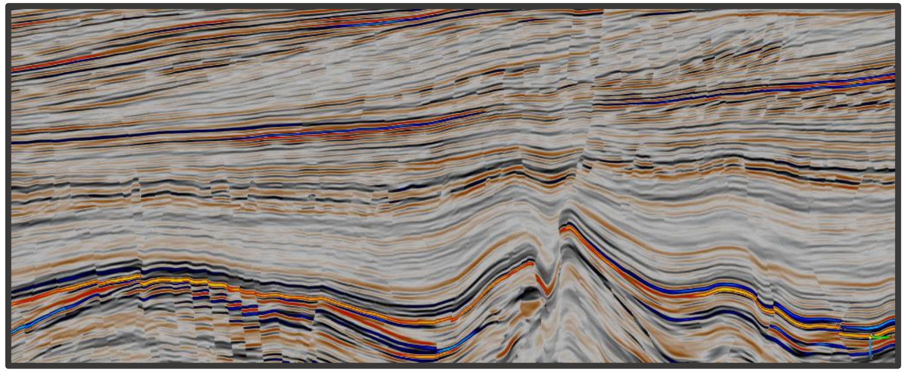
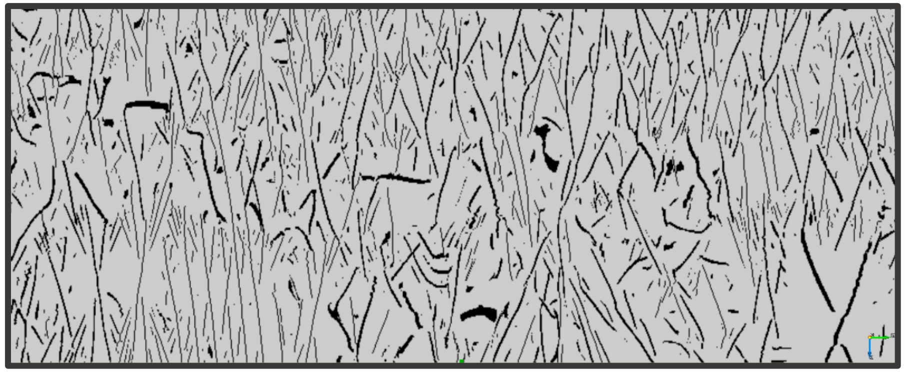
Exercise objective:

To predict seismic features using the *Seismic Image to Image* workflow in the machine learning plugin. In this exercise, we will predict fault locations from seismic data.

Warning 1: To predict real faults use the pre-trained U-Net fault predictor
In this exercise we train a U-Net to predict faults from pre-processed seismic input. The input is Edge-Preserved Smoothed (EPS) seismic data. The target is a mask volume with ones (faults) and zeros (no-faults) that was created from Thinned Fault Likelihood (TFL) computed from the EPS volume. **Note** that from a geoscience perspective this is not a meaningful exercise because we do not need a machine learning model to predict a desired outcome that can be computed directly with an algorithm. The main purpose of this exercise is to learn how to run image-to-image workflows.



Input EPS* seismic

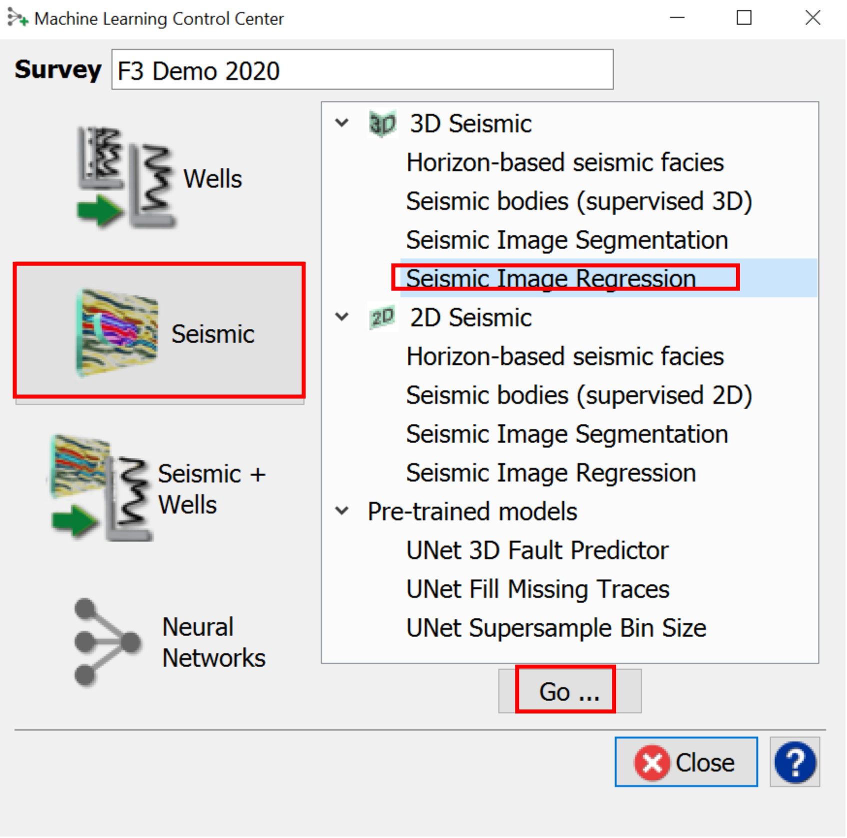


Target mask (0,1) of TFL* from EPS

EPS and TFL-mask are **NOT delivered with F3. To replicate this workflow first create EPS and TFL (from EPS) in the Faults & Fractures plugin. Next create a mask from TFL with the mathematics attribute using this formula: TFL > 0.01 ? 1 : 0*

Exercise objective:

Warning 2: heavy GPU requirements
In this exercise we create 1008 cubelets of 128x128x128 samples. These cubelets are extracted from half the input - and target volumes. The trained U-Net is applied to the full volume. Application is very fast (minutes) but training takes several hours on a GPU. The graphics card we used is a Nvidia GeForce RTX 2080 Ti with 11 GB DDR6 memory. In principle the exercise can also be run on a CPU but then training may take several days.



