Landscape Identification From Aerial Photographs

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The Dataset

We are using the Skyview dataset (found here)

- 12,000 Aerial photographs of different landscape
- Sorted into 15 categories with 800 images each
- Images are 256x256 JPG files

(Residential)

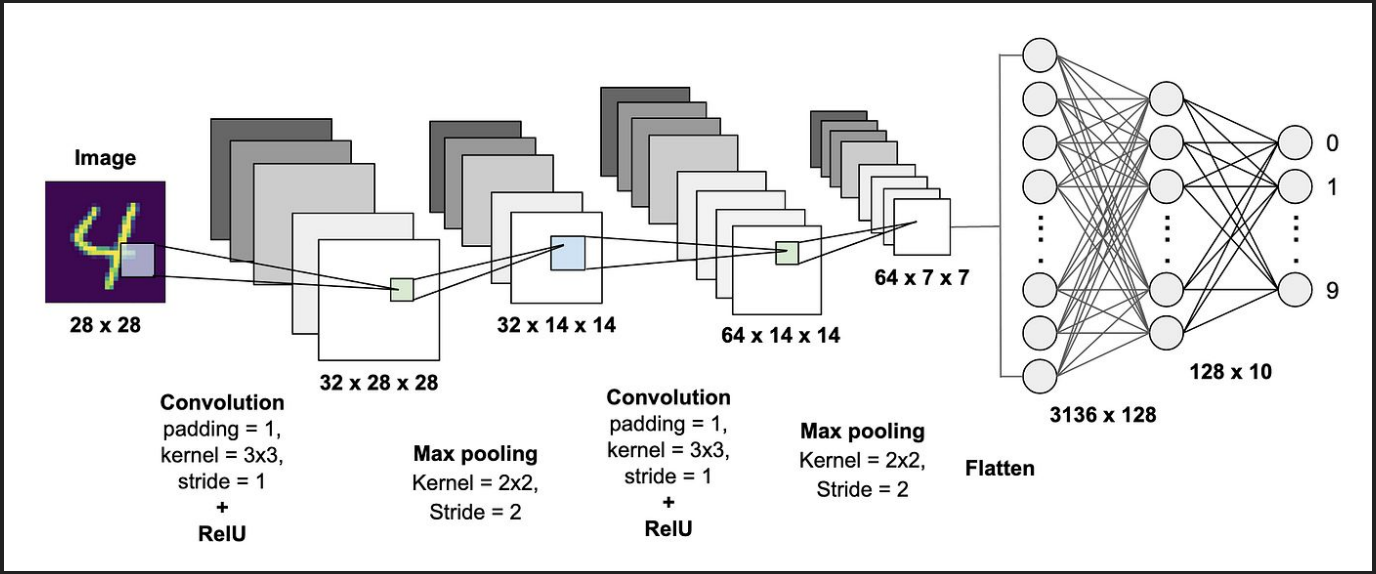
(Agriculture)

Goals for the Project

- Build a model which can correctly classify a provided aerial landscape image into one of the 15 categories
    - Agriculture, Airport, Beach, City, Desert, Forest, Grassland, Highway, Lake, Mountain, Parking, Port, Railway, Residential, River

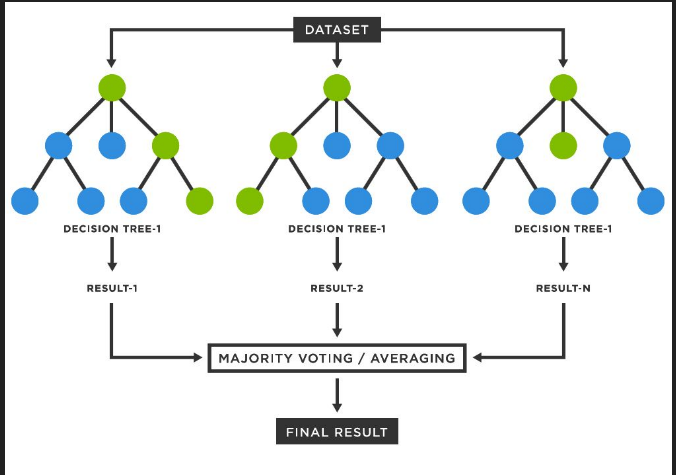
Intended Model

- We plan to use a Convolutional Neural Network (CNN) for our model
    - Composed of convolutional layers, pooling layers, and fully connected layers.
    - Models extract features hierarchically – selecting simple features like patterns and edges and working up to detecting objects or high-level features.



