Final Project

TG5055 Machine Learning in Geophysics

Institut Teknologi Bandung

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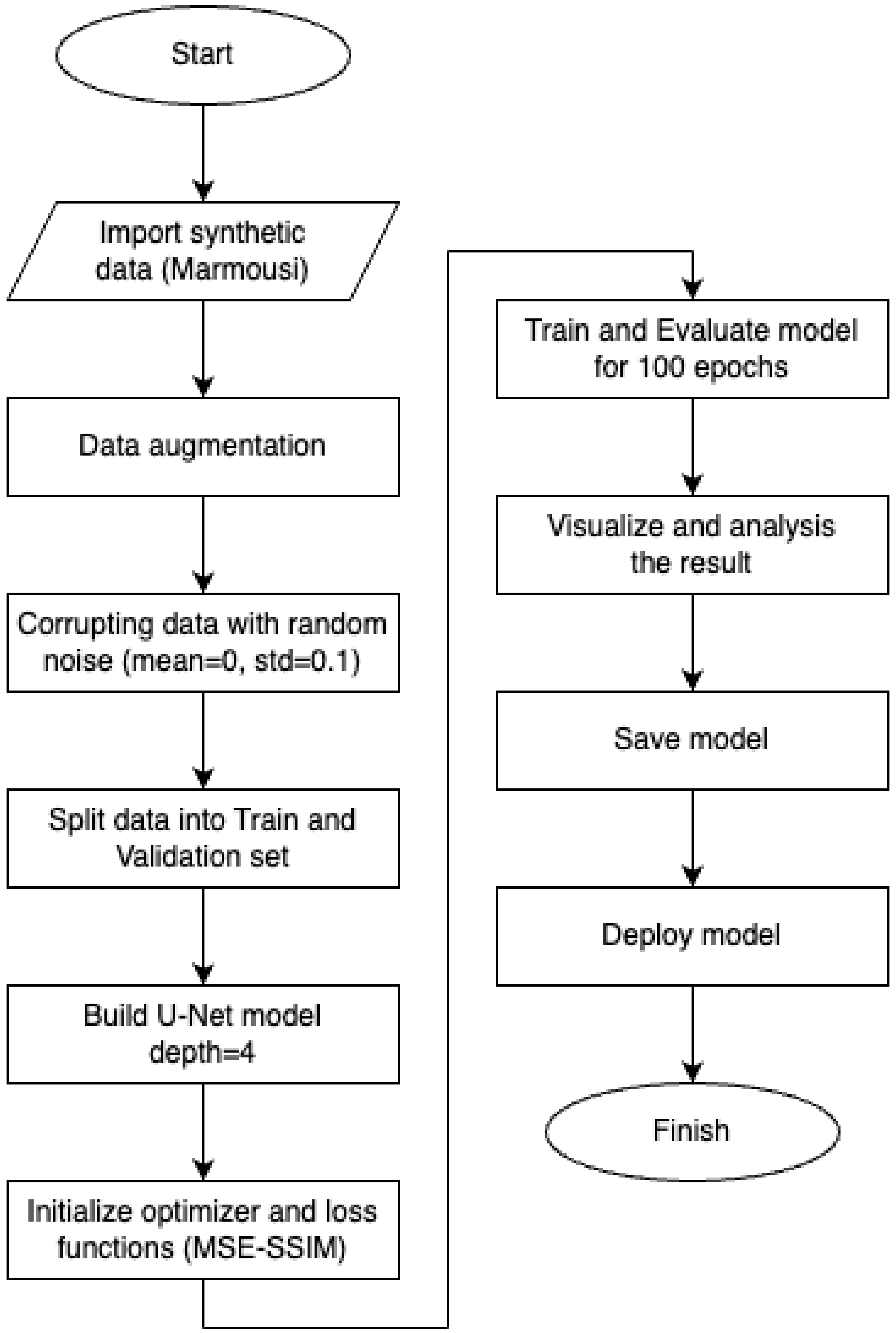
Project Overview

Seismic data plays a critical role in subsurface exploration, such as oil and gas exploration, earthquake monitoring, and geotechnical studies. However, seismic signals are often contaminated with random noise, which can obscure valuable subsurface information.

