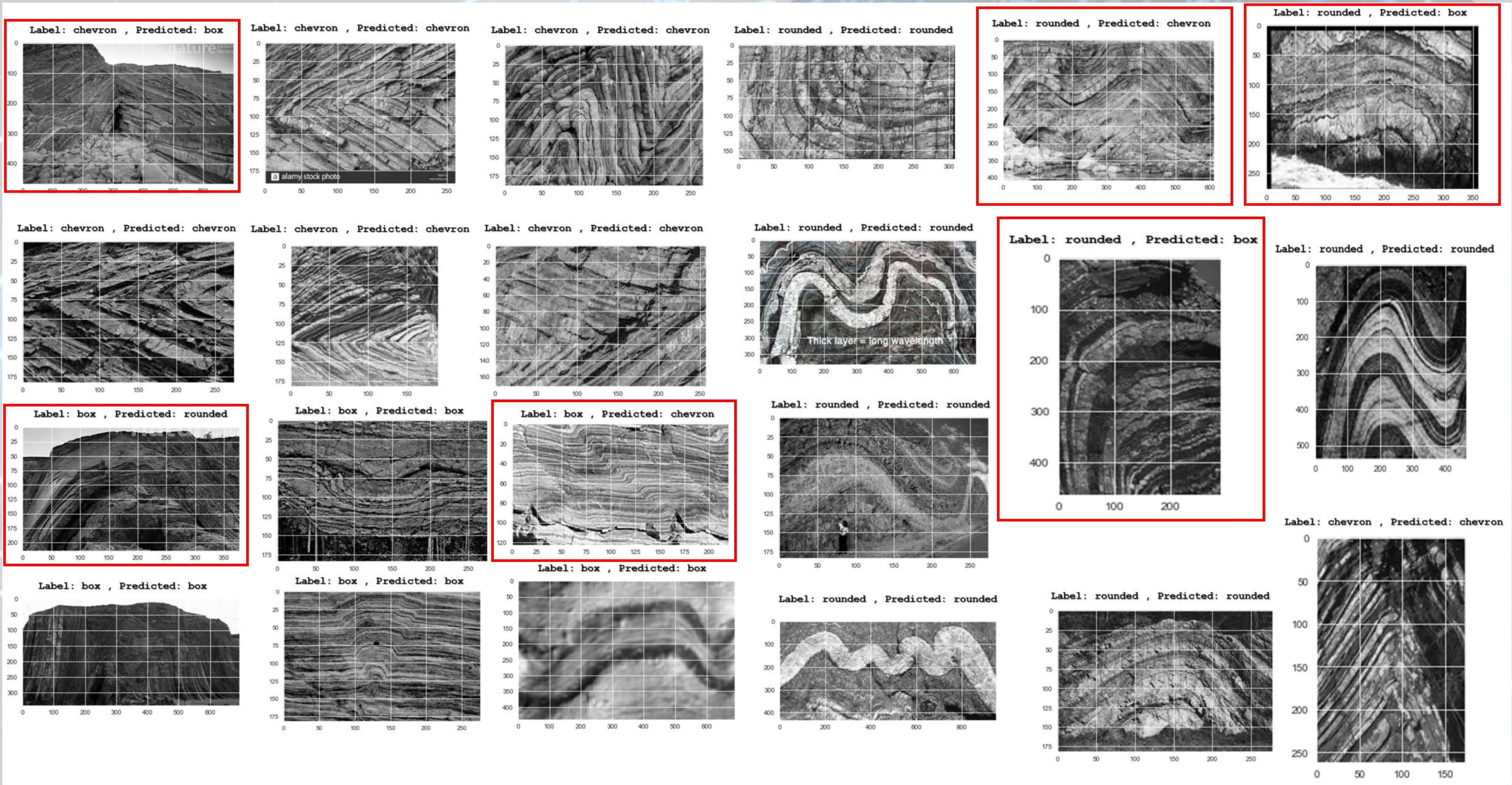


Model Evaluation





Classification Examples

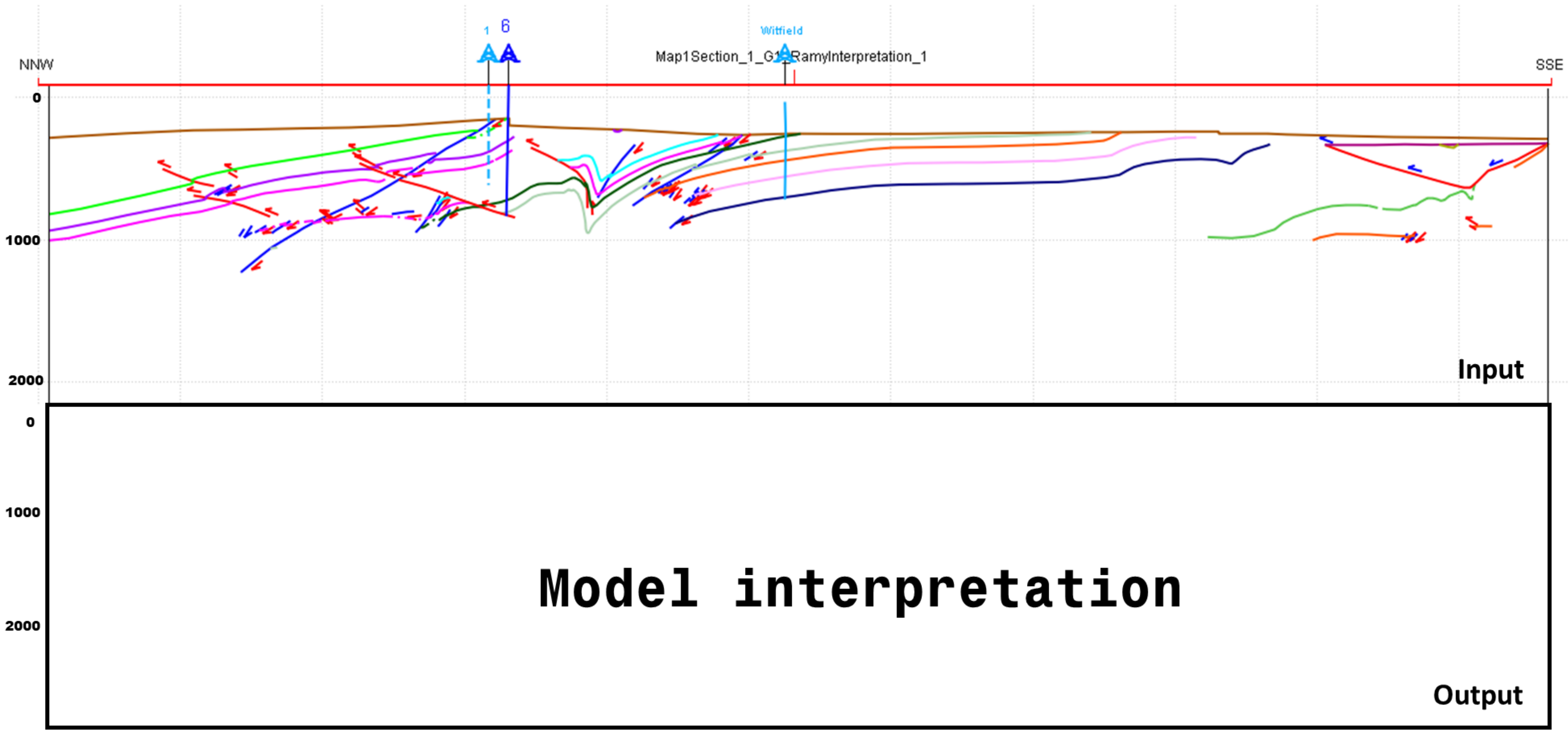


Conclusions

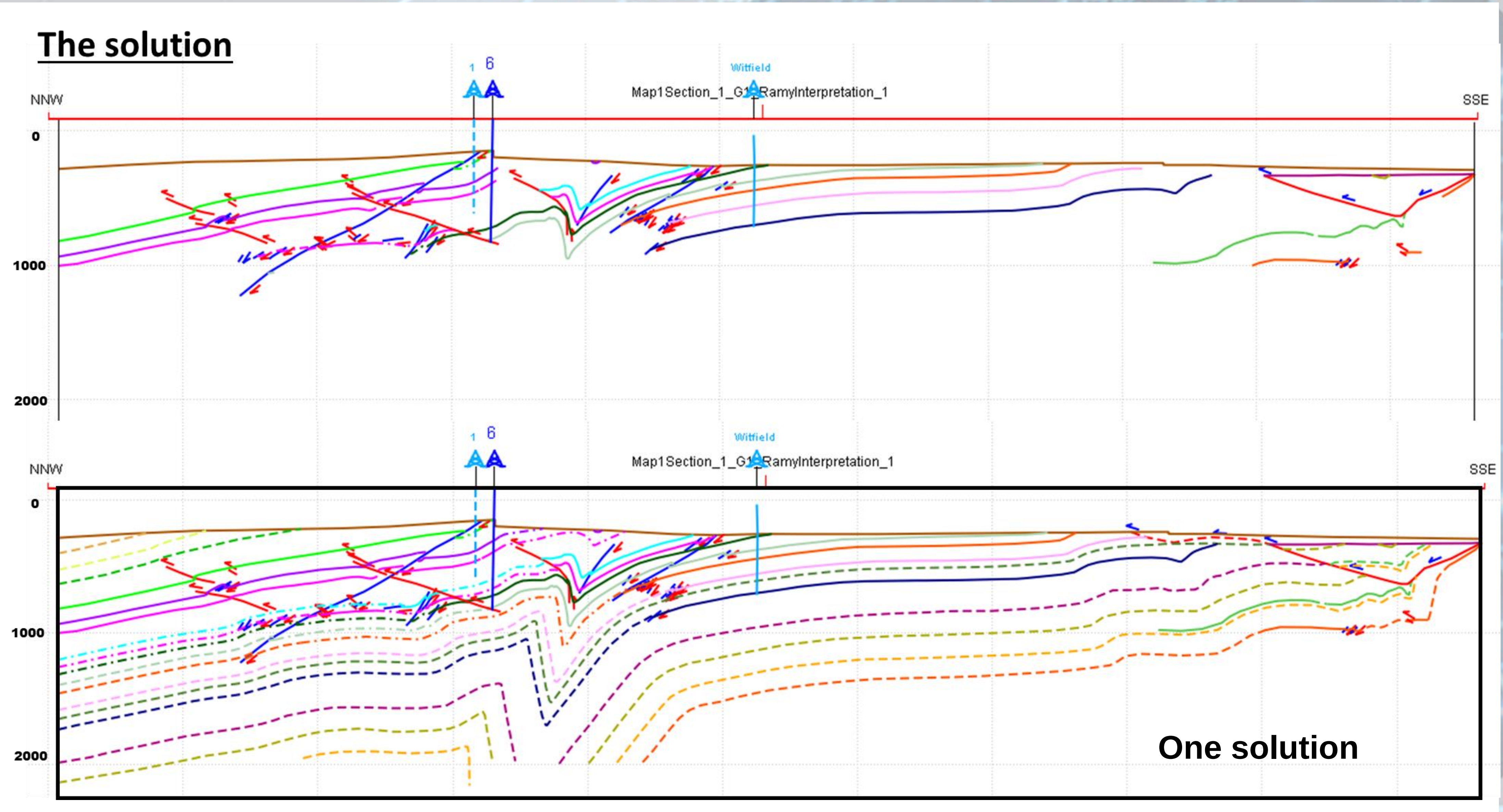
- We proposed modelled **data**, augmentation and normalization as methods to overcome geosciences data limitations.
- **Shallow learning** and feature extraction can be made prior to any deep learning study.
- **Convolutional Neural Networks** (CNNs) can help addressing geosciences classification problems.
- **Deep transfer learning** doing better in this case study.
- **Resnet50** model record the higher accuracy in our study.
- Can deductions be drawn from machine and deep learning studies?

Future work

Example of Test data



Future work


The solution
1
6
Witfield
Map1Section_1_G1_RamyInterpretation_1
NNW
SSE
0
1000
2000
1
6
Witfield
Map1Section_1_G1_RamyInterpretation_1
NNW
SSE
0
1000
2000
One solution

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Thank you for your Attention!

& Any questions?