Random Forest

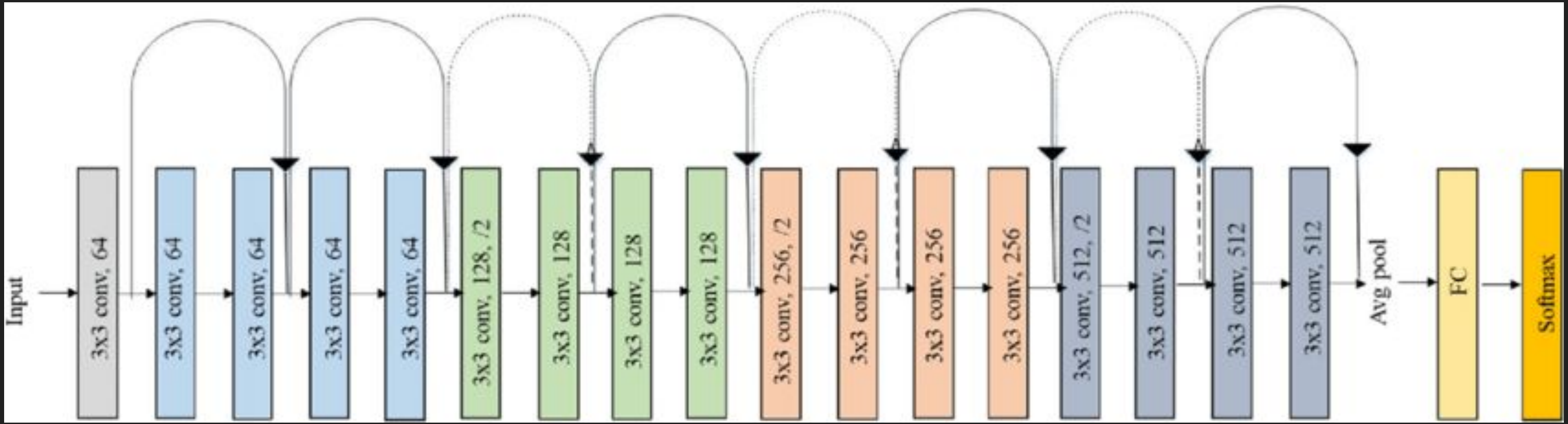
- Additionally, we had the idea to use a Random Forest to compare model effectiveness
  - Extract features from pixel intensities, textures, or histogram of oriented gradients (HOG)
  - Random Forest is an ensemble model using bagging – effectively, groups of models are compared to create a consensus output.
  - Random Forests are expanded versions of decision trees, a hierarchy of decision nodes that all attempt to split data according to some rule.



Some Issues we Encountered

- Learning to work with images rather than traditional data
- Setting up and using TensorFlow / PyTorch
  - We eventually settled on PyTorch for our final version
  - (Tensorflow refused to cooperate with my GPU and was taking up to an hour to train a model)
- Training a model on 12,000 images takes a lot of computing power
  - *Refer to comments above*
  - Utilizing my GPU with PyTorch cut it down to about 10 minutes
- 3 models – Random forest, CNN, RCNN.

Our Model



Input
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
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3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
3x3 conv, 512, /2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Avg pool
FC
Softmax

Model Tuning / Additions

- Swapped the algorithm from SGD to Adam
- Increased epochs to 16 (from 7)
- Setting the learning rate to 0.001
- Lowered batch size to 10 (from 32)

- Added calculation of accuracy by category

Basic Results

```
Epoch 9/16: 100%|
Train Loss: 0.5447 Acc: 0.8207
Val Loss: 0.6560 Acc: 0.7808
Epoch 10/16
----------
Epoch 10/16: 100%|
Train Loss: 0.4841 Acc: 0.8354
Val Loss: 0.5024 Acc: 0.8354
Epoch 11/16
----------
Epoch 11/16: 100%|
Train Loss: 0.4118 Acc: 0.8595
Val Loss: 0.7366 Acc: 0.7754
Epoch 12/16
----------
Epoch 12/16: 100%|
Train Loss: 0.3596 Acc: 0.8788
Val Loss: 0.4666 Acc: 0.8517
Epoch 13/16
----------
Epoch 13/16: 100%|
Train Loss: 0.2950 Acc: 0.8998
Val Loss: 0.9187 Acc: 0.7313
Epoch 14/16
----------
Epoch 14/16: 100%|
Train Loss: 0.2503 Acc: 0.9173
Val Loss: 0.5584 Acc: 0.8233
Epoch 15/16
----------
Epoch 15/16: 100%|
Train Loss: 0.2141 Acc: 0.9277
Val Loss: 0.7547 Acc: 0.8021
Epoch 16/16
----------
Epoch 16/16: 100%|
Train Loss: 0.1760 Acc: 0.9423
Val Loss: 0.4993 Acc: 0.8500
```