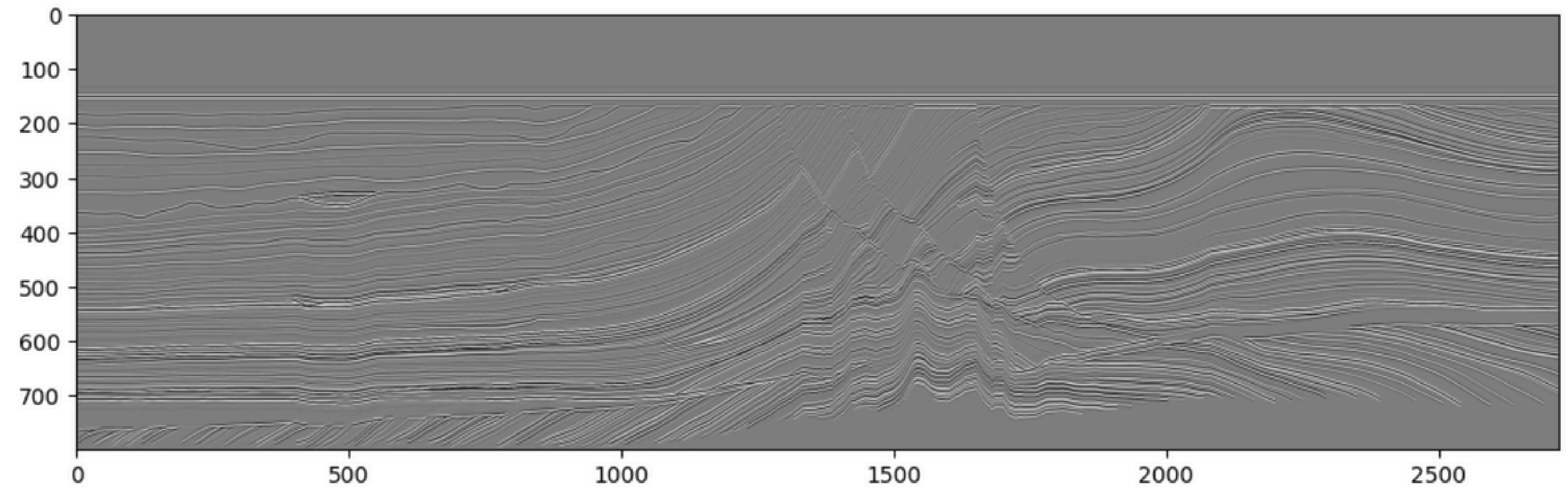
Deep learning, particularly convolutional neural networks (CNNs) like U-Net, has shown great potential in enhancing signal-to-noise ratios while preserving intricate details.

Flowchart Diagram



Data Augmentation

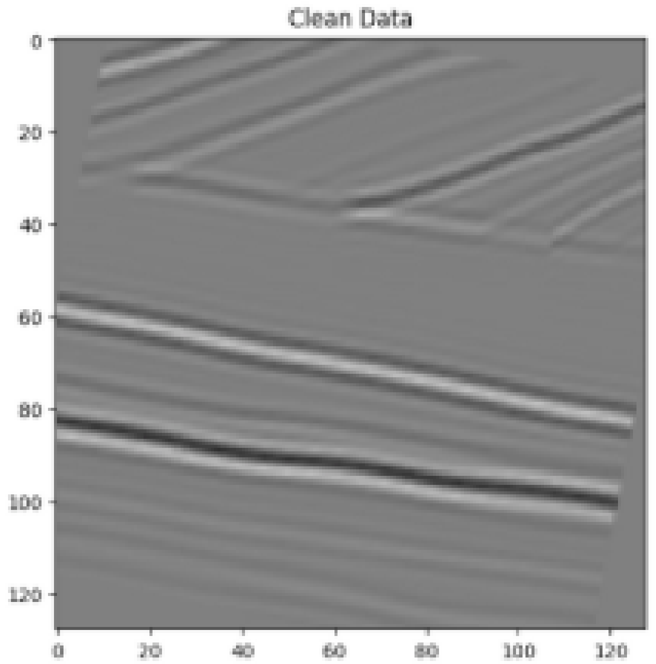
Marmousi Model



Transforms

- Random Horizontal Flip (p=0.5)
- Random Vertical Flip (p=0.5)
- Random Cropping (128x128)
- Polarity Reversal (p=0.5)
- Random Rotation (0-360)

Create 10000 patches



Tensor shape

Shape = (10000, 1, 128, 128)

Patches = 10000

Channel = 1

size = 128x128

Each pixel represents the amplitude value (not RGB)

Marmousi Model : (https://wiki.seg.org/wiki/AGL_Elastic_Marmousi)

The U-Net Architecture Proposed

	U-Net Model											
	Encoder				Bottleneck	Decoder				Final		
Depth number	1	2	3	4		1	2	3	4	1	2	3
Block/Layer	CNN + CB	DS				US				CB	CB	CNN
Input Channel	1	32	64	128	256	512	256	128	64	32	32	32
Output Channel	32	64	128	256	512	256	128	64	32	32	32	1

