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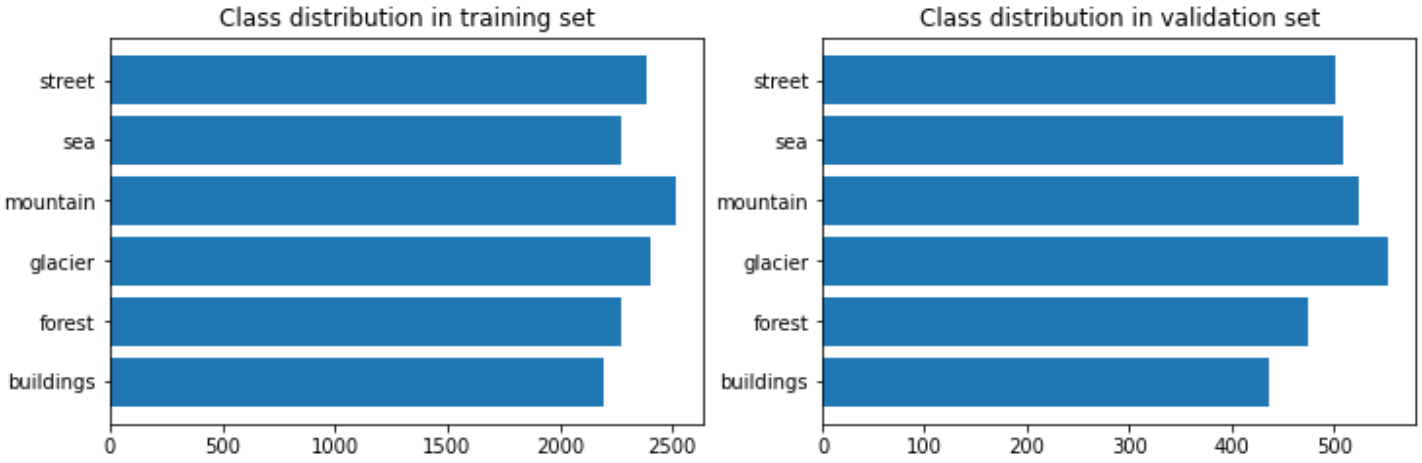
CSCE A415 – Machine Learning
HW #4 – Convolutional Neural Networks
24 April 2021

Convolutional Neural Networks & Image Recognition

Intel Image Classification

This dataset consists of 14,034 training images and 3,000 validation images of size 150 x 150 falling into six classifications: Buildings, Forest, Glacier, Mountain, Sea, and Street. Class counts are not perfectly even within the dataset, but each class is well represented:



Goal

Create an **efficient** CNN to classify images. Final CNN should run in the same amount of time as the Sigmoid and Relu tests shown below using the baseline model (approx. 60-70s per epoch) and should minimize overfitting. For the sake of runtime, a max of 15 epochs will be tested per implementation.

Baseline model:

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling (Rescaling)        (None, 150, 150, 3)       0
_________________________________________________________________
conv2d (Conv2D)              (None, 148, 148, 32)      896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 74, 74, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 175232)            0
_________________________________________________________________
dense (Dense)                (None, 6)                 1051398
=================================================================
Total params: 1,052,294
Trainable params: 1,052,294
Non-trainable params: 0
_________________________________________________________________
```

Baseline batch size is 32.

Rescale first to change RGB values from 0-255 to 0-1 for proper weighting.

Apply one convolutional layer with 32 filters and a 3x3 kernel.

