Transfer Learning Using AlexNet

This example shows how to fine-tune a pretrained AlexNet convolutional neural network to perform classification on a waveform detection problem.

Here we prepare samples divided into 3 classes :

Non-First Break: Noise above effective seismic signals

First Break: First arrival seismic waves

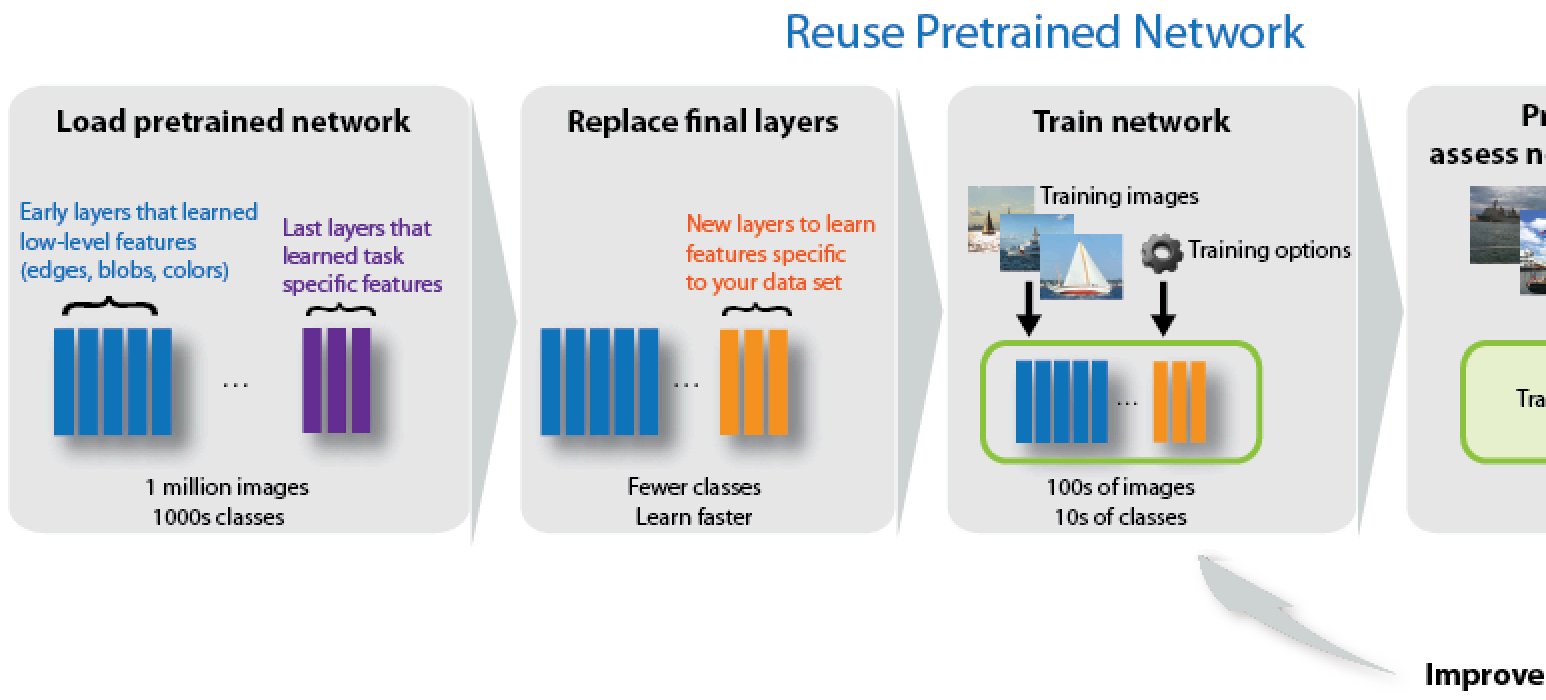
Effective Wave: Seismic Signals after First Break

We spilt up dataset 80% for training and 20% for test.

In our test dataset The prediction accuracy is 91% It can dectect different kinds of waveform very precisely.