Block	Block / Layer
CB	CNN (k=3, s=1, p=1)
	BN
	CNN (k=3, s=1, p=1)
	BN

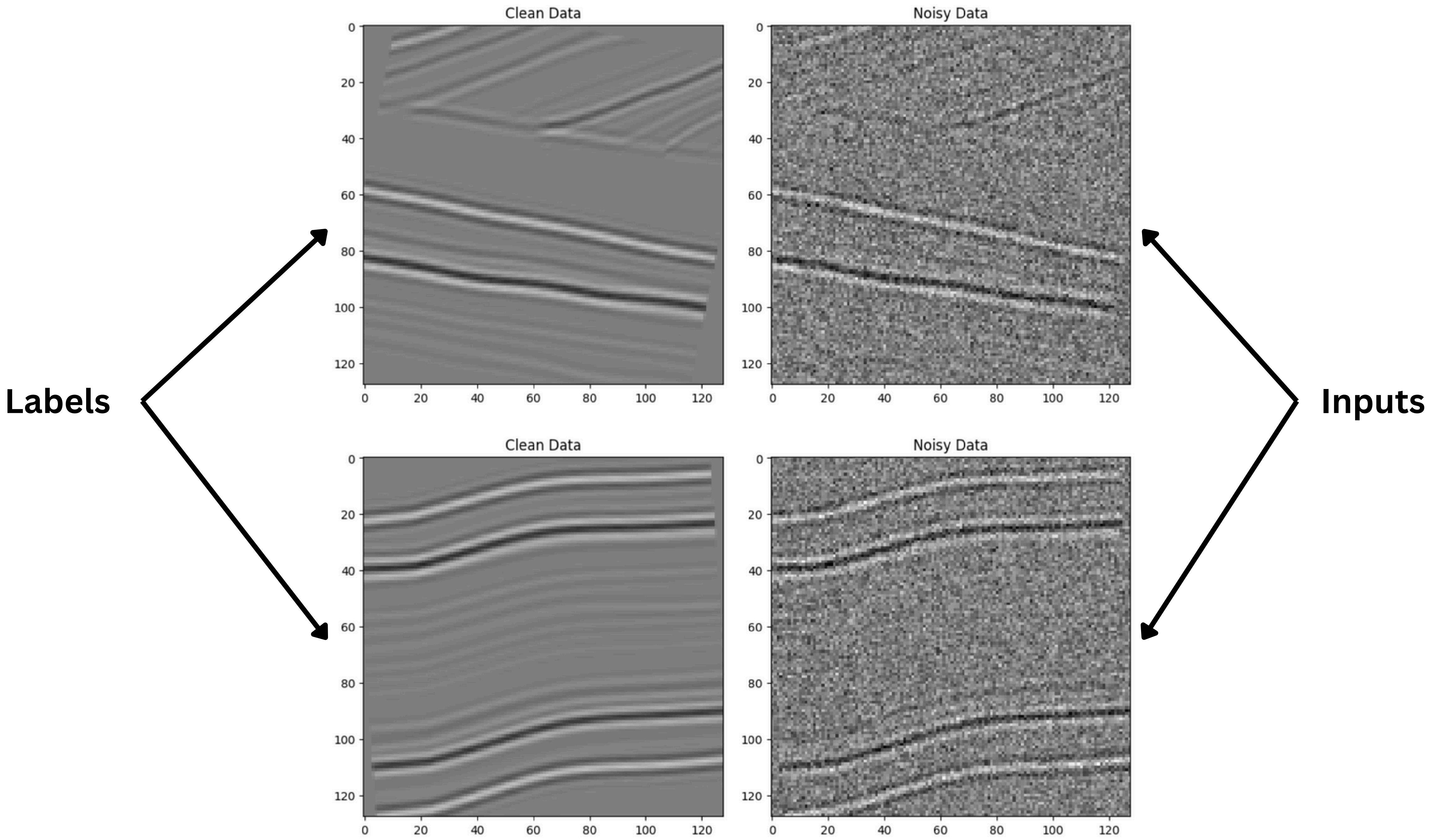
Block	Block / Layer
DS	MaxPooling (k=2, s=2)
	CB

