Detect change

Available with Image Analyst license.

To find change between the two images from two different time periods, use the Detect Change Using Deep Learning tool. The tool will create a classified raster showing the changes. The image below shows three images: an image from time period one, an image from time period two, and the change between them.

A typical change detection workflow using deep learning consists of three main steps:

1. Create and export training samples. Create training samples using the **Label Objects for Deep Learning** pane, and use the Export Training Data For Deep Learning tool to convert the samples to deep learning training data.
2. Train the deep learning model. Use the Train Deep Learning Model tool to train a model using the training samples you created in the previous step.
3. Perform inferencing. Use the Detect Change Using Deep Learning tool. You will use the model you created in step 2.

For more examples, supported metadata formats, and model type architecture documentation, see Deep learning model architectures.

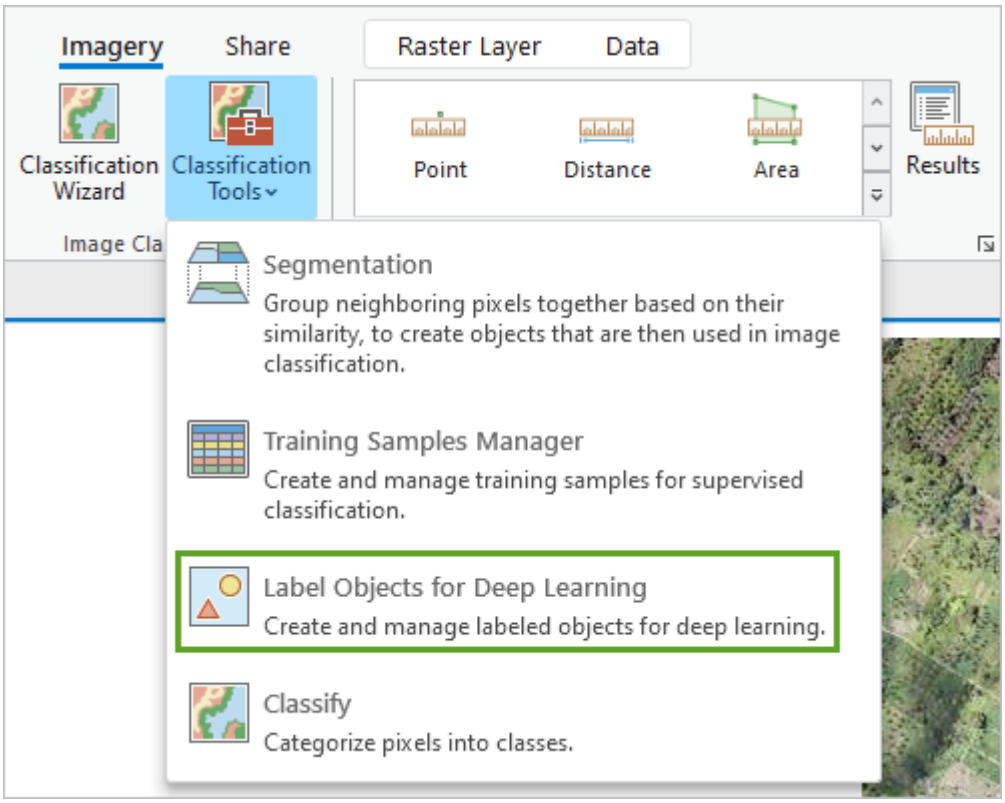
Create and export training samples

Create a training schema and training samples, and export the training data.

If you have existing training samples in a raster dataset or a feature class, you can use the Export Training Data For Deep Learning tool and proceed to the Train a deep learning model section below.

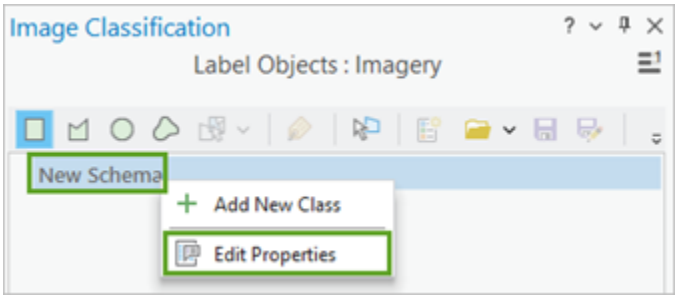
1. Create a training schema. This schema will be used as the legend, so it needs to include all the classes in your deep learning workflow.