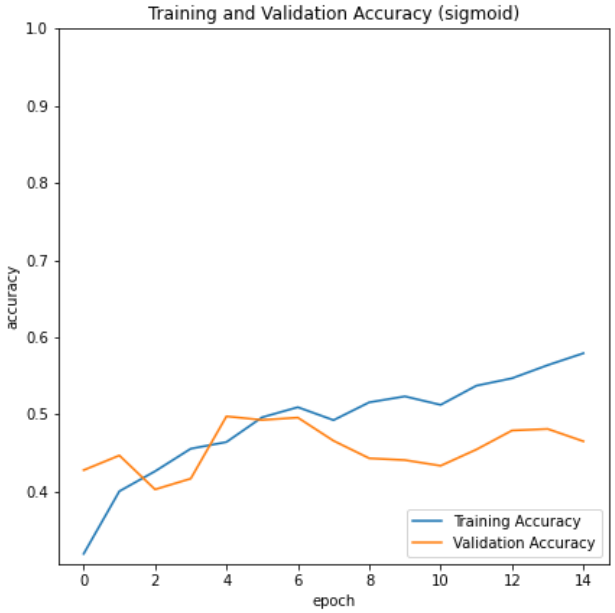
Apply one 2x2 max pool layer to reduce parameters.

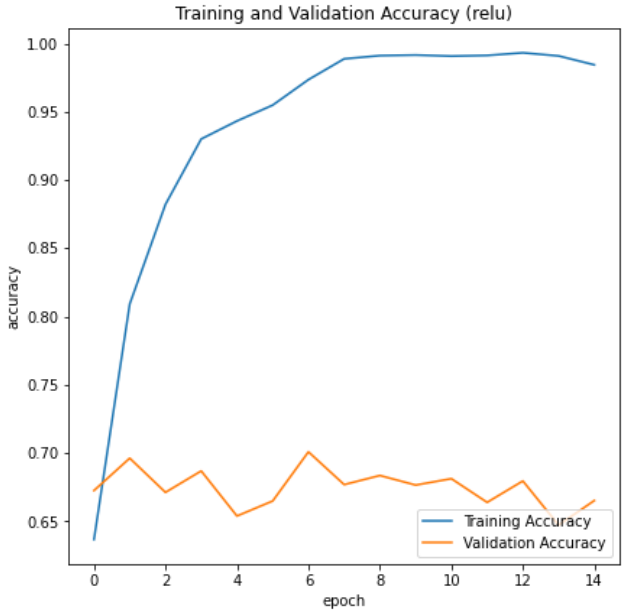
Flatten and run through a final softmax layer to predict class.

Testing Hyperparameters

Sigmoid vs Relu

Activation Function	Sigmoid	Relu
Runtime per epoch	62s	58s
Training accuracy	~57%	~99%
Validation accuracy	~47%	~66%



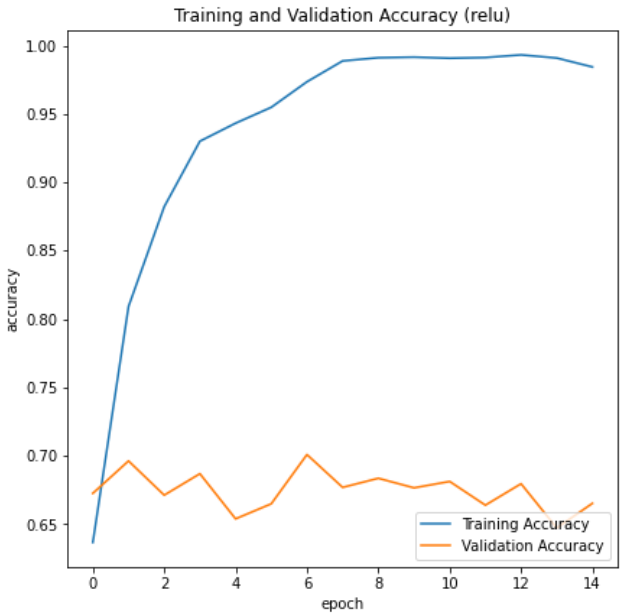


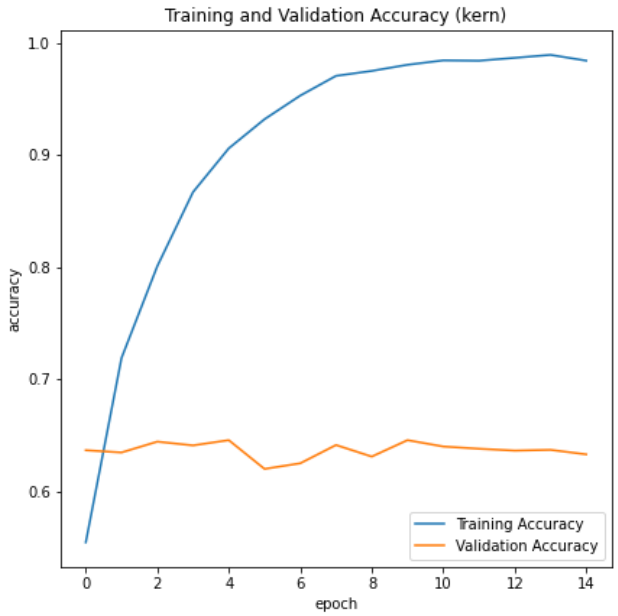
Overall, Relu performed much better than Sigmoid with a validation accuracy of 66% vs 47%. Neither model showed an increase in validation accuracy with an increasing number of epochs. Both models overfit the training data, especially the Relu model, which showed a 33% difference in training vs validation accuracy.