Analysis

```
Port: 93.94%
Railway: 77.3%
Grassland: 83.82%
Residential: 95.95%
City: 84.66%
Mountain: 70.39%
Agriculture: 86.16%
Desert: 95.62%
Beach: 84.83%
Forest: 97.18%
Airport: 47.65%
Parking: 84.83%
Lake: 85.47%
Highway: 84.62%
River: 71.18%
```

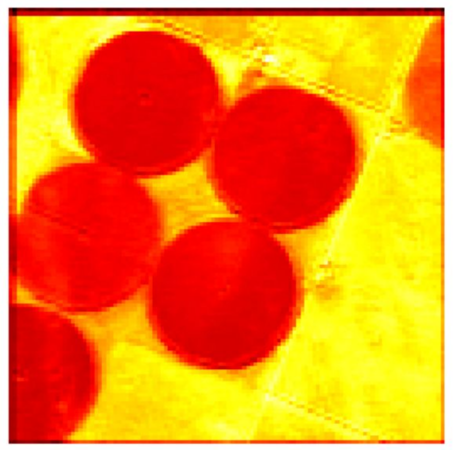
```
Total test set accuracy was 82.8333%
Accuracy without Airport data was 85.16%
```

Confusion Matrix

Actual Values

Predicted Values

	Agriculture	Airport	Beach	City	Desert	Forest	Grassland	Highway	Lake	Mountain	Parking	Port	Railway	Residential	River
Agriculture	138	8	4	0	4	0	5	1	5	6	1	1	0	1	17
Airport	0	72	3	1	2	0	1	2	0	3	4	1	6	0	5
Beach	0	4	152	1	0	0	0	0	0	2	0	2	0	1	3
City	1	3	0	139	0	0	0	5	0	4	3	3	10	0	0
Desert	1	1	1	0	153	0	0	0	0	3	1	0	0	0	1
Forest	1	0	0	2	0	139	19	1	4	10	0	0	0	1	1
Grassland	1	0	0	0	0	3	146	0	2	3	0	0	0	0	1
Highway	5	19	6	2	0	0	1	133	2	2	7	3	9	1	3
Lake	1	1	1	0	1	0	0	0	147	0	0	0	0	0	2
Mountain	4	7	0	1	0	0	1	0	0	126	0	0	3	1	11
Parking	0	0	0	1	0	0	0	0	0	0	124	0	0	0	0
Port	0	2	7	1	0	0	0	0	1	0	1	156	0	0	2
Railway	2	21	4	5	0	0	1	15	1	8	2	0	110	1	2
Residential	2	11	0	11	1	0	0	0	0	7	3	0	2	143	1
River	3	1	1	0	0	1	0	0	11	6	0	0	1	0	122

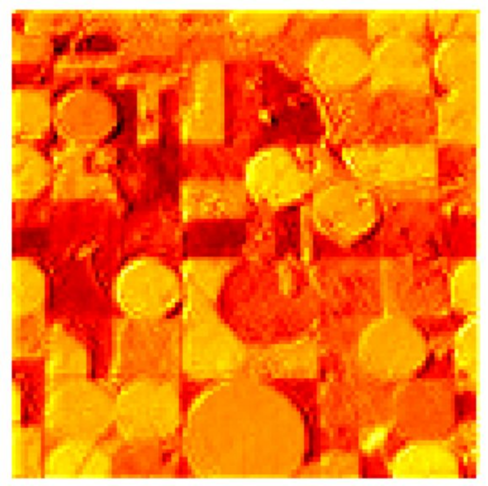


Agriculture

Actual Values

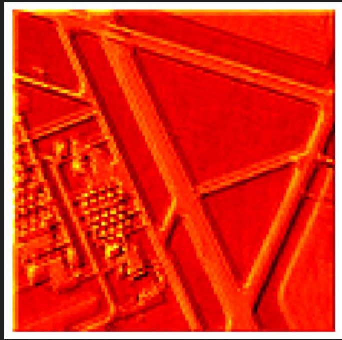
Predicted Values

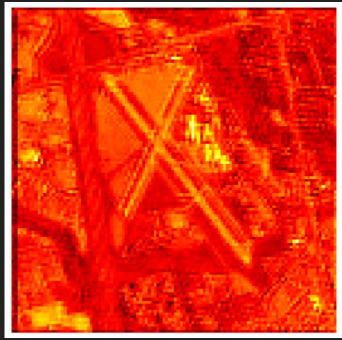
	Agriculture
Agriculture	138
Airport	0
Beach	0
City	1
Desert	1
Forest	1
Grassland	1
Highway	5
Lake	1
Mountain	4
Parking	0
Port	0
Railway	2
Residential	2
River	3