1. Add the image to be used to generate the training samples to a map.
2. In the **Contents** pane, select the image that you added.
3. Click the **Imagery** tab.
4. Click **Classification Tools**, and click **Label Objects for Deep Learning**.

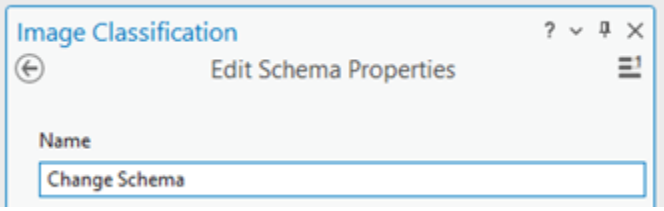


The **Image Classification** pane appears with a blank schema.

5. In the **Image Classification** pane, right-click **New Schema** and click **Edit Properties**.

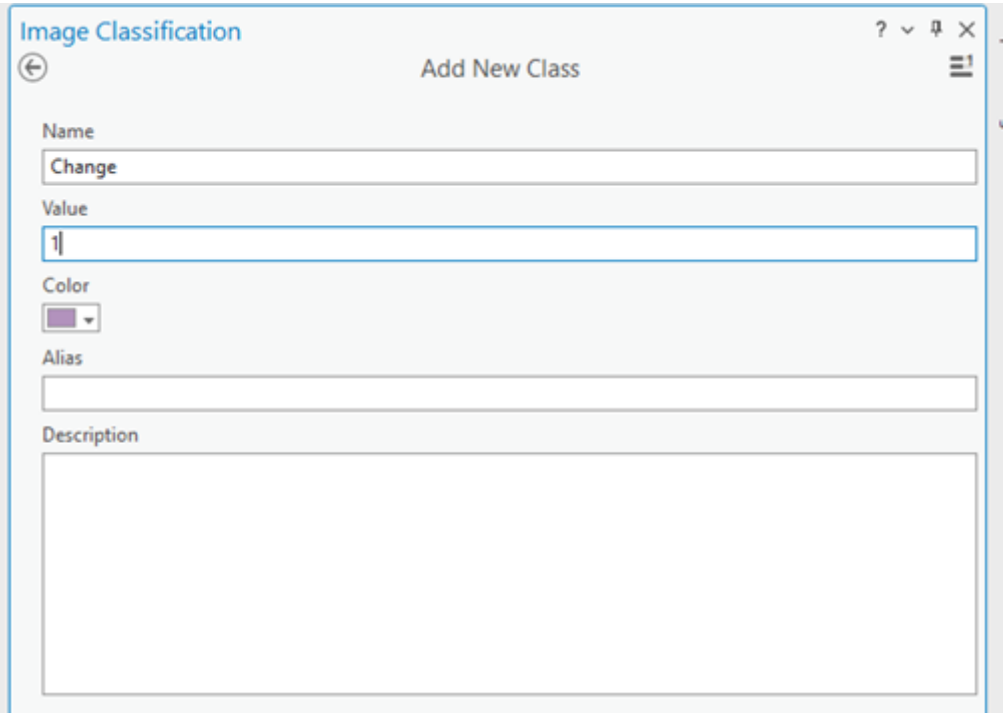


6. Type in a name for the schema.



7. Click **Save**.

2. Add a new class to your schema.
    1. Right-click on the schema you created, and choose **Add New Class**.
    2. Type in a **Name** for your class.



    3. Provide a value for the class.

        The value cannot be 0.

    4. Optionally, choose a color for the class.
    5. Click **OK**.

        The class is added to the schema in the **Image Classification** pane.