Relu appears to be a superior activation function for this application. It will be used in all following tests.

3x3 Kernel vs 5x5 Kernel

Kernel Size	3x3	5x5
Runtime per epoch	58s	71s
Training accuracy	~99%	~99%
Validation accuracy	~66%	~64%

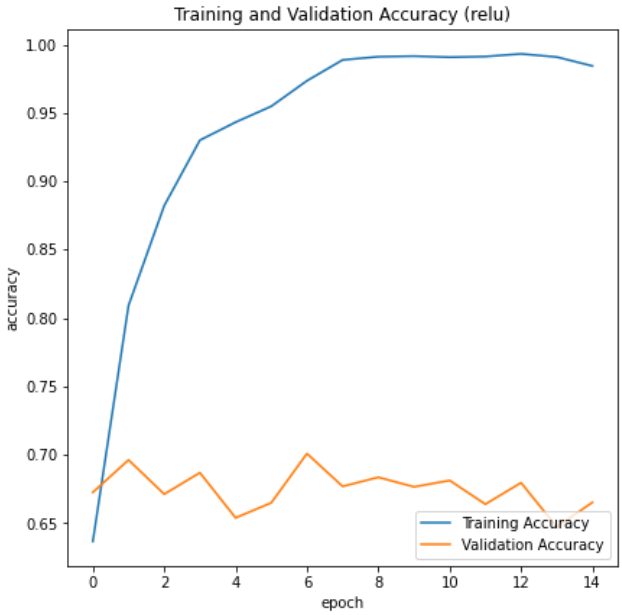


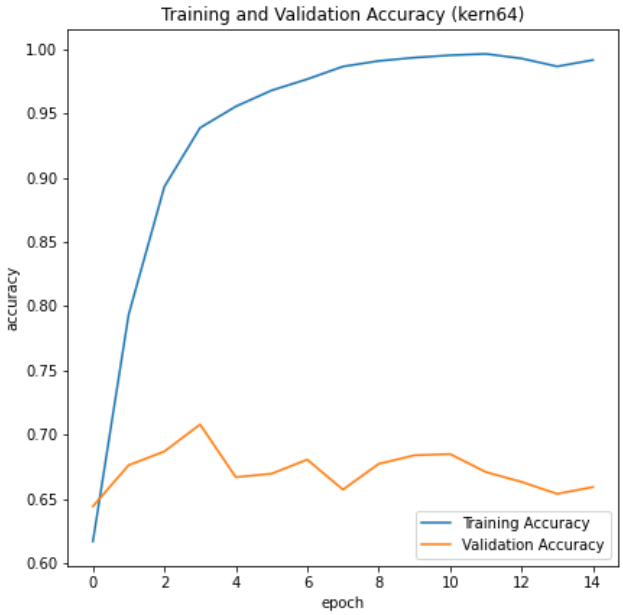


Using a larger kernel in the convolutional layer increases runtime by about 13s (22%) but has no significant effect on accuracy or overfitting.