Deep Learning with PyTorch

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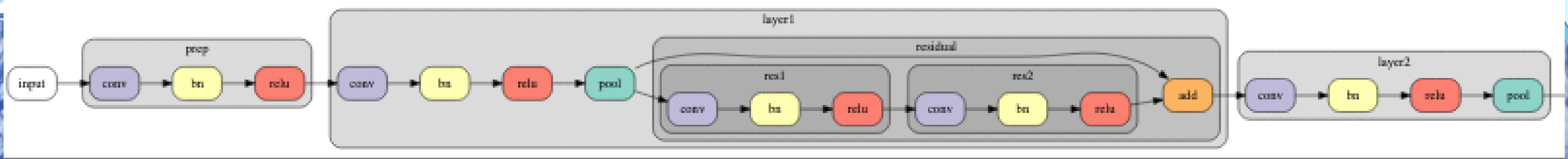

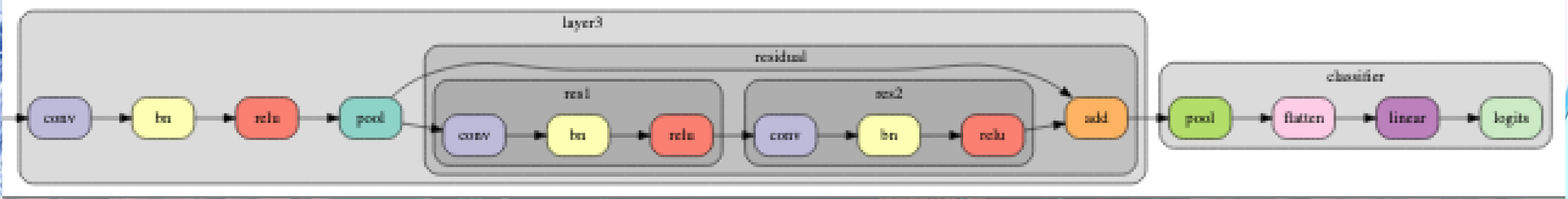

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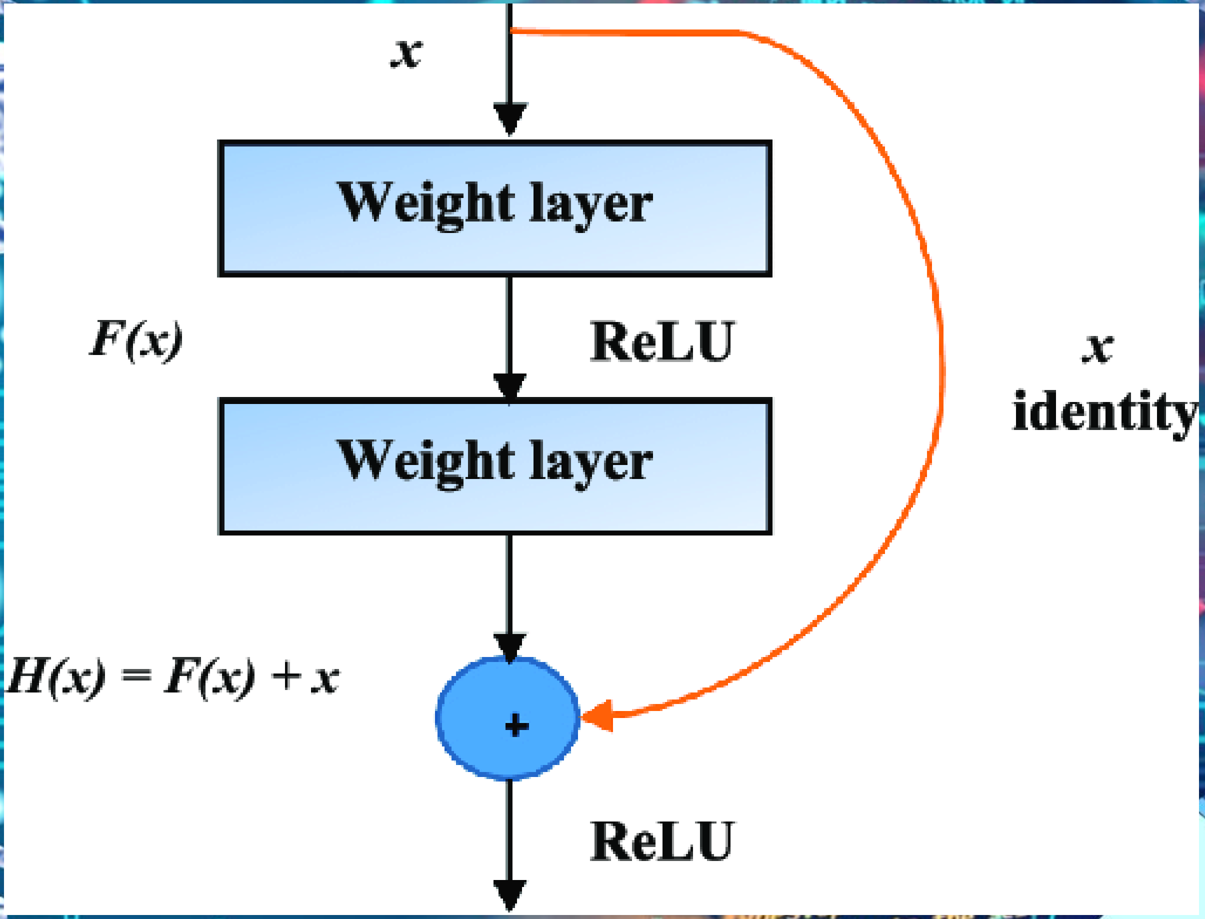