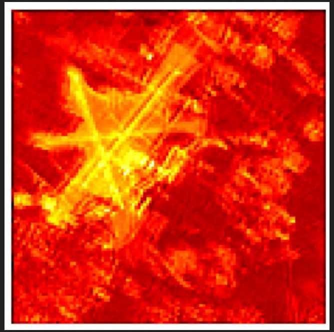


```
Agriculture: 86.16%
```

Airport





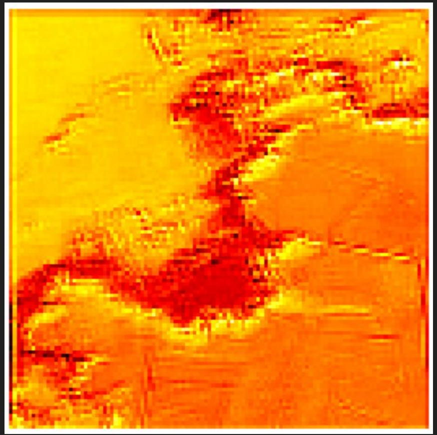


Predicted Values

Actual Values

	Airport
Agriculture	8
Airport	72
Beach	4
City	3
Desert	1
Forest	0
Grassland	0
Highway	19
Lake	1
Mountain	7
Parking	0
Port	2
Railway	21
Residential	11
River	1

Airport: 47.65%



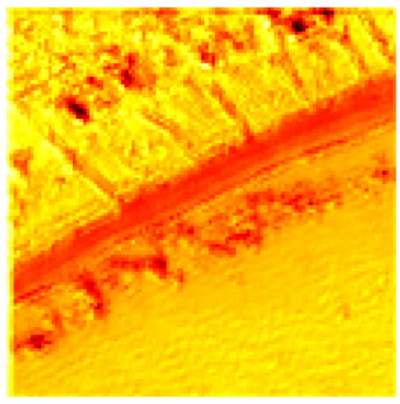
Beach

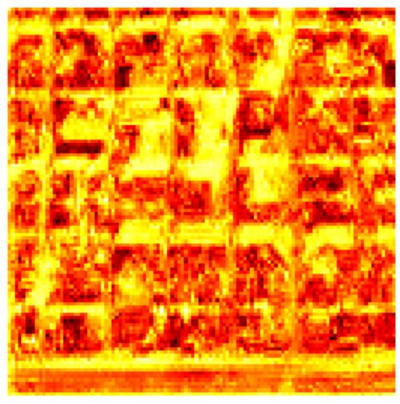
Actual Values

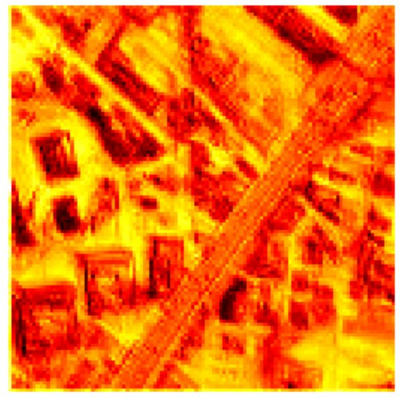
Predicted Values

	Beach
Agriculture	4
Airport	3
Beach	152
City	0
Desert	1
Forest	0
Grassland	0
Highway	6
Lake	1
Mountain	0
Parking	0
Port	7
Railway	4
Residential	0
River	1