Workflow:

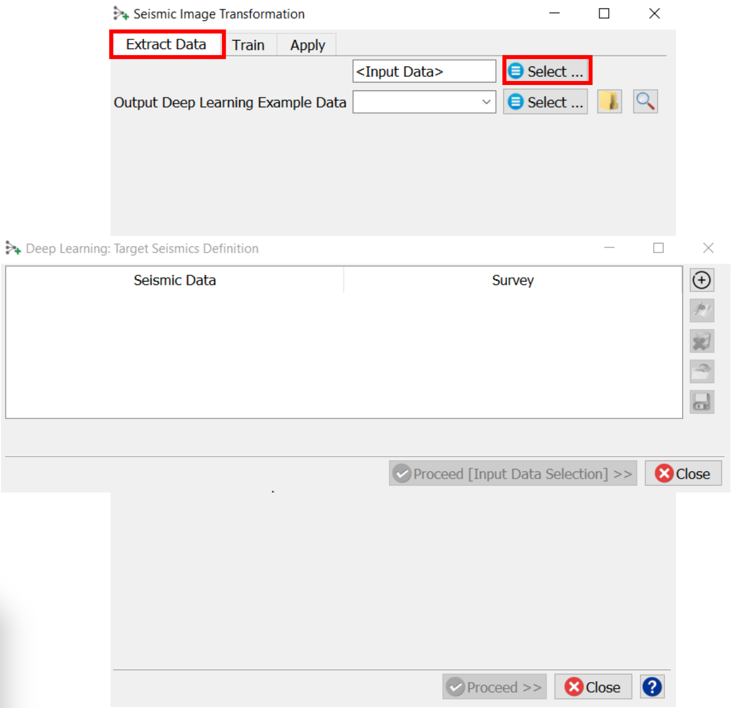
1. **Open** the *Machine Learning Control Center* with the  icon.
2. **Click** on *Seismic*.
3. **Select** *Seismic Image to Image*, and **Hit** *Go*.

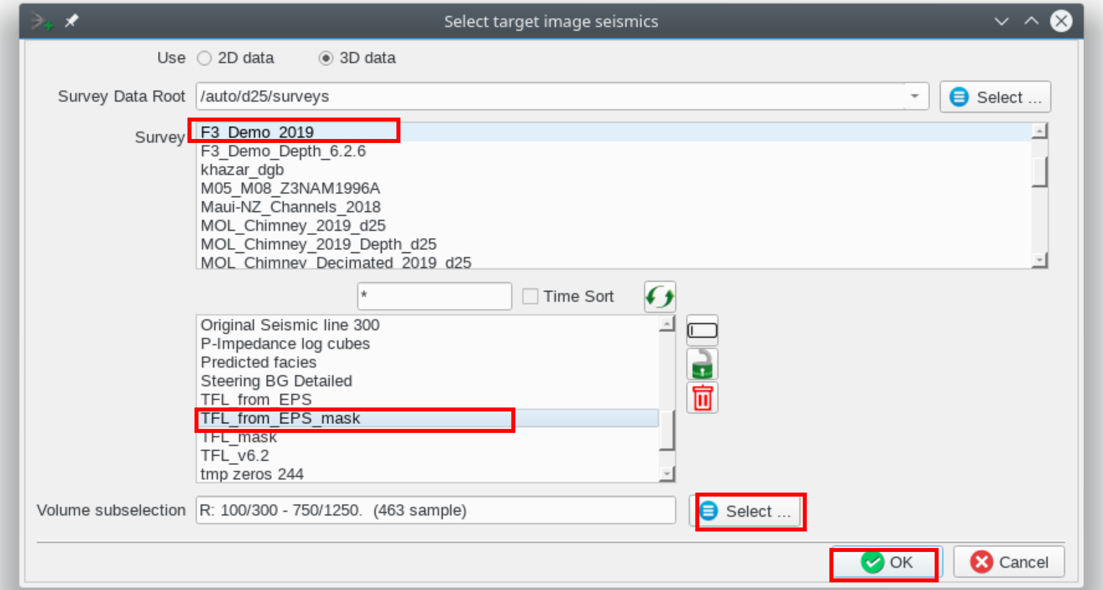
Workflow cont'd:

4. *Seismic Image Transformation* window pops up.

5. **Select** *Target Data* in the *Extract Data* tab. ***Click*** ⊕ *on the target data specification.*