AlexNet has been trained on over a million images and can classify images into 1000 object categories (such as keyboard, coffee mug, pencil, and many animals). The network has learned rich feature representations for a wide range of images. The network takes an image as input and outputs a label for the object in the image together with the probabilities for each of the object categories.

Transfer learning is commonly used in deep learning applications. You can take a pretrained network and use it as a starting point to learn a new task. Fine-tuning a network with transfer learning is usually much faster and easier than training a network with randomly initialized weights from scratch. You can quickly transfer learned features to a new task using a smaller number of training images.



Load Data

Unzip and load the new images as an image datastore. `imageDatastore` automatically labels the images based on folder names and stores the data as an `ImageDatastore` object. An image datastore enables you to store large image data, including data that does not fit in memory, and efficiently read batches of images during training of a convolutional neural network.

```
filefolder = 'D:\MaiHao\Code\MATLAB\DeepLearnBookPractice\FirstArrival\Data'
```

```
filefolder = 
'D:\MaiHao\Code\MATLAB\DeepLearnBookPractice\FirstArrival\Data'
```

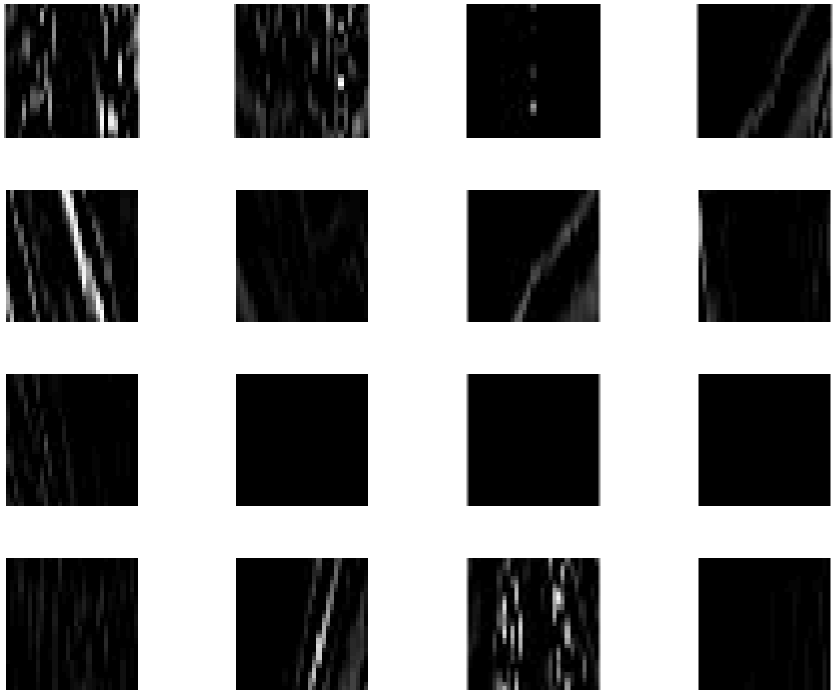
```
imds = imageDatastore(filefolder, ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');
```

Divide the data into training and validation data sets. Use 70% of the images for training and 30% for validation. `splitEachLabel` splits the `images` datastore into two new datastores.

```
[imdsTrain,imdsValidation] = splitEachLabel(imds,0.9,'randomized');
```

This very small data set now contains 55 training images and 20 validation images. Display some sample images.

```
numTrainImages = numel(imdsTrain.Labels);
idx = randperm(numTrainImages,16);
figure
for i = 1:16
    subplot(4,4,i)
    I = readimage(imdsTrain,idx(i));
    imshow(I)
end
```



Load Pretrained Network

Load the pretrained AlexNet neural network. If Neural Network Toolbox™ Model *for AlexNet Network* is not installed, then the software provides a download link. AlexNet is trained on more than one million images and can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the model has learned rich feature representations for a wide range of images.

```
net = alexnet;
```