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```
# Data transforms (normalization & data augmentation) # tt.RandomCrop(64, padding=4, padding_mode='reflect')
stats = ((0.485, 0.456, 0.406), (0.229, 0.224, 0.225))
randomrotate = 10 # 0.175 rad
train_tfms = tt.Compose([tt.Resize((image_size, image_size)),
                         tt.RandomCrop(image_size, padding=4, padding_mode='reflect'),
                         tt.Resize(image_size),
                         tt.CenterCrop(image_size),
                         tt.RandomHorizontalFlip(),
                         tt.RandomVerticalFlip(),
                         tt.Pad((2, 5, 0, 5)),
                         #tt.RandomRotation(randomrotate),
                         tt.RandomAffine(0, translate=(0.4, 0.5)),
                         tt.RandomRotation(randomrotate, resample=PIL.Image.NEAREST, expand=False, center=(40,
                         #tt.RandomResizedCrop(256, scale=(0.5,0.9), ratio=(1, 1)),
                         tt.ColorJitter(brightness=0.1, contrast=0.1, saturation=0.1, hue=0.1), ##
                         tt.ToTensor(),
                         tt.Normalize(*stats,inplace=True)])
valid_tfms = tt.Compose([tt.Resize((image_size, image_size)), tt.ToTensor(), tt.Normalize(*stats)])

test_tfms = tt.Compose([tt.Resize((image_size, image_size)), tt.ToTensor(), tt.Normalize(*stats)])
```

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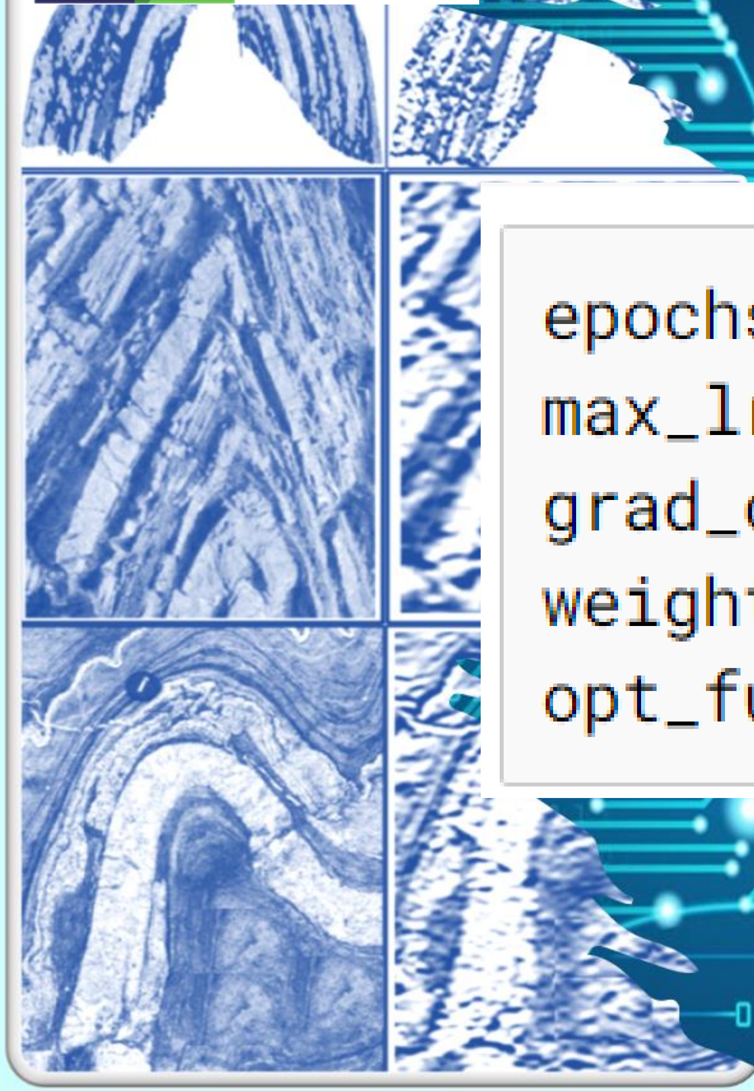