6. In the *Select target image seismic* window, **Select** the *Survey* and the target cube *TFL_from_EPS_mask*



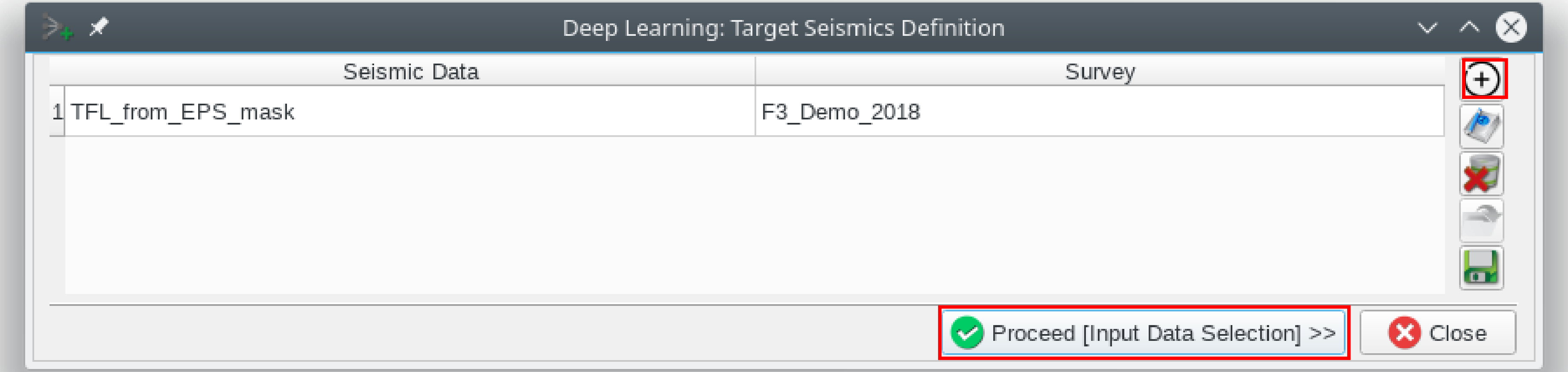


Workflow cont'd:

7. The *Deep Learning: Target Seismics Definition* window pops up.

8. **Press** *Proceed [Input Data Selection]*

*Additional seismic attributes can be added using the icon . Keep the defaults data.

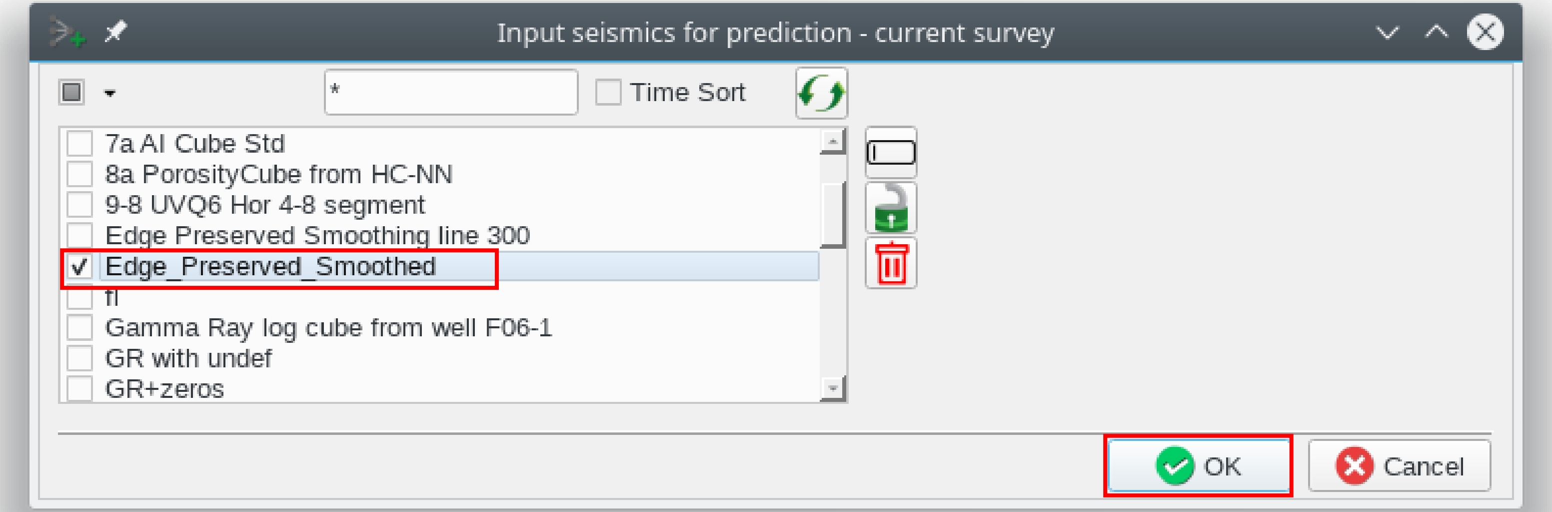


* The option to select data from other surveys is available only in commercial projects

Workflow cont'd:

9. **Select** *Edge Preserved Smoothed as* input seismic to be used for the prediction

10. **Press** OK

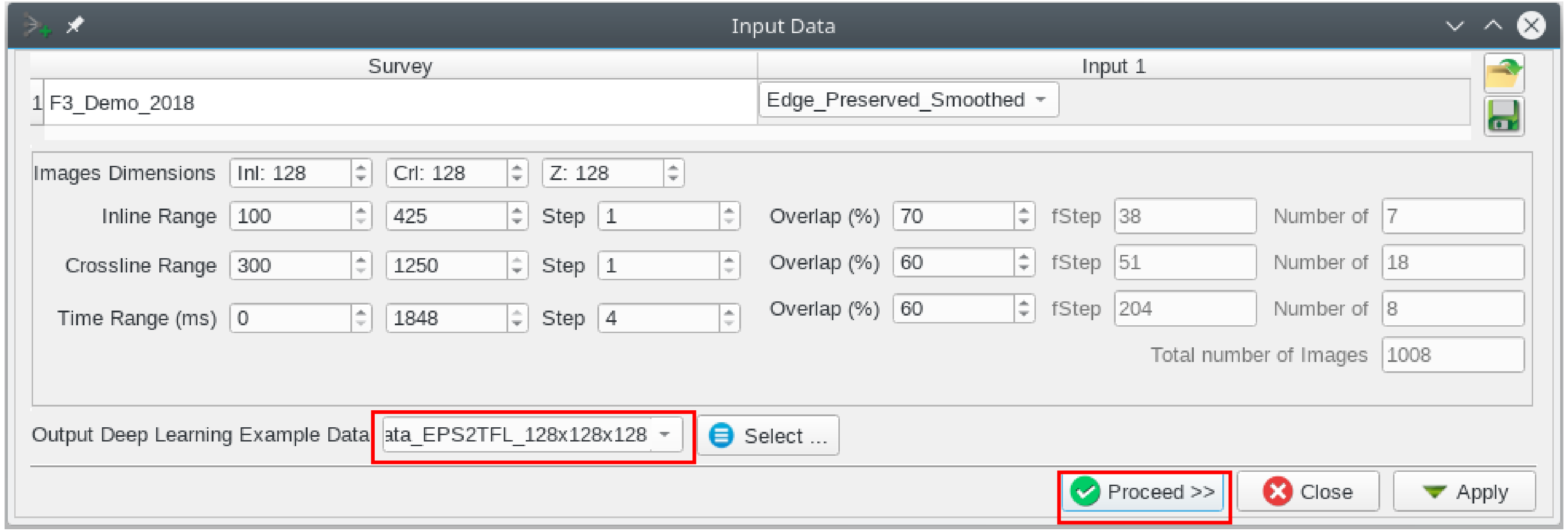


Workflow cont'd:

11. In the *Input Data* window **set** the *Image dimensions* of the cubelets to 128 x 128 x 128 samples. Note: to extract 2D images set one of the dimensions to 0.

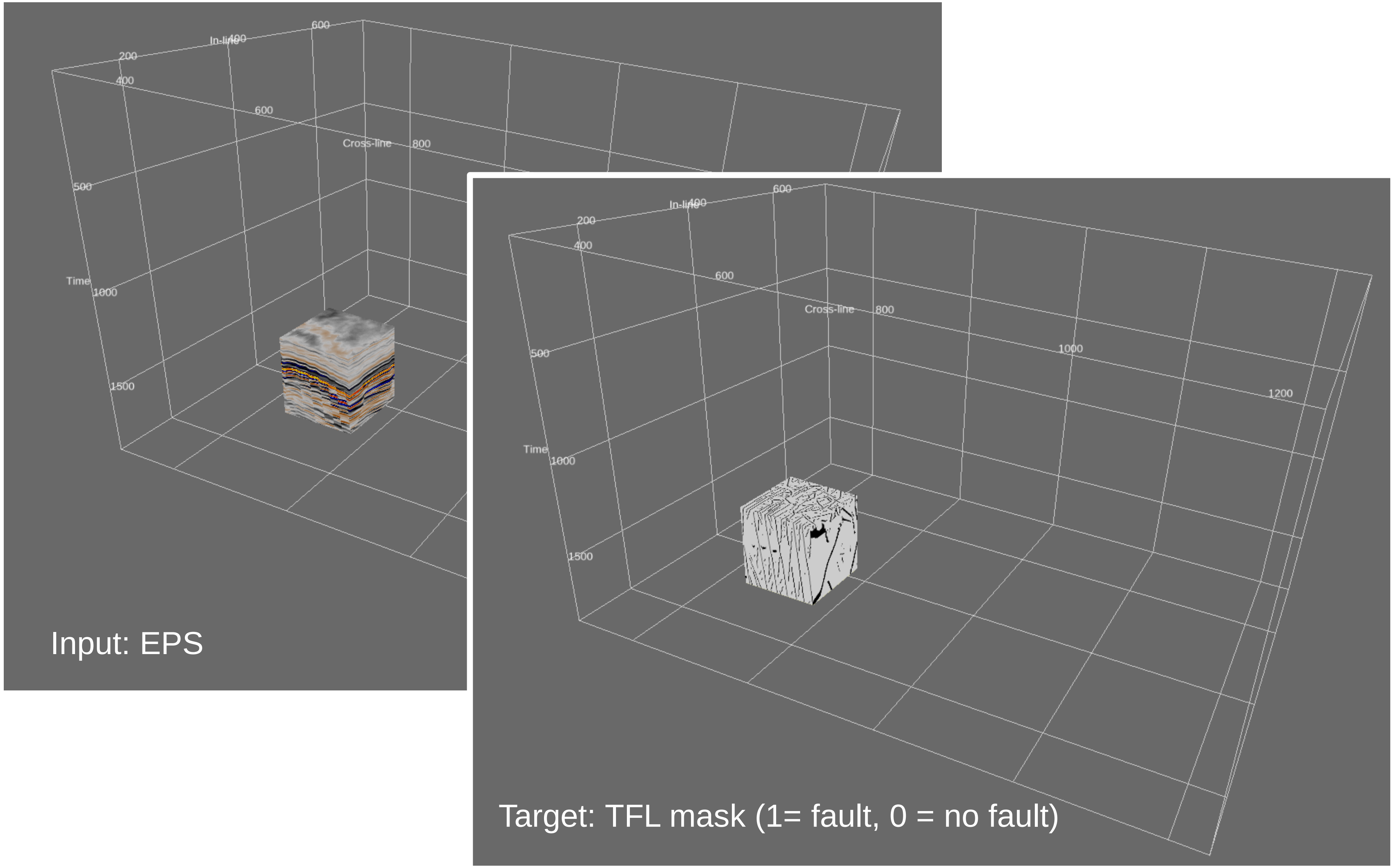
12. **Specify** the *Inline, Crossline, Time Ranges* and the corresponding *Overlap** percentages to such that we extract approx. 1000 cubelets from one half of the input and target volumes (see image for specifications).

13. **Specify** a name for the *Output Deep Learning Example Data* (e.g. ML_train_data_EPS2TFL_128x128x128) and **press** Proceed.