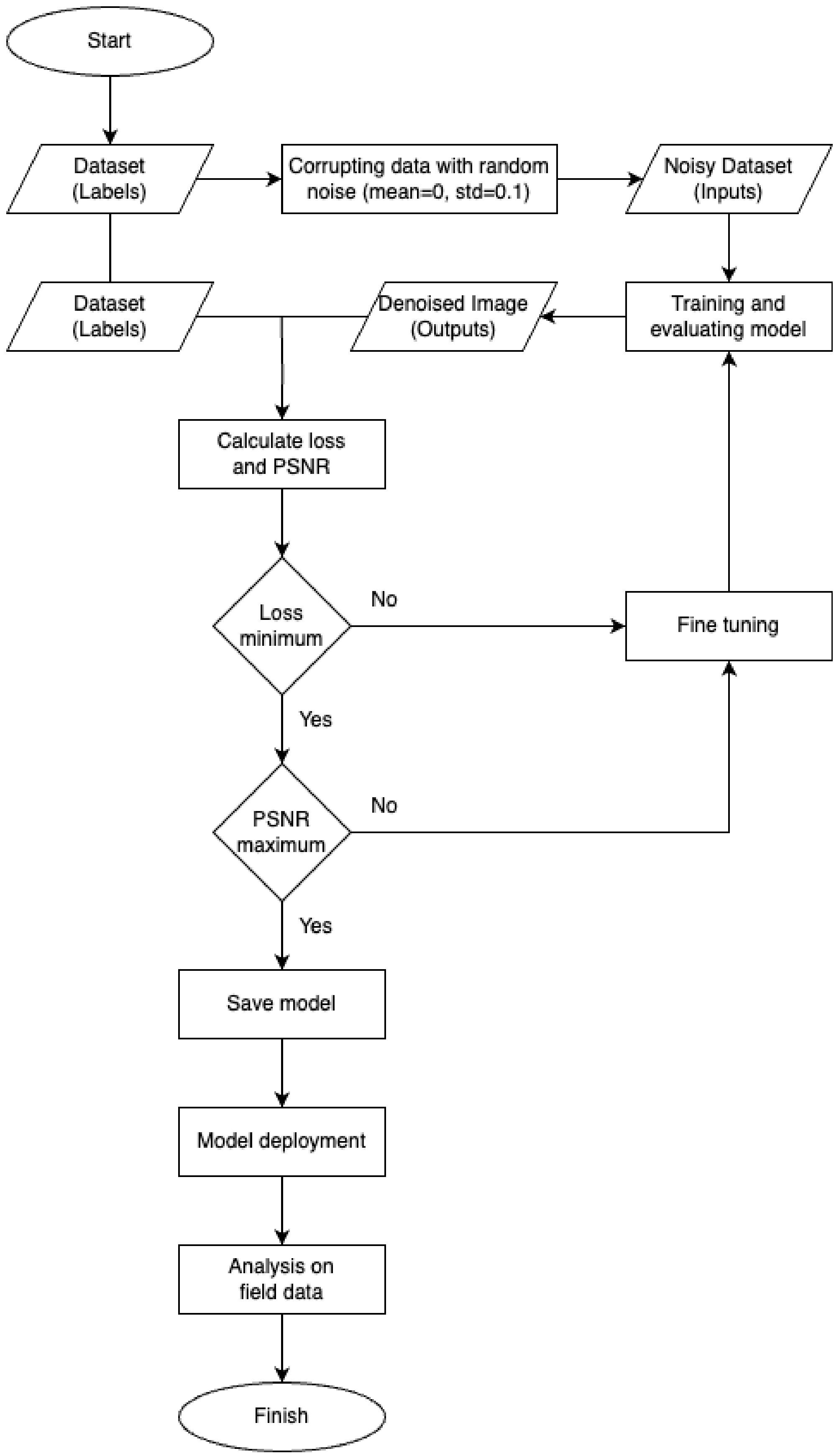
Block	Block / Layer
Bottleneck	DS
	CB

Block	Block / Layer
US	CNN Transpose (k=2, s=2)
	CB

U-Net is a CNN for image segmentation, using an encoder to capture features and a decoder with skip connections to restore spatial details. It excels in medical imaging and tasks like denoising and super-resolution. (Ronneberger, 2015)