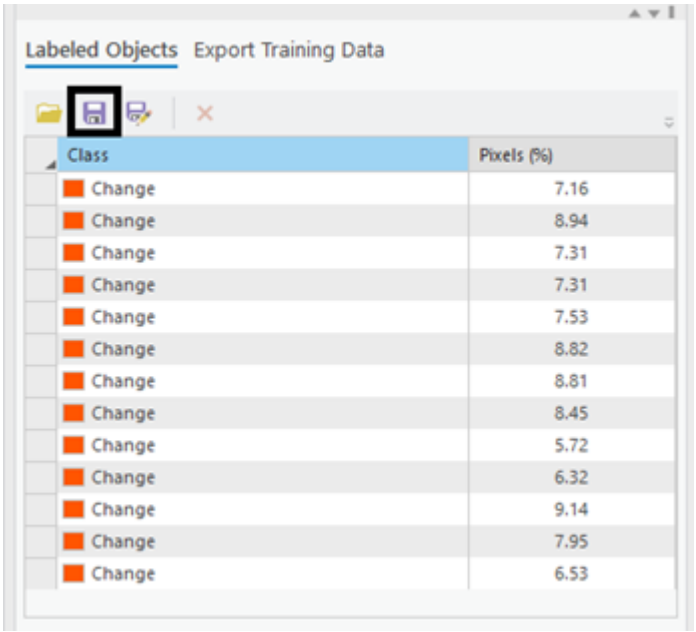
    6. Optionally, repeat steps 2a through 2e to add more classes.
3. Create training samples. These training samples show the areas of change that occurred between the two image, so we can train the deep learning model.
    1. In the **Image Classification** pane, select the class you want to create a training sample for.

2. Choose a drawing tool, such as **Polygon**.
3. Draw a polygon around the pixels that you want to represent the class. It is ok if your polygons overlap, however if you are not sure about an object, do not include it in your training samples. A new record is added in the **Labeled Objects** group of the **Image Classification** pane.

4. Use steps 3a through 3c to create training samples for each class in your schema.

   It is recommended that you collect a statistically significant number of training samples to represent each class in your schema.

4. When you finish creating training samples, click **Save** in the **Image Classification** pane.



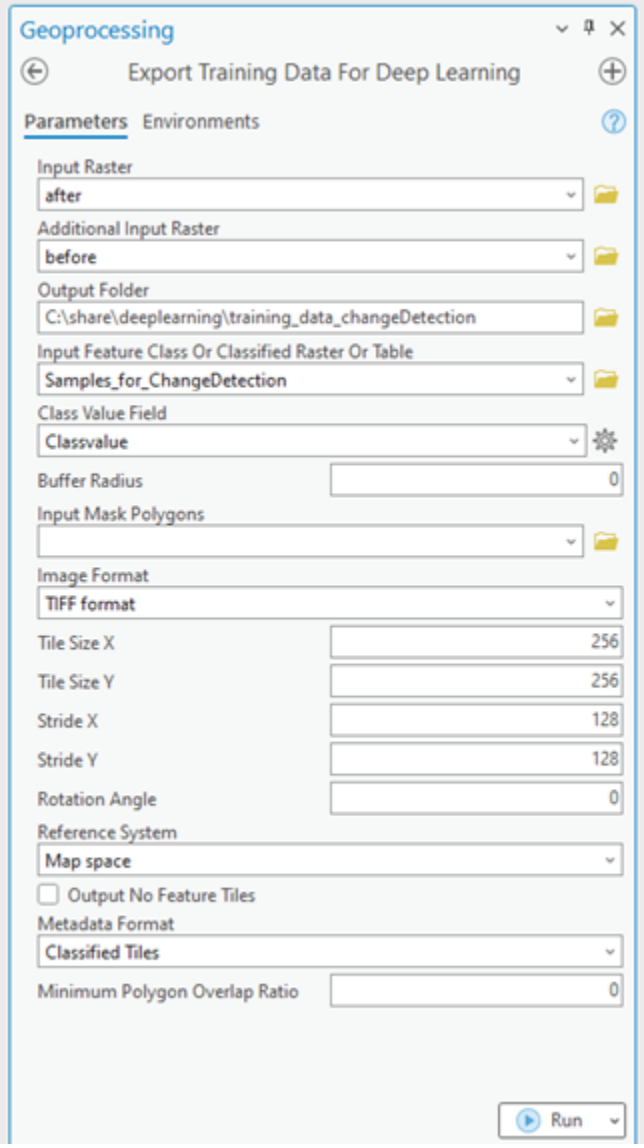
    1. In the **Save current training sample window**, browse to the geodatabase.
    2. Provide a name for the feature class, and click **Save**.
5. Close the **Image Classification** pane.
6. Open the Export Training Data For Deep Learning tool so you can export your training samples as image chips. These image chips will be used to train the deep learning model.