**Overlap*: if the number of examples that can be extracted from a given range and overlap does not fit exactly, the last example is extracted from the boundary backwards.*

Example cubelets. Dimensions are: 128 x 128 x 128 samples



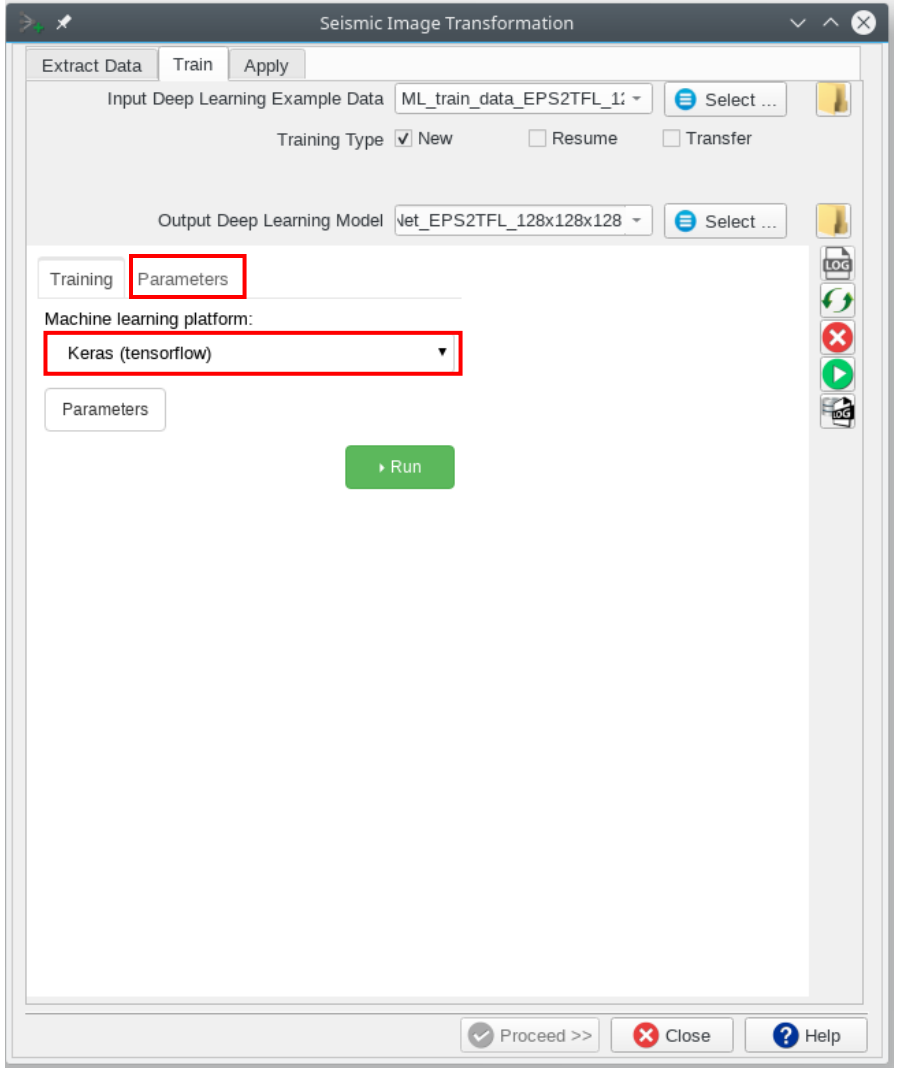
Workflow cont'd:

14. Specify the *Output Deep Learning Model* name (e.g. ML_U-Net_EPS2TFL_128x128x128)

15. In the *Train* tab, **Select** Keras (tensorflow) as *Machine learning platform*

16. **Select** the *Parameters* tab

The machine learning plugin supports two platforms: Keras (tensorflow) for deep learning (convolutional neural networks) and Scikit Learn for all sorts of other machine learning models (e.g. Random Forests). Supported models and training parameters are specified in the Parameters tab.



Workflow cont'd:

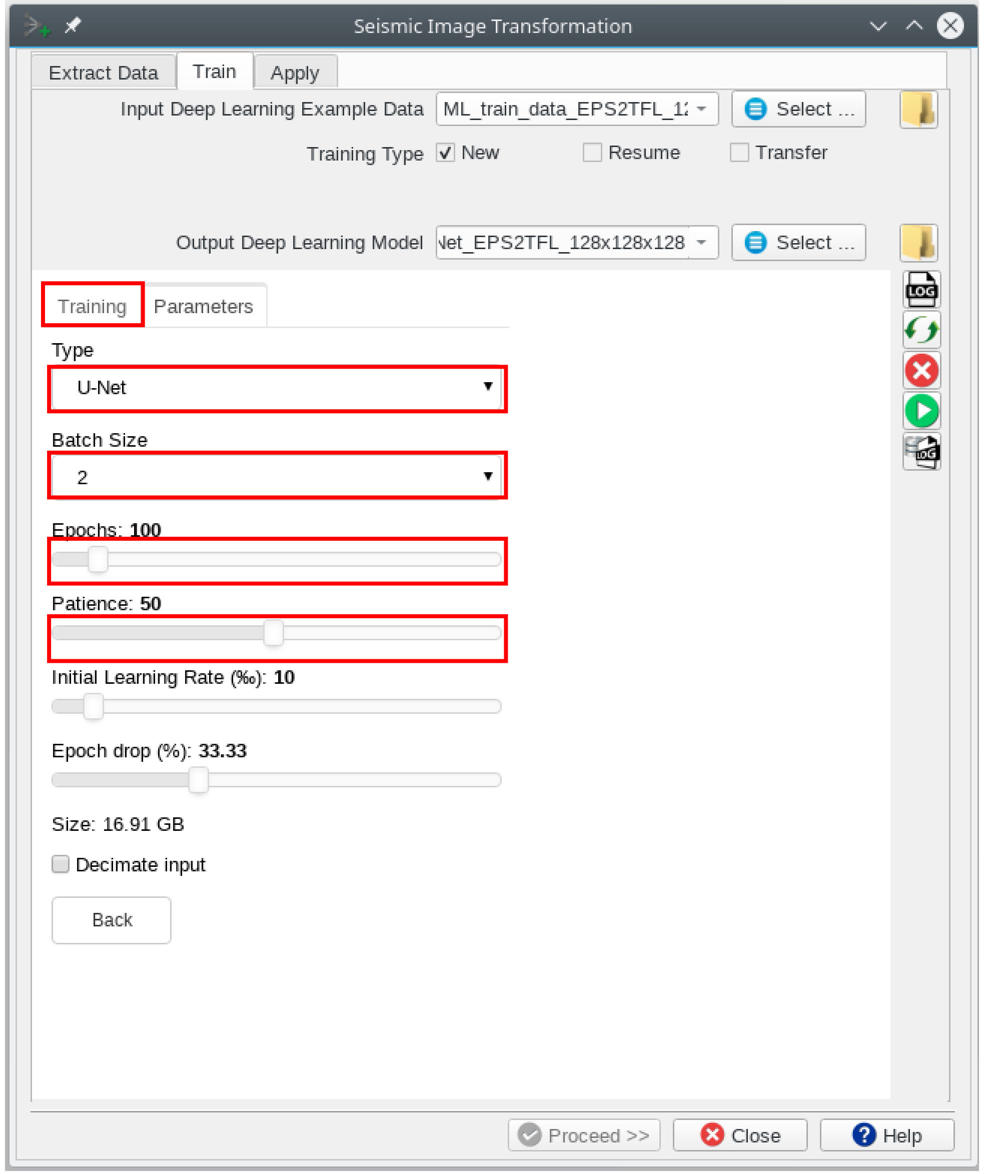
17. In the *Parameters* tab **Select** *Type* U-Net

18. **Set** *Batch Size* to 2. A U-Net needs a lot of GPU memory in the training phase. If memory is exceeded, training stops with an error message. You can then try to rerun with a smaller batch size. Try with the largest possible batch size as training performance increases with batch size.

19. **Set** the number of *Epochs* to 100 (this is the number of training cycles through all examples that are offered in batches of Batch Size).

20. **Set** *Patience* to 50. This parameter avoids early stopping when the error does not decrease after this number of Epochs.

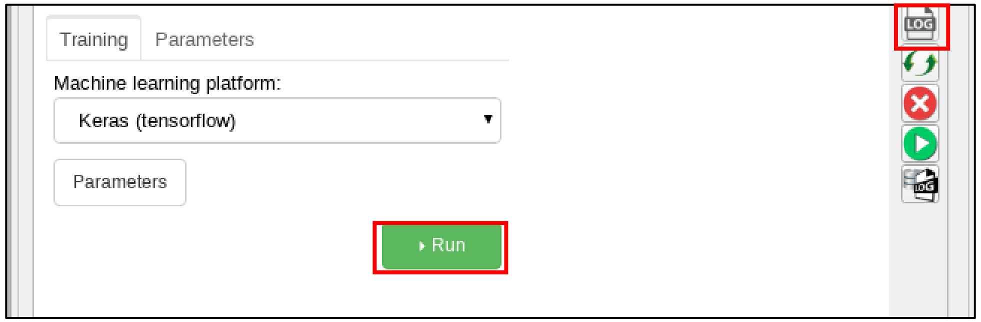
21. **Go back** to the *Training* tab.

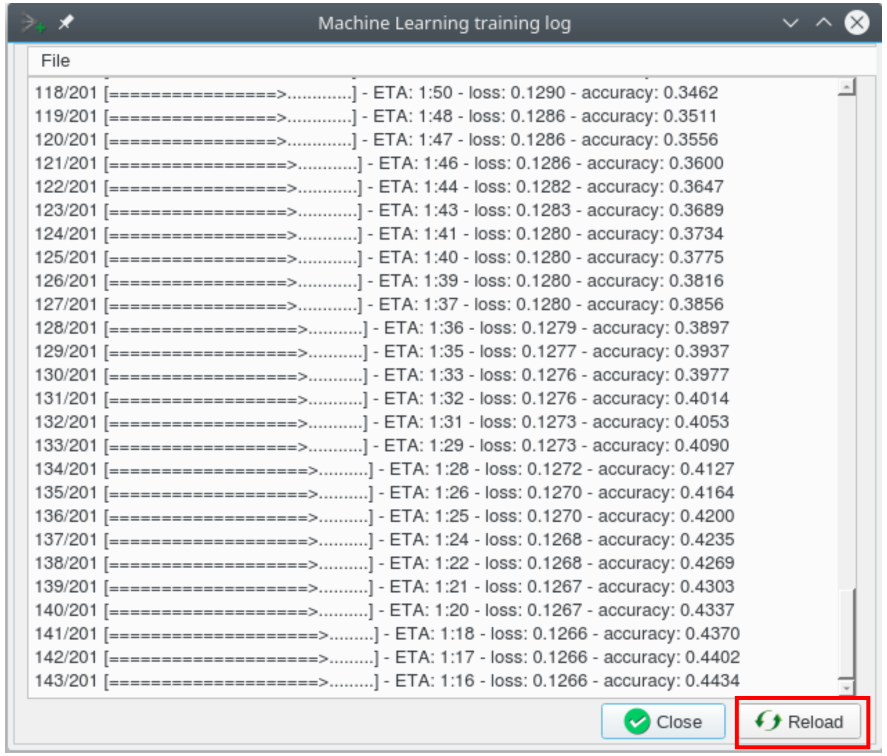


Workflow cont'd:

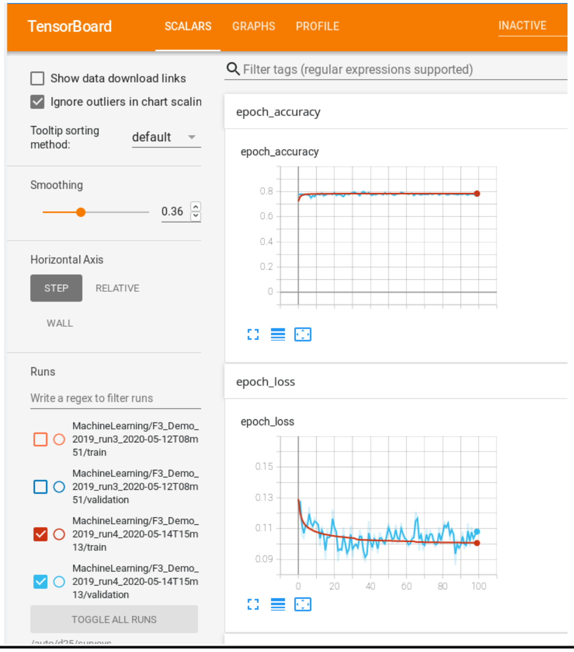
22. In the *Training* tab **Press** *Run*

23. The Machine Learning training log window pops up. This window can also be started by pressing the LOG icon. **Press** *Reload* to refresh.





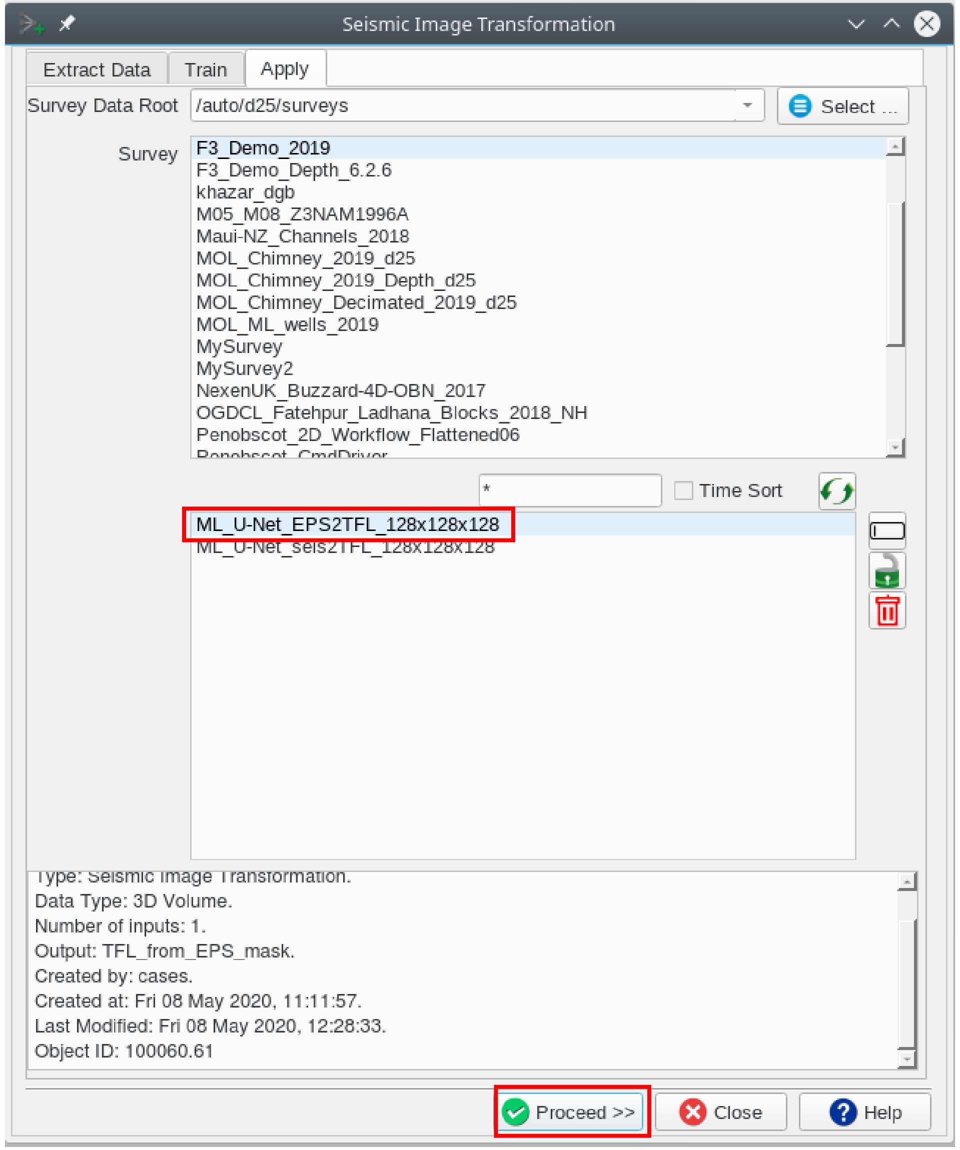
24. *TensorBoard*, a program to examine models and track training performance is started automatically in a browser.



Workflow cont'd:

25. When training is finished, **Select** the *Apply* tab

26. **Select** the trained model ML_U-Net_EPS2TFL_128x128x128 and **Press** Proceed.