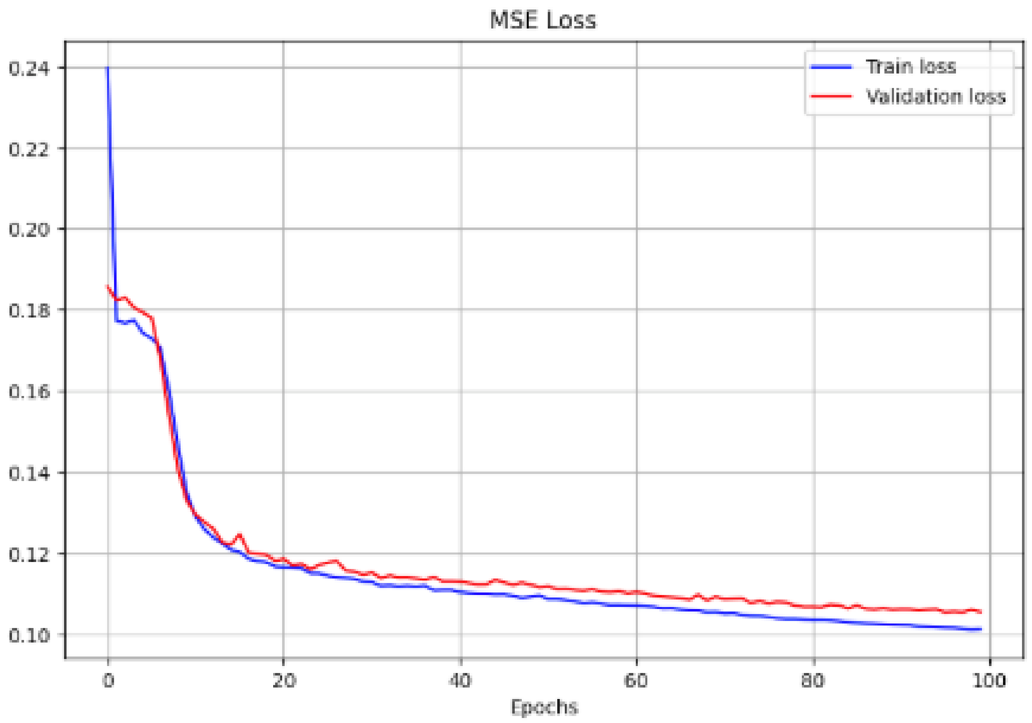
Noising, Train, and Evaluate Data

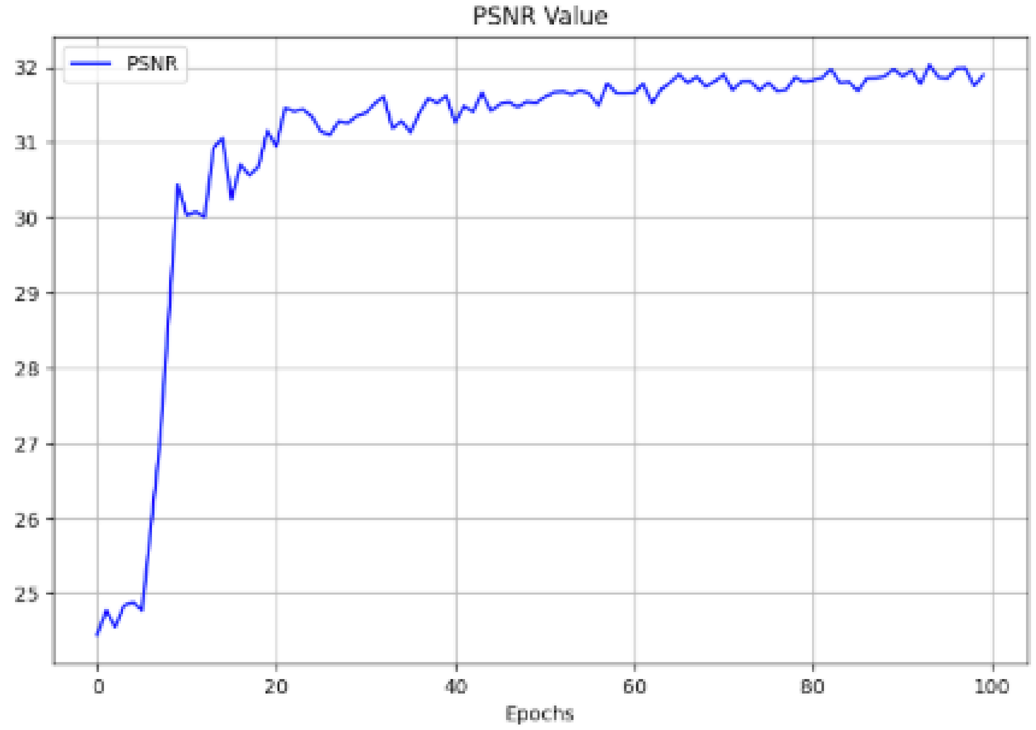




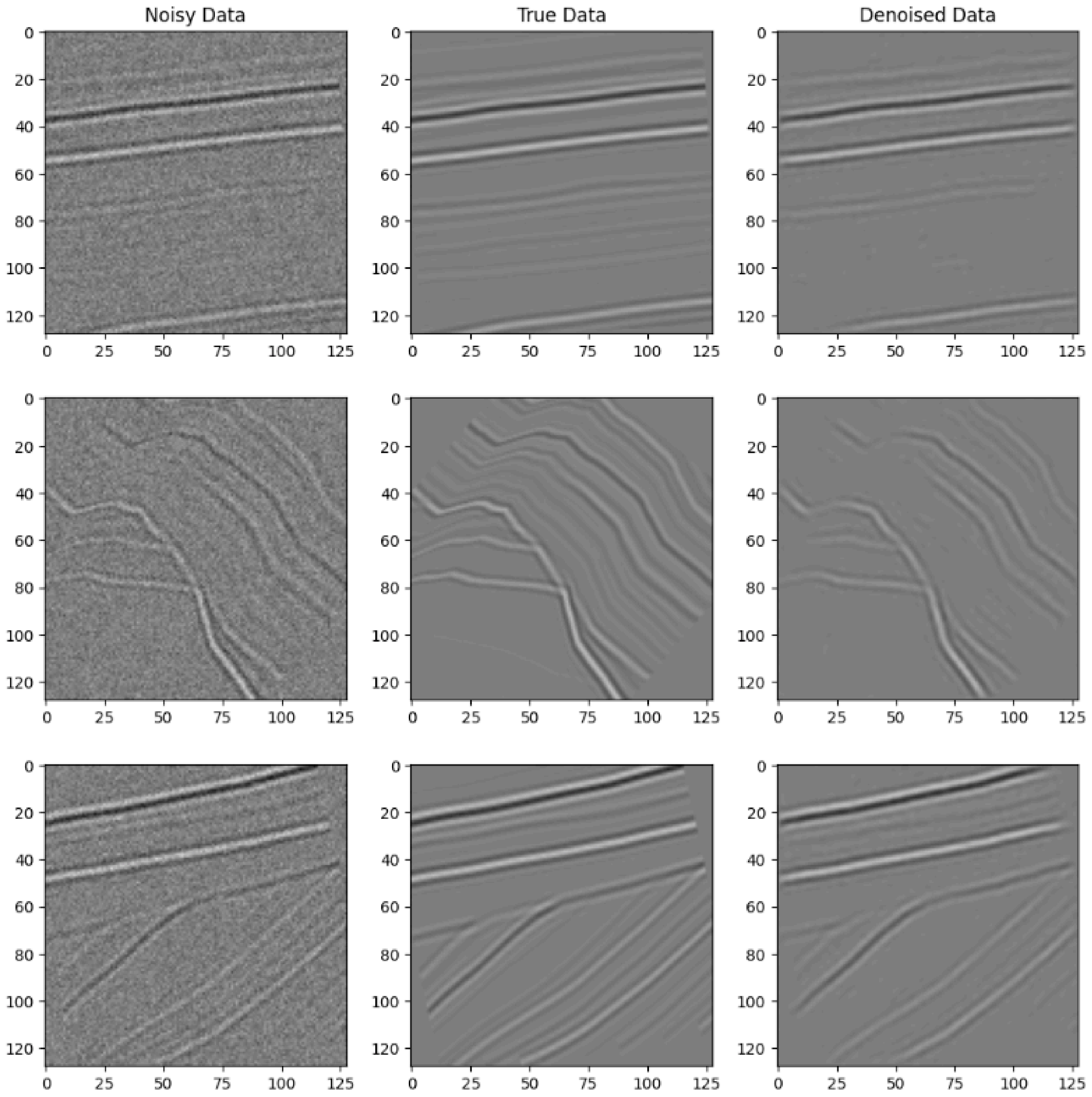
Hyperparameters and Training Results

Hyperparameters	
Learning rate	0.01
Batch size	16
Epochs	100
Optimizer	Adam
Loss function	MSE-SSIM