32 Filters vs 64 Filters

Filter Count	32	64
Runtime per epoch	58s	101s
Training accuracy	~99%	~99%
Validation accuracy	~66%	~66%

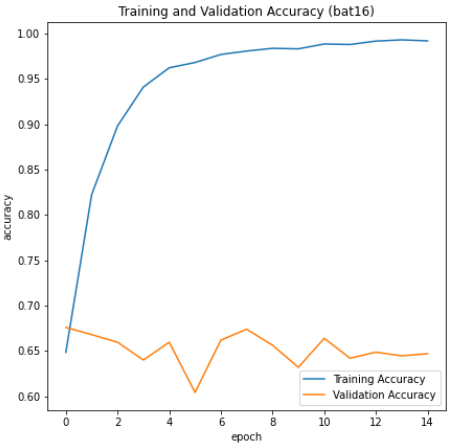


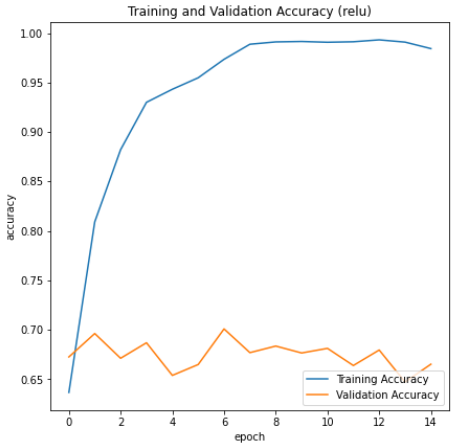


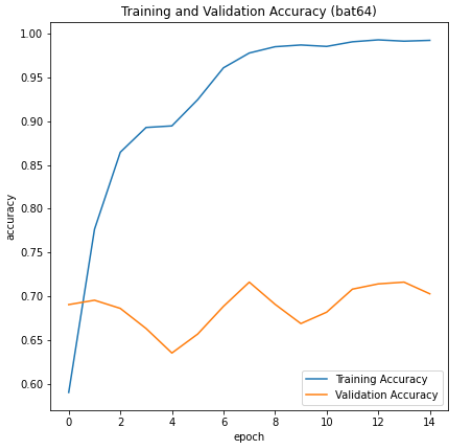
Doubling the filter count in the convolutional layer increases runtime by about 43s (74%) but has no significant effect on accuracy or overfitting. It may be worth testing a larger filter count with increased max pooling parameters afterward to reduce runtime.

16 vs 32 vs 64 Batch Sizes

Batch Size	16	32	64
Runtime per epoch	61s	58s	56s
Training accuracy	~99%	~99%	~99%
Validation accuracy	~65%	~66%	~70%



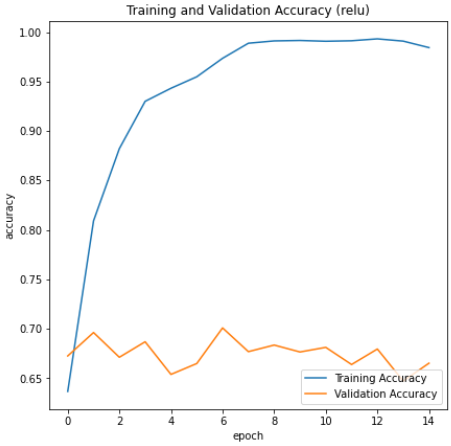


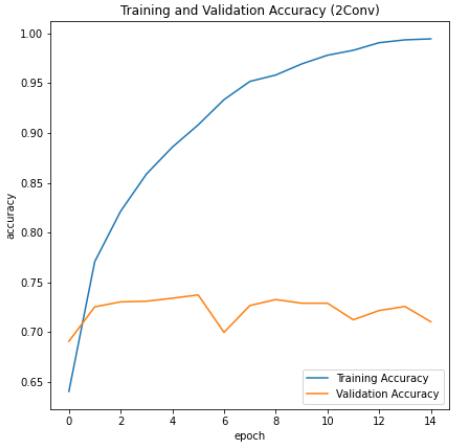


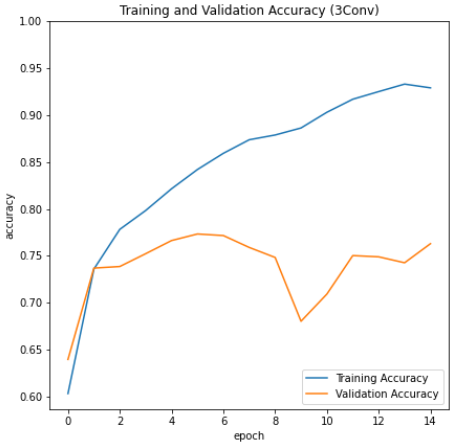
Increasing the batch size slightly improved both runtime and validation accuracy. A batch size of 64 will be used moving forward.