```
epochs = 80
max_lr = 0.0007
grad_clip = 0.1
weight_decay = 1e-4
opt_func = torch.optim.Adam
```

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Cross-entropy loss, or log loss, measures the performance of a classification model whose output is a probability value between 0 and 1. ... Cross-entropy and log loss are slightly different depending on context, but in machine learning when calculating error rates between 0 and 1 they resolve to the same thing.

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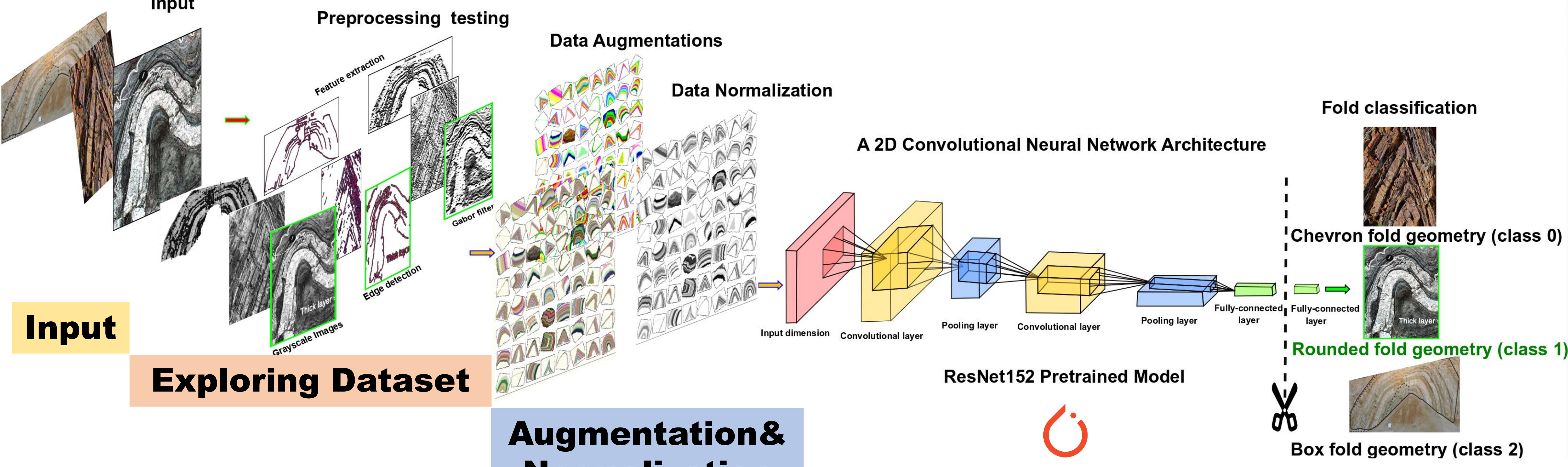
Transfer Learning workflow

ResNet50 Model



Input

Exploring Dataset

Augmentation& Normalization

Modelling

Image classification workflow

Output