Final Results	
Training loss	0.101
Validation loss	0.105
PSNR Value	31.89

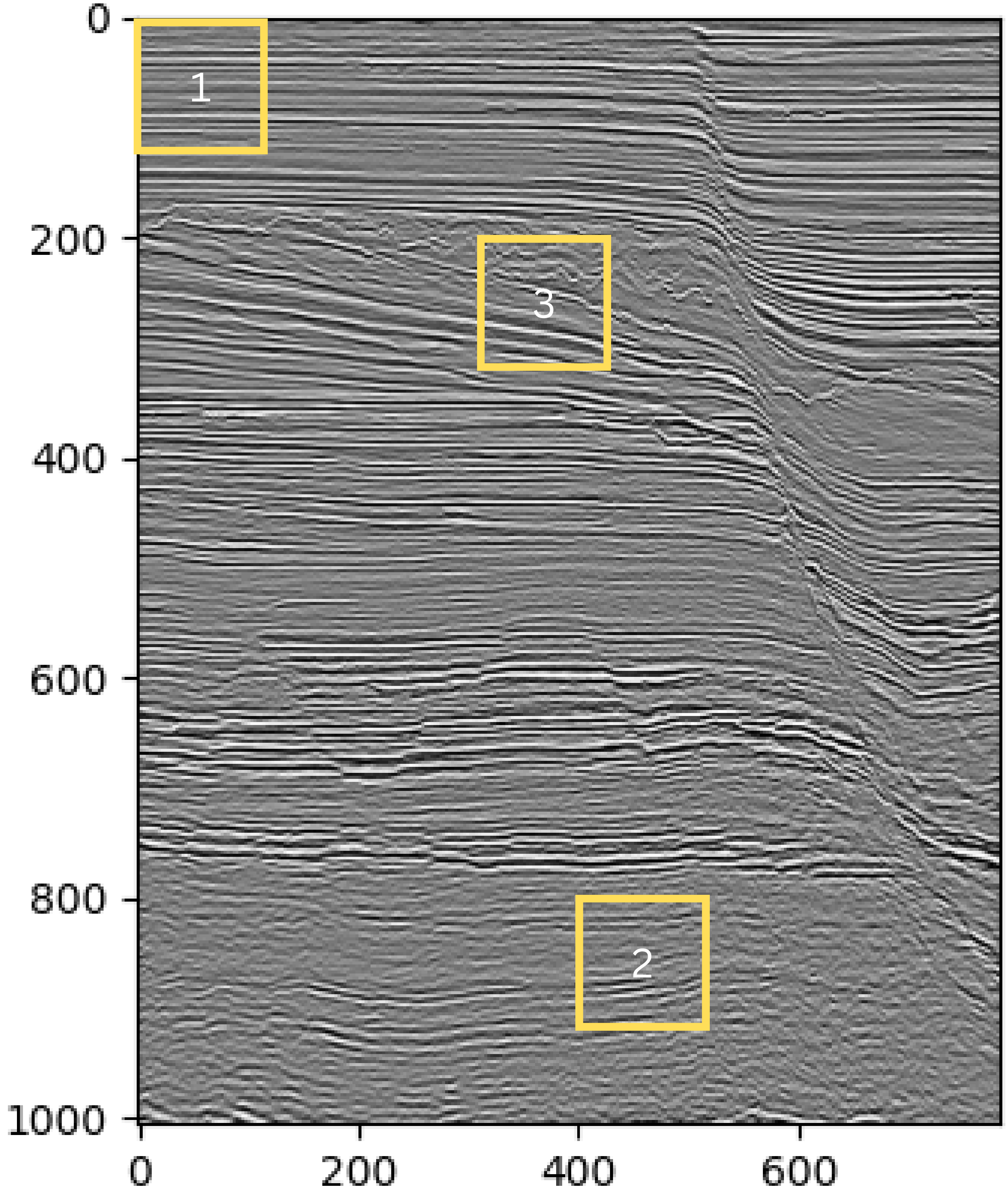


Analysis

The image on the side shows a noisy image (left) that has undergone denoising, resulting in an output (right) that closely resembles the label image (center). The denoised result appears more similar to the label image, indicating that the random noise added to the noisy image has been effectively removed.

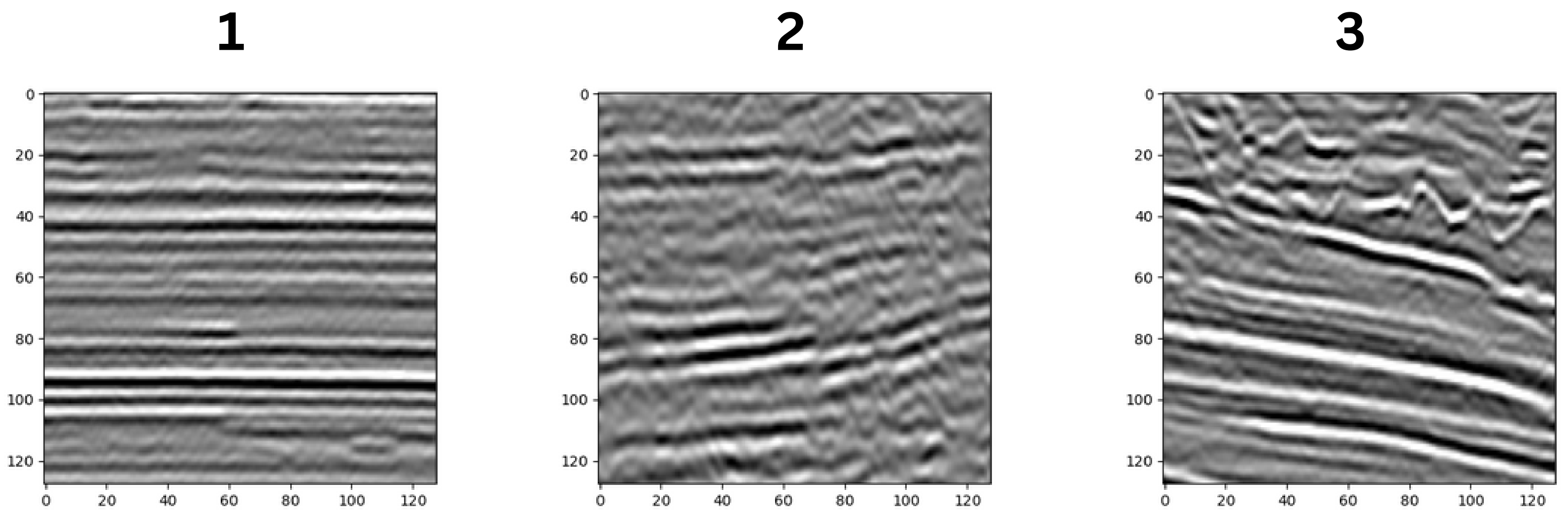
This proves that, qualitatively, the network is functioning well and is ready to be implemented on real data.