    An image chip is a small image that contains one or more objects to be detected.

    1. Specify the **Input Raster**. Generally, this is the earliest image before any changes.
    2. Specify the **Additional Input Raster**. Generally, this is latest image after the changes.
    3. Specify the **Input Feature Class Or Classified Raster Or Table**. This is your labeled objects training samples file that you created.
    4. Select the **Class Value Field**. The specified label feature class for the changes. The feature class contains a field named `ClassValue`, which you will select.
    5. Specify the **Output Folder**. This is the path and name of the folder where the output image chips and metadata will be stored.
    6. Provide the **Output Folder** value.

        This is the path and name of the folder where the output image chips and metadata will be stored.

    7. Optionally, choose the **Meta Data Format**. The metadata formats that is best for change detection is **Classified tiles**.
    8. Click **Run** to export the training data.



Train a deep learning model

The Train Deep Learning Model tool uses the labeled image chips to determine the combinations of pixels in each image to represent the object. You will use these training samples to train a deep learning model. In the tool, only the **Input Training Data** and **Output Model** parameters are required.

Since your input training data is based on the **Metadata Format**, an appropriate **Model Type** will be assigned by default. The tool will also update the drop-down list of **Model Type** parameters with the appropriate model types that support the selected metadata format. The **Batch Size**, **Model Arguments**, and **Backbone Model** parameters are populated based on the **Model Type**. The output model will then be used to inference the change between the two images.

1. Open the Train Deep Learning Model tool.
2. For the **Input Training Data** parameter, browse to and select the training data folder where the image chips are stored.
3. For the **Output Model** parameter, provide the file path and name of the folder where the output model will be saved after training.
4. Optionally, specify a value for the **Max Epochs** parameter.

   An epoch is a full cycle through the training dataset. During each epoch, the training dataset you stored in the image chips folder is passed forward and backward through the neural network one time. Generally, 20 to 50 epochs are used for initial review. The default value is 20. If the model can be further improved, you can retrain it using the same tool.

5. Optionally, change the **Model Type** parameter in the drop-down list. The model type will determine the deep learning algorithm and neural network that you will use to train your model, such as the **Change Detector** architecture. For more information about models, see Deep Learning Models in ArcGIS . For documentation examples, supported metadata, and model architecture details, see Deep learning model architectures.
6. Optionally, change the **Model Arguments** parameter value.

   The **Model Arguments** parameter is populated with information from the model definition. These arguments vary depending on the model architecture that was specified. A list of model arguments supported by the tool are available in the **Model Arguments** parameter.

7. Optionally, set the **Batch Size** parameter value.

   This parameter determines the number of training samples that will be trained at a time. A batch size value can be determined by various factors such as number of image chips, GPU memory (if GPU is used), and learning rate, if a custom value is used. Typically, the default batch size produces good results.

8. Optionally, provide the **Learning Rate** parameter value.

   If no value is provided, the optimal learning rate is extracted from the learning curve during the training process.

9. Optionally, specify the **Backbone Model** parameter value.

   The default value is based on the model architecture. You can change the default backbone model using the drop-down list.

10. Optionally, provide the **Pre-trained Model** parameter value.

A pretrained model with similar classes can be fine-tuned to fit the new model. The pretrained model must have been trained with the same model type and backbone model that will be used to train the new model.