Beach: 84.83%







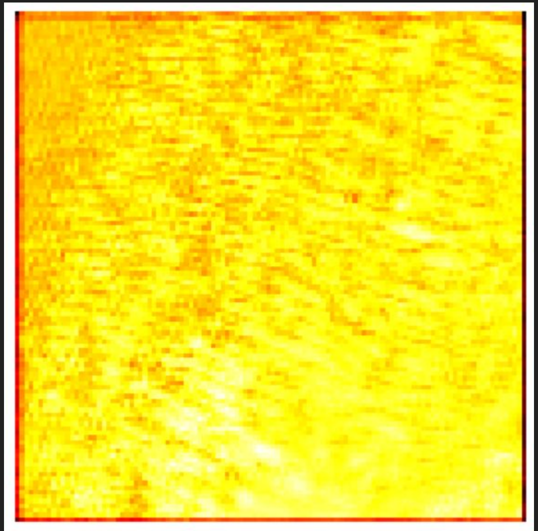
City

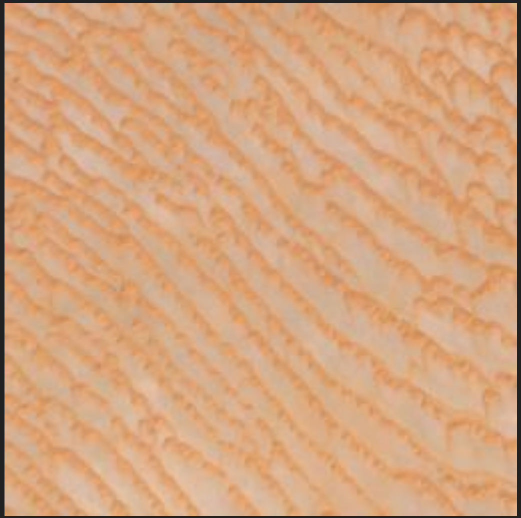
Actual Values

Predicted Values

	City
Agriculture	0
Airport	1
Beach	1
City	139
Desert	0
Forest	2
Grassland	0
Highway	2
Lake	0
Mountain	1
Parking	1
Port	1
Railway	5
Residential	11
River	0

```
City: 84.66%
```





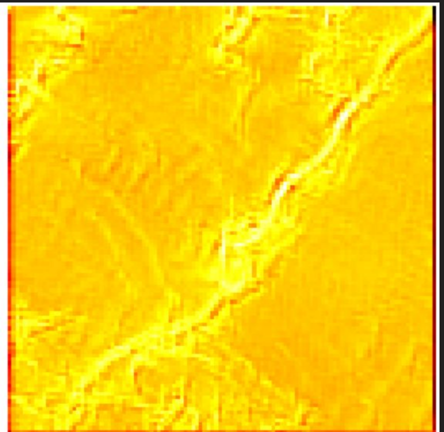
Desert

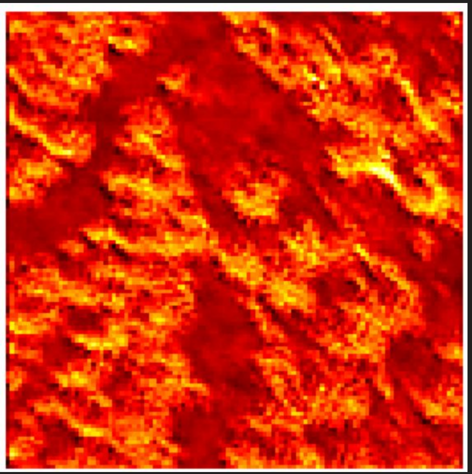
Actual Values

Predicted Values

	Desert
Agriculture	4
Airport	2
Beach	0
City	0
Desert	153
Forest	0
Grassland	0
Highway	0
Lake	1
Mountain	0
Parking	0
Port	0
Railway	0
Residential	1
River	0

Desert: 95.62%





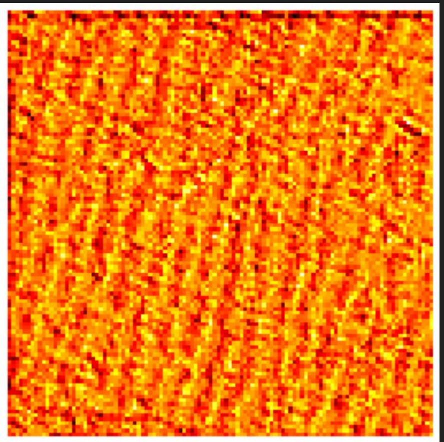
Forest

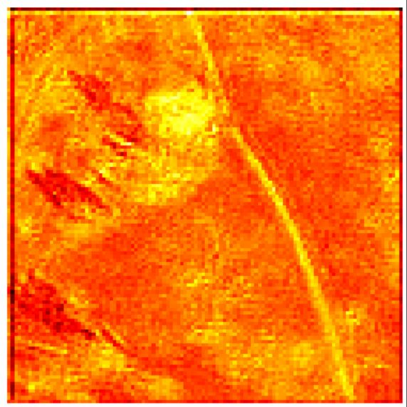
Actual Values

Predicted Values

	Forest
Agriculture	0
Airport	0
Beach	0
City	0
Desert	0
Forest	139
Grassland	3
Highway	0
Lake	0
Mountain	0
Parking	0
Port	0
Railway	0
Residential	0
River	1

```
Forest: 97.18%
```