Inline = 590



Real Dataset

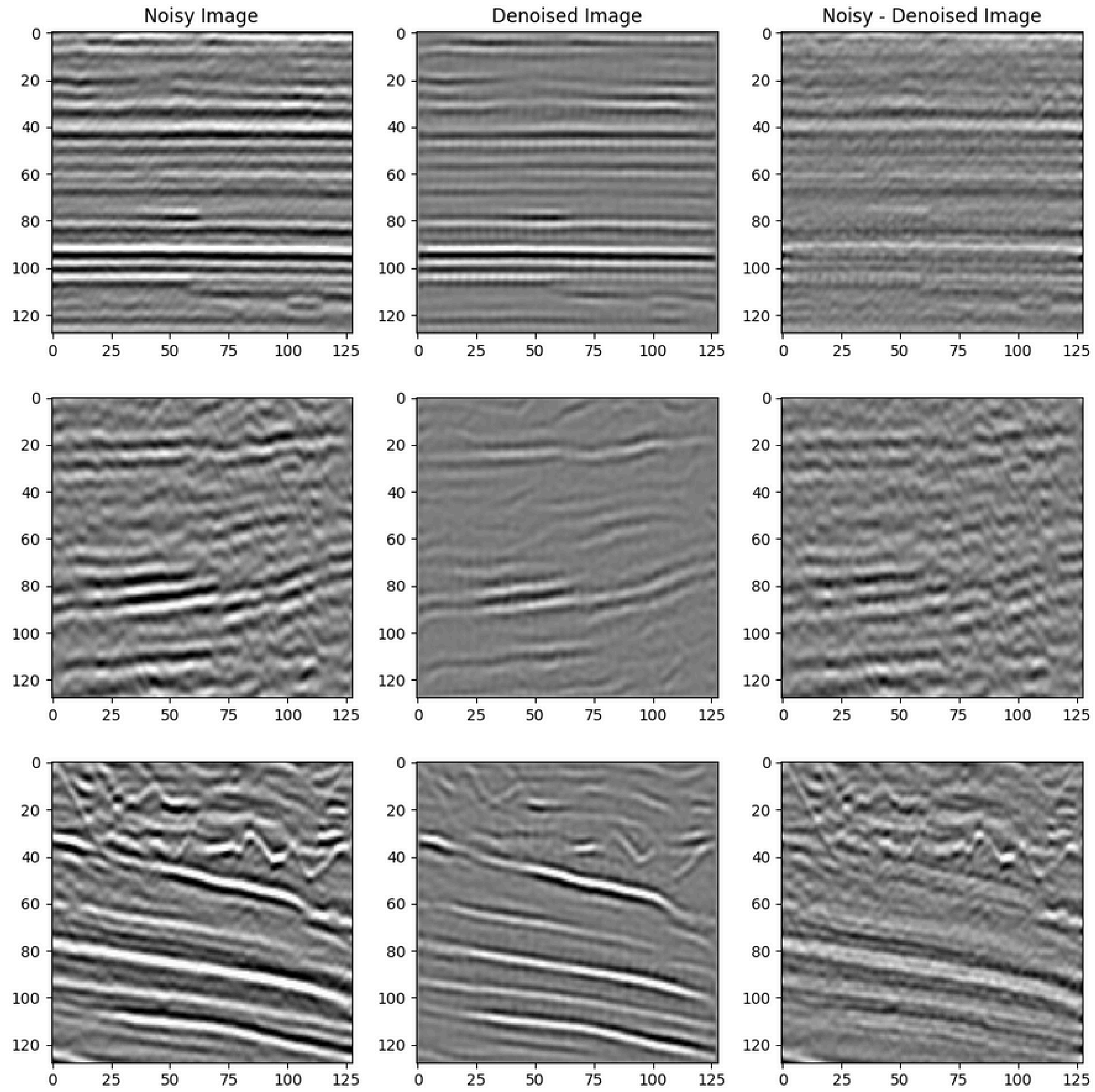
The real dataset being used is the sampe dataset that being used for the 2020 SEG Annual Meeting Machine Learning Interpretation Workshop where I pick the last inline section and take 3 samples (128x128) to test the model



Shape = (590, 782, 1006)

Dataset by NZPAM: https://www.nzpam.govt.nz/maps-geoscience/geodata-catalogue
2020 SEG Annual Meeting Machine Learning Interpretation Workshop https://public.3.basecamp.com/p/JyT276MM7krjYrMoLqLQ6xST

Model Deployment Analysis



Based on the deployment results, the random noise present in the input file can be successfully removed. However, the model still has a drawback where some reflectors are eliminated, leading to a decrease in amplitude where it was initially high becomes low after denoising due to their unintetnion removal.

A further recommendation is to apply normalization technique during model training to ensure that the interval and distribution of amplitude values across pixels are more controlled, potentially resulting in better outcomes. Another suggestion is to conduct a more detailed geological analysis after denoising, as important components such as faults may have been unintentionally removed by the network.

Thank you

References

Ronneberger, O., Fischer, P., & Brox, T. (2015). U-NET: Convolutional Networks for Biomedical Image Segmentation. In Lecture notes in computer science (pp. 234–241). https://doi.org/10.1007/978-3-319-24574-4_28

Li, J., Wu, X., & Hu, Z. (2020). Deep learning for simultaneous seismic image super-resolution and denoising. SEG International Exposition and 90th Annual Meeting. https://doi.org/10.1190/segam2020-3426412.1