Number of Convolutional Layers

# of Conv Layers	1	2	3
Runtime per epoch	58s	92s	101s
Training accuracy	~99%	~99%	~93%
Validation accuracy	~66%	~72%	~75%







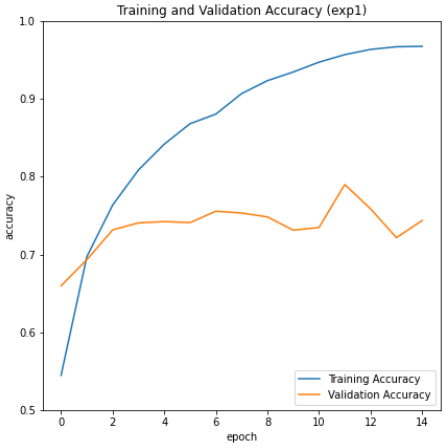
Adding convolutional layers increased validation accuracy at the expense of runtime. At three convolutional layers, overfitting was reduced with the difference between training and validation accuracy dropping to 18%.

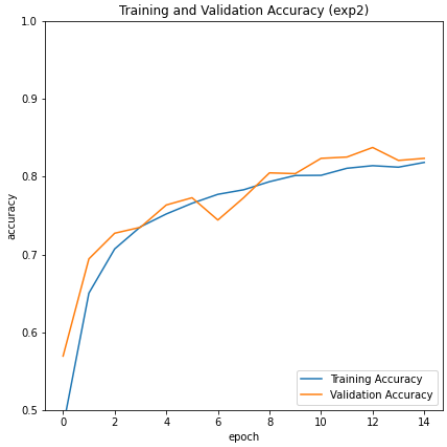
Refining Hyperparameters

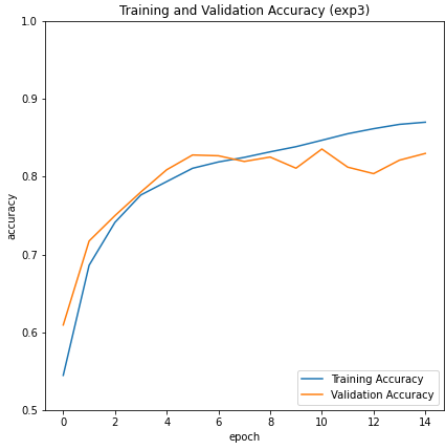
Experimental Models

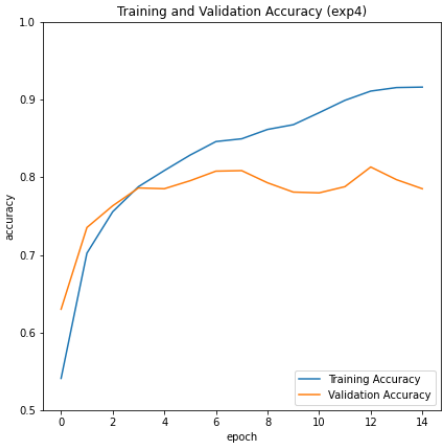
Model	Parameter Summary	Stats	Result Summary
Exp1	Two convolutional layers with max pooling after each to reduce runtime and dropouts after each to reduce overfitting. An additional fully connected layer is added between the flatten and classification.	Time/epoch: 140s Training acc: ~96% Validat acc: ~74%	Model is not efficient enough (takes too long to run). It is slower, less accurate, and overfits more than the 3conv model above.