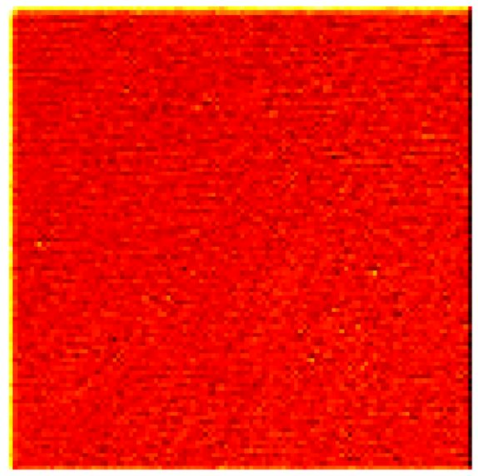


Grassland

Actual Values

Predicted Values

	Grassland
Agriculture	5
Airport	1
Beach	0
City	0
Desert	0
Forest	19
Grassland	146
Highway	1
Lake	0
Mountain	1
Parking	0
Port	0
Railway	1
Residential	0
River	0



```
Grassland: 83.82%
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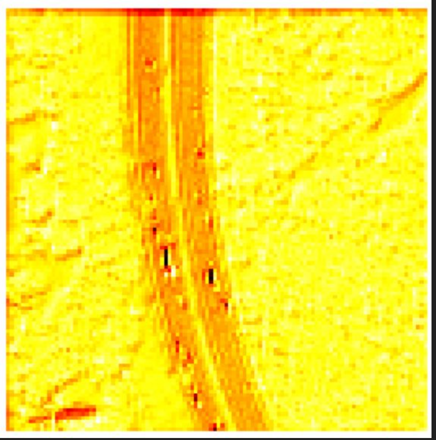
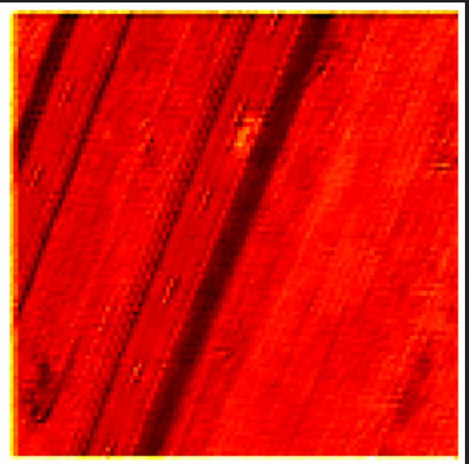


Highway

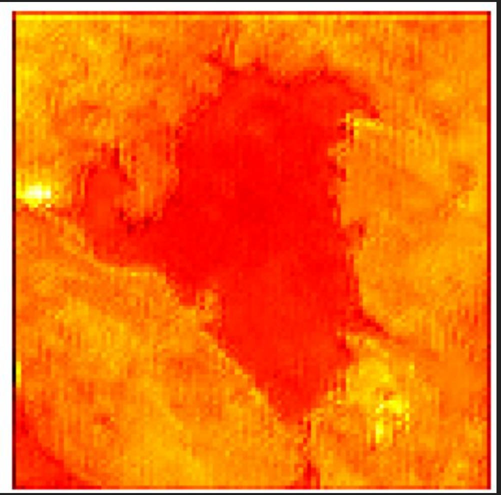
Actual Values

Predicted Values

	Highway
Agriculture	1
Airport	2
Beach	0
City	5
Desert	0
Forest	1
Grassland	0
Highway	133
Lake	0
Mountain	0
Parking	0
Port	0
Railway	15
Residential	0
River	0



Highway: 84.62%

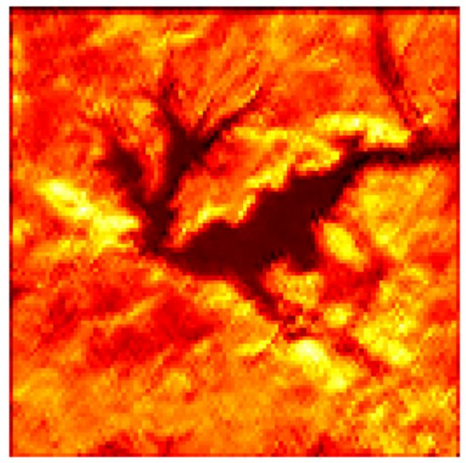


Lake

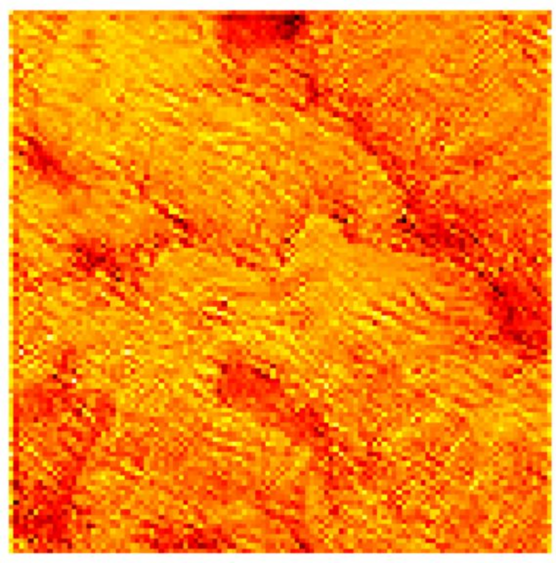
Actual Values

	Lake
Agriculture	5
Airport	0
Beach	0
City	0
Desert	0
Forest	4
Grassland	2
Highway	2
Lake	147
Mountain	0
Parking	0
Port	1
Railway	1
Residential	0
River	11

Predicted Values



```
Lake: 85.47%
```



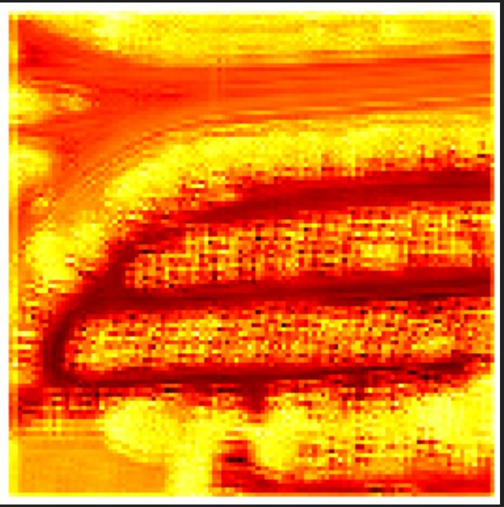
Mountain

Actual Values

Predicted Values

	Mountain
Agriculture	6
Airport	3
Beach	2
City	4
Desert	3
Forest	10
Grassland	3
Highway	2
Lake	0
Mountain	126
Parking	0
Port	0
Railway	8
Residential	7
River	6

Mountain: 70.39%



Parking

Actual Values

Predicted Values

	Parking
Agriculture	1
Airport	4
Beach	0
City	3
Desert	1
Forest	0
Grassland	0
Highway	7
Lake	0
Mountain	0
Parking	124
Port	1
Railway	2
Residential	3
River	0

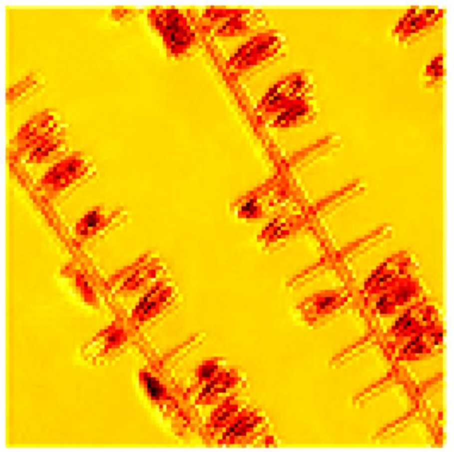
```
Parking: 84.83%
```

Port

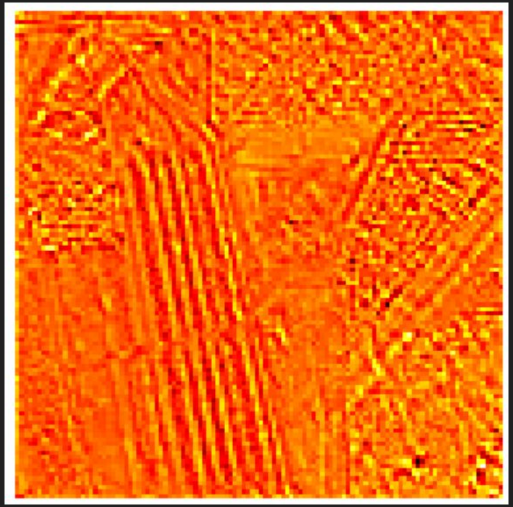
Actual Values

	Port
Agriculture	1
Airport	1
Beach	2
City	3
Desert	0
Forest	0
Grassland	0
Highway	3
Lake	0
Mountain	0
Parking	0
Port	156
Railway	0
Residential	0
River	0

Predicted Values



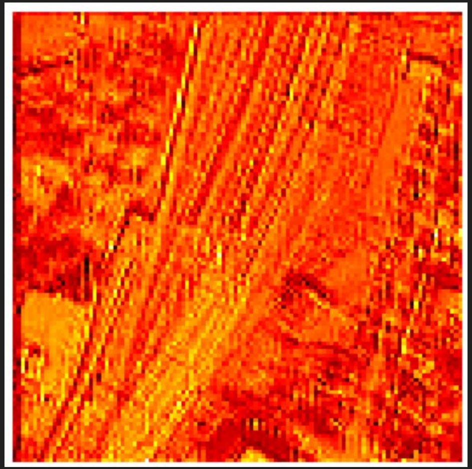
```
Port: 93.94%
```