Display the network architecture. The network has five convolutional layers and three fully connected layers.

```
net.Layers
```

```
ans = 
  25x1 Layer array with layers:

     1   'data'     Image Input                   227x227x3 images with 'zerocenter' normalization
     2   'conv1'    Convolution                   96 11x11x3 convolutions with stride [4  4] and padding [0  0  0
     3   'relu1'    ReLU                          ReLU
     4   'norm1'    Cross Channel Normalization   cross channel normalization with 5 channels per element
     5   'pool1'    Max Pooling                   3x3 max pooling with stride [2  2] and padding [0  0  0  0]
     6   'conv2'    Convolution                   256 5x5x48 convolutions with stride [1  1] and padding [2  2  2
     7   'relu2'    ReLU                          ReLU
     8   'norm2'    Cross Channel Normalization   cross channel normalization with 5 channels per element
     9   'pool2'    Max Pooling                   3x3 max pooling with stride [2  2] and padding [0  0  0  0]
    10   'conv3'    Convolution                   384 3x3x256 convolutions with stride [1  1] and padding [1  1  1
    11   'relu3'    ReLU                          ReLU
```

```
12   'conv4'    Convolution               384 3x3x192 convolutions with stride [1  1] and padding [1  1  1
13   'relu4'    ReLU                      ReLU
14   'conv5'    Convolution               256 3x3x192 convolutions with stride [1  1] and padding [1  1  1
15   'relu5'    ReLU                      ReLU
16   'pool5'    Max Pooling               3x3 max pooling with stride [2  2] and padding [0  0  0  0]
17   'fc6'      Fully Connected           4096 fully connected layer
18   'relu6'    ReLU                      ReLU
19   'drop6'    Dropout                   50% dropout
20   'fc7'      Fully Connected           4096 fully connected layer
21   'relu7'    ReLU                      ReLU
22   'drop7'    Dropout                   50% dropout
23   'fc8'      Fully Connected           1000 fully connected layer
24   'prob'     Softmax                   softmax
25   'output'   Classification Output     crossentropyex with 'tench' and 999 other classes
```

The first layer, the image input layer, requires input images of size 227-by-227-by-3, where 3 is the number of color channels.

```
inputSize = net.Layers(1).InputSize
```

```
inputSize = 1×3
   227   227     3
```

Replace Final Layers

The last three layers of the pretrained network `net` are configured for 1000 classes. These three layers must be fine-tuned for the new classification problem. Extract all layers, except the last three, from the pretrained network.

```
layersTransfer = net.Layers(2:end-3);
```

Transfer the layers to the new classification task by replacing the last three layers with a fully connected layer, a softmax layer, and a classification output layer. Specify the options of the new fully connected layer according to the new data. Set the fully connected layer to have the same size as the number of classes in the new data. To learn faster in the new layers than in the transferred layers, increase the `WeightLearnRateFactor` and `BiasLearnRateFactor` values of the fully connected layer.

```
numClasses = numel(categories(imdsTrain.Labels))
```

```
numClasses = 3
```

```
layers = [
    imageInputLayer([31 31 1])
    layersTransfer
    fullyConnectedLayer(numClasses,'WeightLearnRateFactor',20,'BiasLearnRateFactor',20)
    softmaxLayer
    classificationLayer];
```

Train Network

The network requires input images of size 31-by-31-by-1, but the images in the image datastores have different sizes. Use an augmented image datastore to automatically resize the training images. Specify additional augmentation operations to perform on the training images: randomly flip the training images along the vertical axis, and randomly translate them up to 30 pixels horizontally and vertically. Data augmentation helps prevent the network from overfitting and memorizing the exact details of the training images.

```
pixelRange = [-30 30];
imageAugmenter = imageDataAugmenter( ...
    'RandXReflection',true, ...
    'RandXTranslation',pixelRange, ...
    'RandYTranslation',pixelRange);
augimdsTrain = augmentedImageDatastore(inputSize(1:2),imdsTrain, ...
    'DataAugmentation',imageAugmenter);
```

To automatically resize the validation images without performing further data augmentation, use an augmented image datastore without specifying any additional preprocessing operations.

```
augimdsValidation = augmentedImageDatastore(inputSize(1:2),imdsValidation);
```

Specify the training options. For transfer learning, keep the features from the early layers of the pretrained network (the transferred layer weights). To slow down learning in the transferred layers, set the initial learning rate to a small value. In the previous step, you increased the learning rate factors for the fully connected layer to speed up learning in the new final layers. This combination of learning rate settings results in fast learning only in the new layers and slower learning in the other layers. When performing transfer learning, you do not need to train for as many epochs. An epoch is a full training cycle on the entire training data set. Specify the mini-batch size and validation data. The software validates the network every `ValidationFrequency` iterations during training.

```
options = trainingOptions('sgdm', ...
    'MiniBatchSize',10, ...
    'MaxEpochs',6, ...
    'InitialLearnRate',1e-4, ...
    'ValidationData',augimdsValidation, ...
    'ValidationFrequency',3, ...
    'ValidationPatience',Inf, ...
    'Verbose',false, ...
    'Plots','training-progress');
```

Train the network that consists of the transferred and new layers. By default, `trainNetwork` uses a GPU if one is available (requires Parallel Computing Toolbox™ and a CUDA® enabled GPU with compute capability 3.0 or higher). Otherwise, it uses a CPU. You can also specify the execution environment by using the `'ExecutionEnvironment'` name-value pair argument of `trainingOptions`.

```
netTransfer = trainNetwork(augimdsTrain,layers,options);
```

错误使用 trainNetwork (line 154)

```
The training images are of size 227x227x1 but the input layer expects images of size 31x31x1.
```

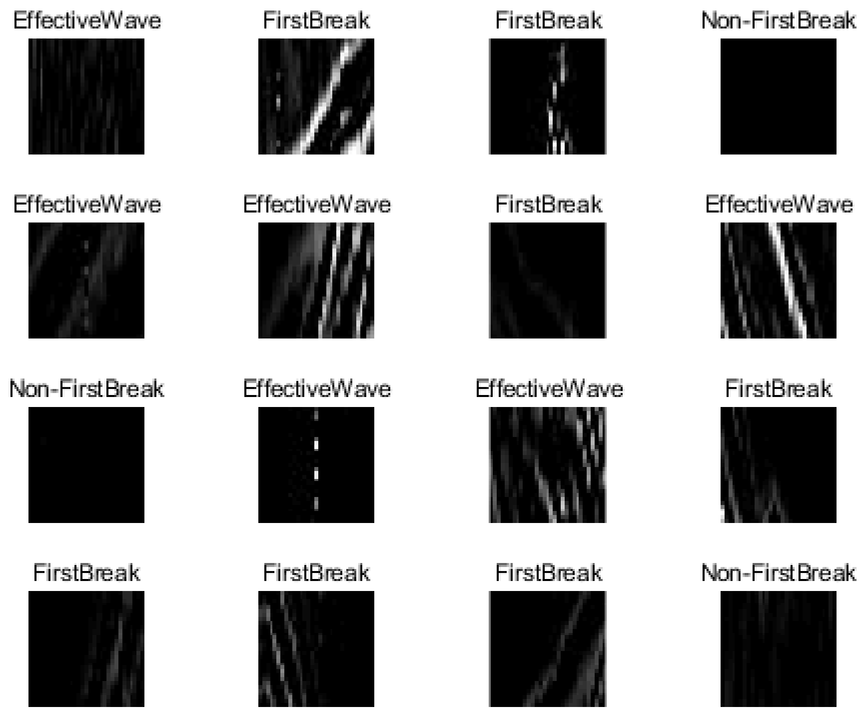
Classify Validation Images

Classify the validation images using the fine-tuned network.

```
[YPred,scores] = classify(netTransfer,augimdsValidation);
```

Display four sample validation images with their predicted labels.

```
idx = randperm(numel(imdsValidation.Files),16);
figure
for i = 1:16
    subplot(4,4,i)
    I = readimage(imdsValidation,idx(i));
    imshow(I)
    label = YPred(idx(i));
    title(string(label));
end
```



Calculate the classification accuracy on the validation set. Accuracy is the fraction of labels that the network predicts correctly.

```
YValidation = imdsValidation.Labels;
```

```
accuracy = mean(YPred == YValidation)
```

```
accuracy = 0.9130
```

This trained network has high accuracy. If the accuracy is not high enough using transfer learning, then try feature extraction instead.