Exp2	Three convolutional layers with max pooling after each. Max pooling size is increased for the first two layers to improve runtime. Dropouts are added after each max pool to reduce overfitting. Two additional fully connected layers are added between the flatten and classification.	Time/epoch: 60s Training acc: ~83% Validat acc: ~81%	Increased max pooling parameters greatly decreases model runtime. Adding additional fully connected layers and convolutional layers helps improve accuracy.
Exp3-Exp9	Same as Expr2. Each model experiments with different dropouts, filter counts, and/or batch normalization	Batch normalization decreased accuracy and increased overfitting, so it was not used in the final model. Increased filter counts within the convolutional layers coupled with max pooling had no significant effect on runtime but also showed no increase in overall model accuracy and no decrease in overfitting.	

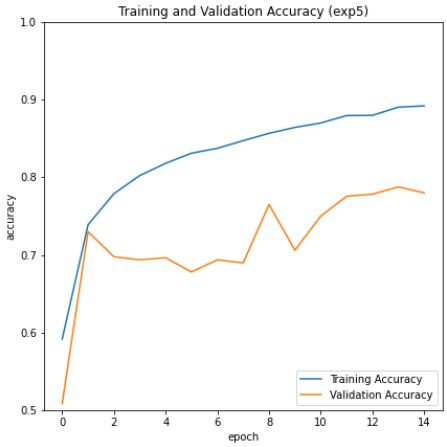
Model accuracy:

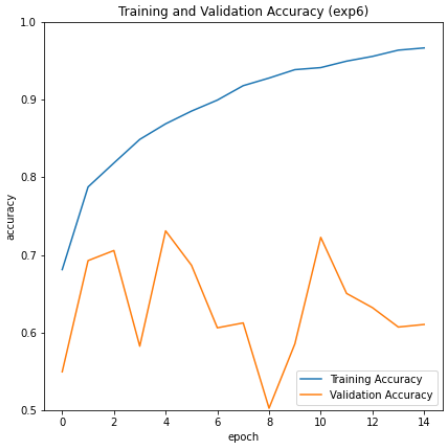


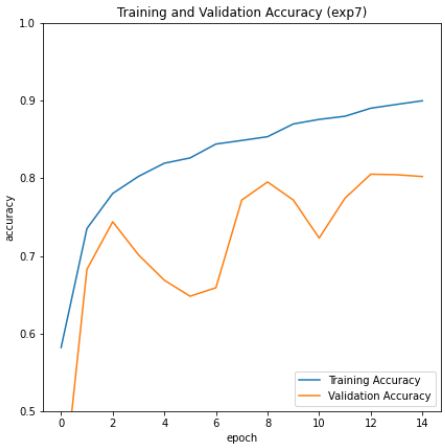


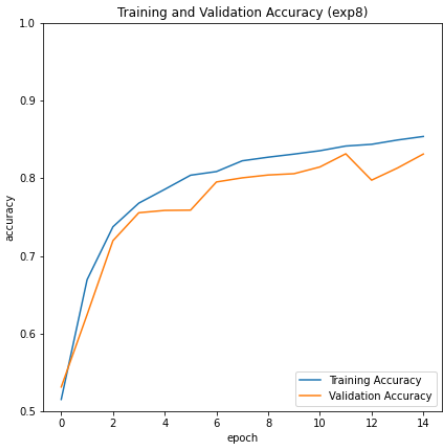


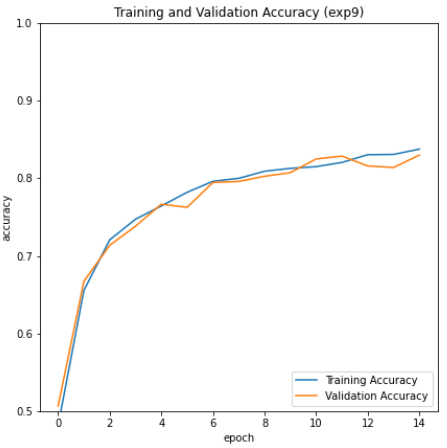












Final Model

```
Model: "sequential_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
rescaling_19 (Rescaling)      (None, 150, 150, 3)       0
_________________________________________________________________
conv2d_41 (Conv2D)            (None, 150, 150, 32)      896
_________________________________________________________________
max_pooling2d_41 (MaxPooling  (None, 37, 37, 32)        0