Railway

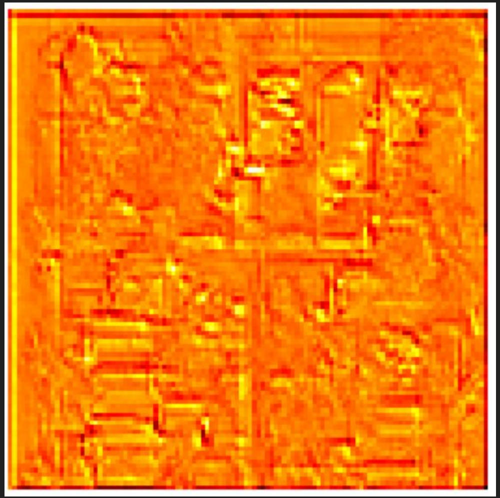
Actual Values

Predicted Values



	Railway
Agriculture	0
Airport	6
Beach	0
City	10
Desert	0
Forest	0
Grassland	0
Highway	9
Lake	0
Mountain	3
Parking	0
Port	0
Railway	110
Residential	2
River	1

Railway: 77.3%

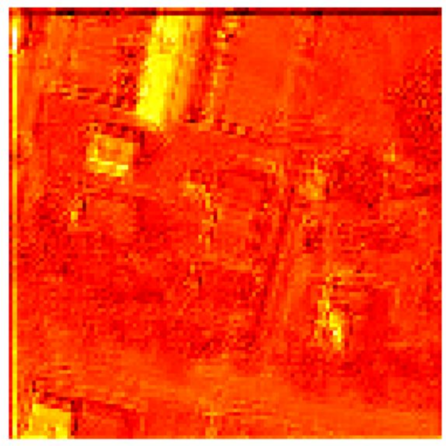


Residential

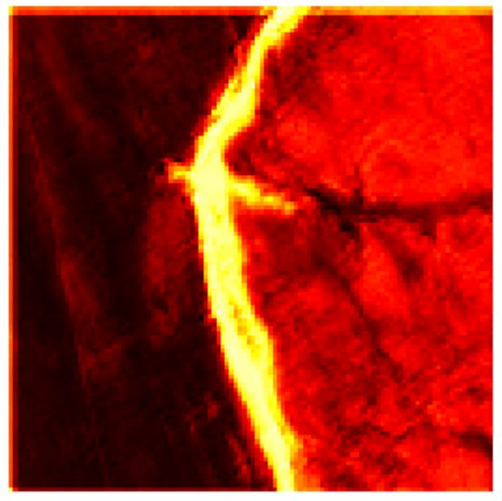
Actual Values

Predicted Values

	Residential
Agriculture	1
Airport	0
Beach	1
City	0
Desert	0
Forest	1
Grassland	0
Highway	1
Lake	0
Mountain	1
Parking	0
Port	0
Railway	1
Residential	143
River	0



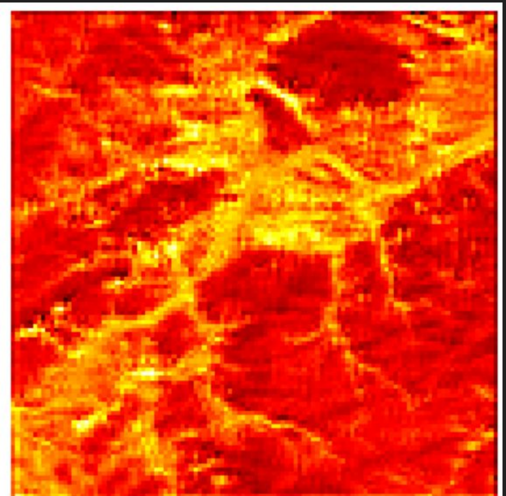
```
Residential: 95.95%
```



River

Actual Values

Predicted Values



	River
Agriculture	17
Airport	5
Beach	3
City	0
Desert	1
Forest	1
Grassland	1
Highway	3
Lake	2
Mountain	11
Parking	0
Port	2
Railway	2
Residential	1
River	122

```
River: 71.18%
```

Thank you!