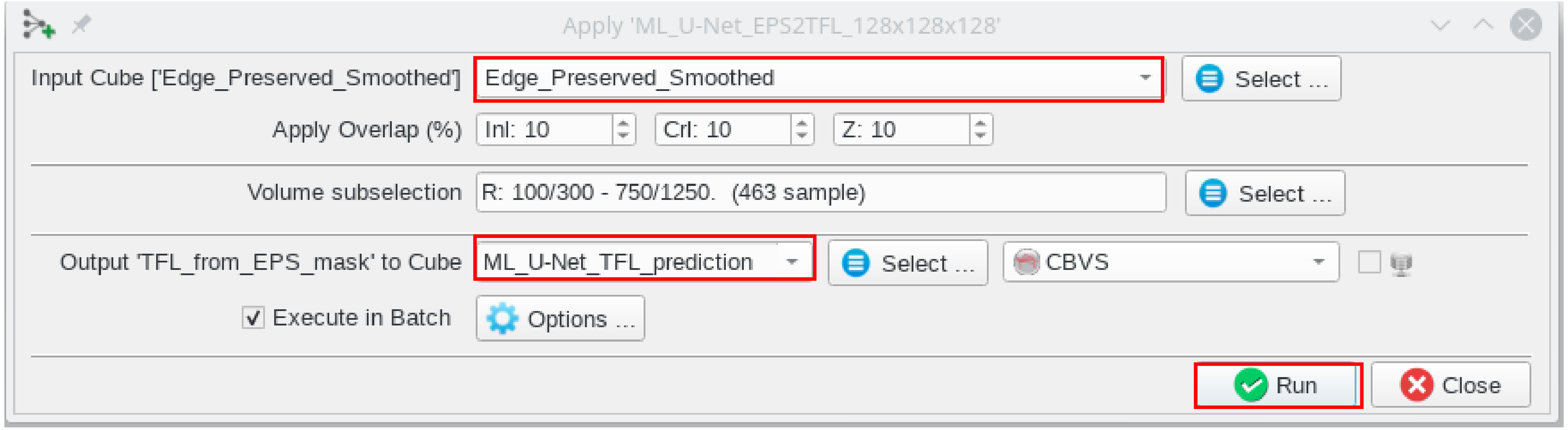


Workflow cont'd:

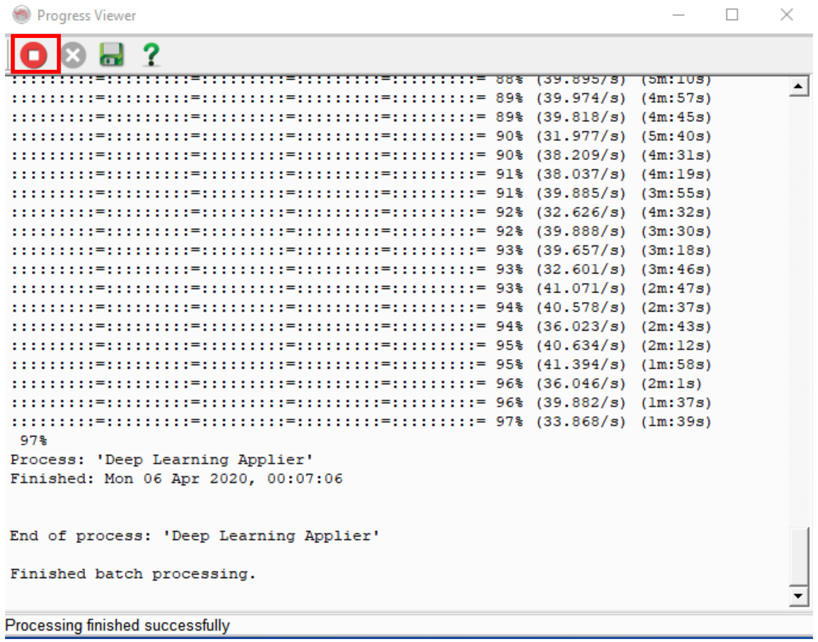
23. In the *Apply* window **Select** the *Input Cube* Edge_Preserved_Smoothed.

24. Specify the *Output Cube* name that will be created by the trained model, e.g. ML_U-Net_TFL_prediction.

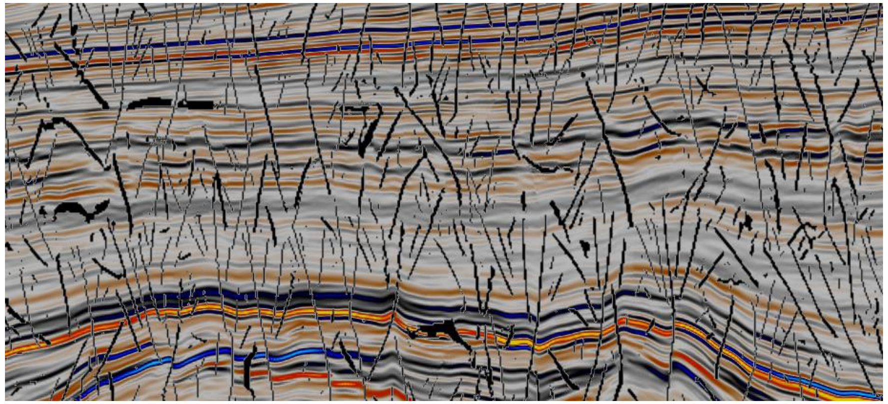
25. **Press** Run to start processing.



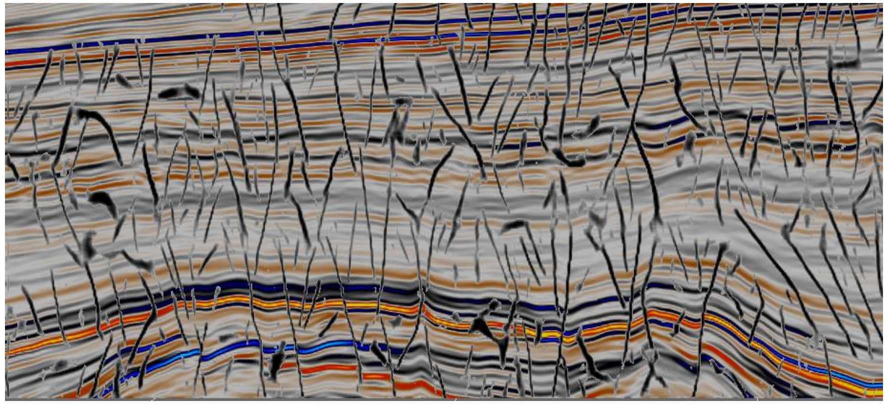
Workflow cont'd:



26. A *Progress Viewer* window pops up. Applying the trained U-Net is very fast. The resulting fault prediction can be viewed e.g. as overlay on the EPS of inline 425.



Inline 500 EPS + TFL mask



Inline 500 EPS + U-Net Prediction