11. Optionally, change the **Validation %** parameter value.

    This is the percentage of training samples that will be used to validate the model. This value depends on various factors such as the number of training samples and the model architecture. Generally, with a small amount of training data, 10 percent to 20 percent is appropriate for validation. If there is a large amount of training data, such as several thousand samples, a lower percentage such as 2 percent to 5 percent of the data is appropriate for validation. The default value is 10.

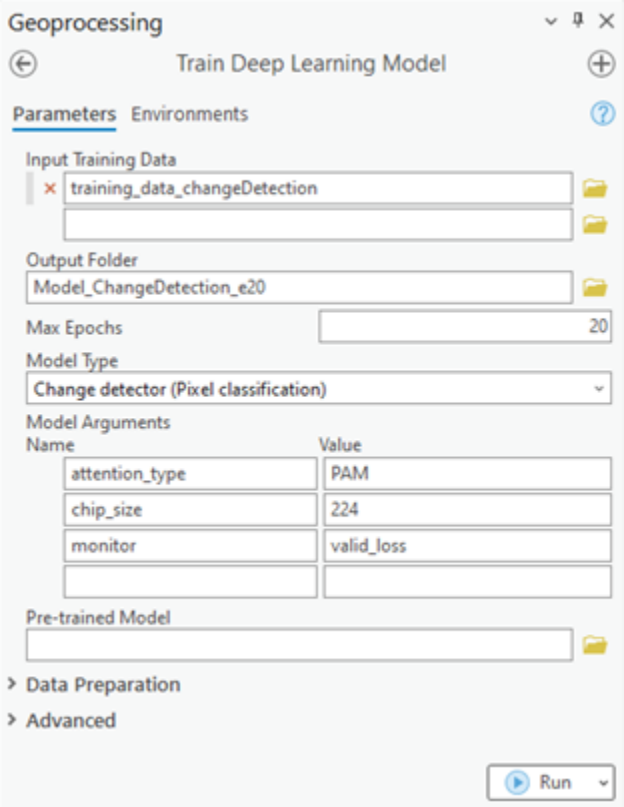
12. Optionally, check the **Stop when model stops improving** parameter.

    When checked, the model training stops when the model is no longer improving regardless of the **Max Epochs** value specified. The default is checked.

13. Optionally, check the **Freeze Model** parameter.

    This parameter specifies whether the backbone layers in the pretrained model will be frozen, so that the weights and biases remain as originally designed. If you check this parameter, the backbone layers are frozen, and the predefined weights and biases are not altered in the **Backbone Model** parameter. If you uncheck this option, the backbone layers are not frozen, and the weights and biases of the **Backbone Model** parameter value can be altered to fit the training samples. This takes more time to process but typically produces better results. The default is checked.

14. Click **Run** to start the training.



Perform inferencing

Inferencing is the process in which information learned during the deep learning training process is used to classify similar pixels and objects in the image. You will use the resulting deep learning model to perform change detection between two rasters images. Use the Detect Change Using Deep Learning tool since you are performing an change detection workflow.

1. Open the Detect Change Using Deep Learning tool.
2. For the **From Raster** parameter, browse and select your image from time period one—the reference image.
3. For the **To Raster** parameter, browse and select your image from time period two—the more current image.
4. For the **Output Classified Raster** parameter, type the name for your output raster. The output classified raster will contain pixel values of 0 and 1, where 0 means `NoChange`, and 1 means `Change`.
5. The **Arguments** parameter will be populated from the information from the **Model Definition**. These arguments will vary, depending on which model architecture is being used. In this example, the **Change Detector** model architecture is used so the following arguments are populated. You can accept the default values or edit them.
    1. `padding`—The number of pixels at the border of image tiles from which predictions are blended for adjacent tiles. Increase the value to smooth the output, which reduces artifacts. The maximum value of the padding can be half the tile size value.

2. `batch_size`—The number of image tiles processed in each step of the model inference. This is dependant on the memory size of the graphics card.

6. Click **Run**, to start the inferencing.