_________________________________________________________________
dropout_25 (Dropout)          (None, 37, 37, 32)        0
_________________________________________________________________
conv2d_42 (Conv2D)            (None, 35, 35, 32)        9248
_________________________________________________________________
max_pooling2d_42 (MaxPooling  (None, 11, 11, 32)        0
_________________________________________________________________
dropout_26 (Dropout)          (None, 11, 11, 32)        0
_________________________________________________________________
conv2d_43 (Conv2D)            (None, 9, 9, 64)          18496
_________________________________________________________________
max_pooling2d_43 (MaxPooling  (None, 4, 4, 64)          0
_________________________________________________________________
dropout_27 (Dropout)          (None, 4, 4, 64)          0
_________________________________________________________________
flatten_19 (Flatten)          (None, 1024)              0
_________________________________________________________________
dense_38 (Dense)              (None, 256)               262400
_________________________________________________________________
dense_39 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_40 (Dense)              (None, 6)                 774
=================================================================
Total params: 324,710
Trainable params: 324,710
Non-trainable params: 0
_________________________________________________________________
```

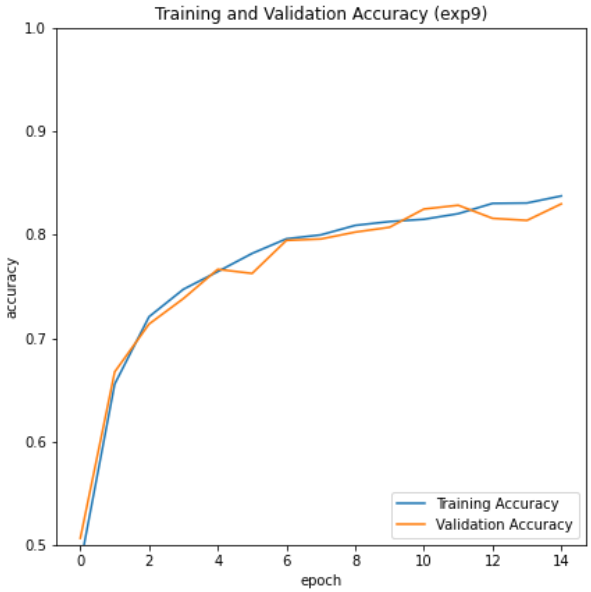
Rescaling: 0-255 RGB values to 0-1

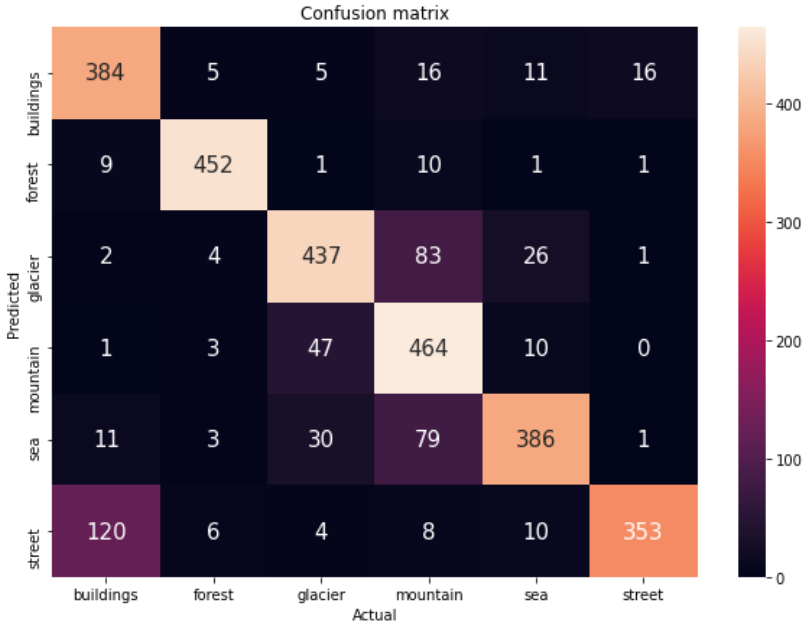
Conv: 32 filters, 3x3 kernel, 1 stride, relu
MaxPool: 4x4
Dropout: 0.4 rate

Conv: 32 filters, 3x3 kernel, 1 stride, relu
MaxPool: 3x3
Dropout: 0.4 rate

Conv: 64 filters, 3x3 kernel, 1 stride, relu
MaxPool: 2x2
Dropout: 0.4 rate

Flatten
Dense: 256 nodes, relu
Dense: 128 nodes, relu
Dense (classification layer): 6 nodes, softmax





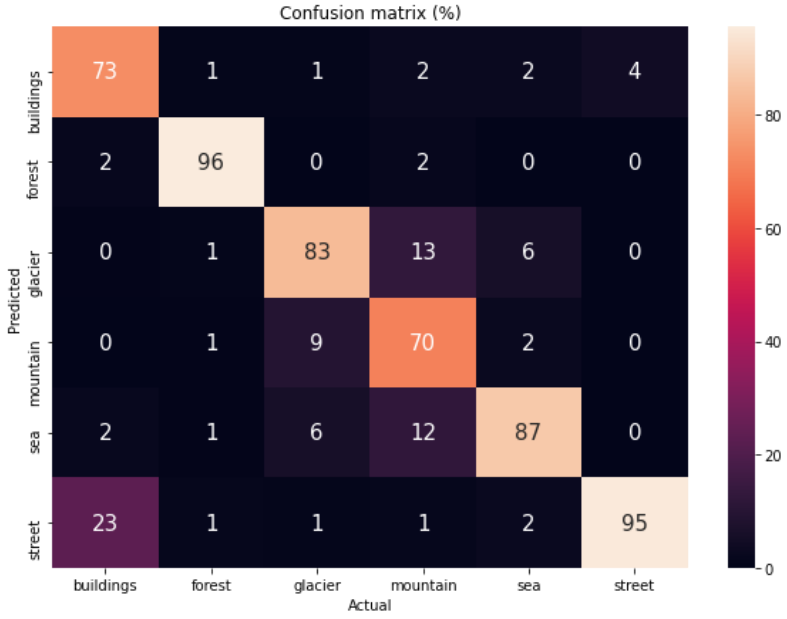
Summary

The final model shows a validation accuracy of about 83% with no apparent overfitting at 15 epochs and has a runtime of 61s per epoch: comparable to the baseline model. Notable weaknesses in the model:

- 23% of buildings incorrectly classified as streets
- 13% of mountains incorrectly classified as glaciers & 12% incorrectly classified as sea
- 9% of glaciers incorrectly classified as mountains & 6% incorrectly classified as sea

Overall accuracy per class:

- Buildings: 73%
- Forest: 96%
- Glacier: 83%
- Mountain: 70%
- Sea: 87%
- Street: 95%



Further Prediction Visualization

The final model has been saved and submitted with this writeup and Jupyter notebook. If you'd like, download the seg_pred image folder from https://www.kaggle.com/puneet6060/intel-image-classification and place it in the root directory of this notebook. At the bottom of the notebook is a script that will test random images in the folder and show a breakdown of classification probabilities for each picture.

Example: