

# Investigating a New Approach to Classifying Geospatial Polygons

DATS 6203 – Machine Learning II, Group 1  
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## Introduction

### 1. **Background**

### 2. Project Goal

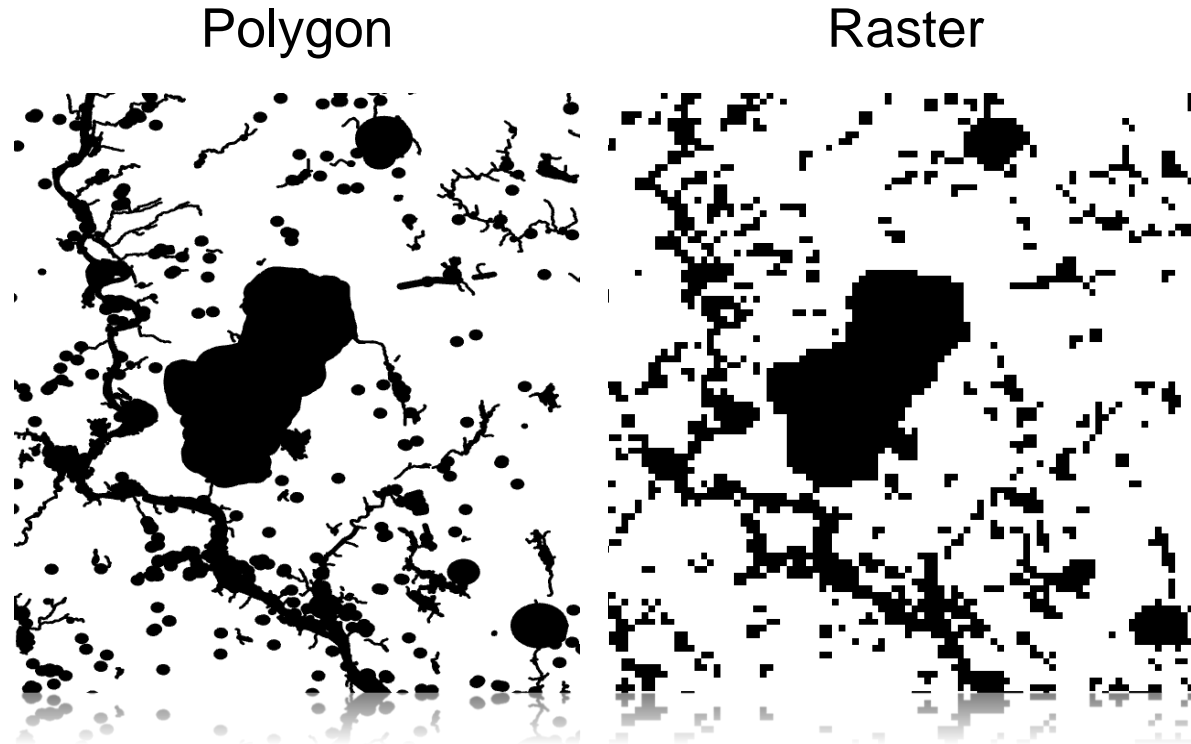
- Countless applications of GIS
- Common experience dealing with unsourceable data

## Introduction

1. Background
2. **Project Goal**

The goal of our project is to develop a deep learning framework for classifying spatial polygons, based solely on their geometry, that is more flexible, light-weight, and accurate than existing frameworks.

- Growing popularity of machine learning in GIS
- Advantages of deep learning



## Literature Review

1. **Related Work**
2. Existing Framework
3. Our Framework
4. Comparisons



Cornell University

arXiv.org &gt; stat &gt; arXiv:1806.03857

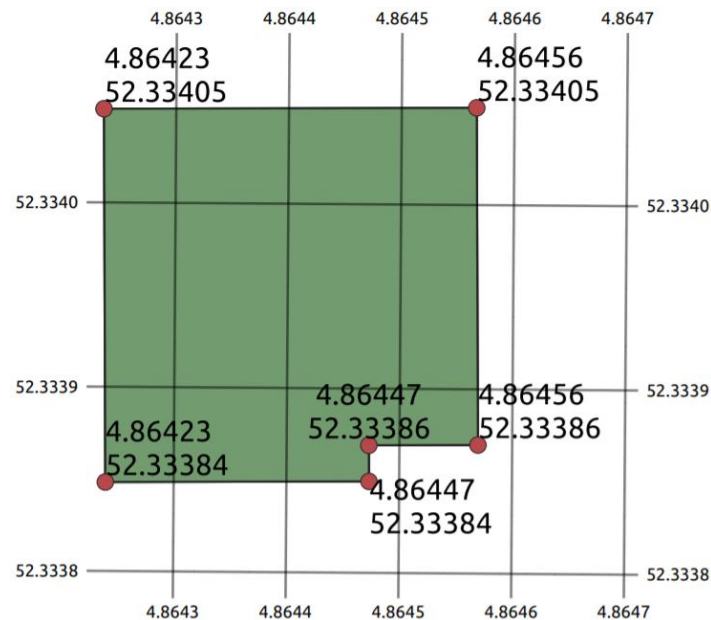
Statistics &gt; Machine Learning

## Deep Learning for Classification Tasks on Geospatial Vector Polygons

Rein van 't Veer, Peter Bloem, Erwin Folmer

(Submitted on 11 Jun 2018 (v1), last revised 11 Jun 2019 (this version, v2))

“Can deep learning models achieve accuracies comparable with shallow learning models in analysing geospatial vector shapes?”



Polygon coordinates	Center: remove mean of [4.8644271, 52.3339057]	Scale: divide by scale factor of 2.64501e-4
4.86447, 52.33384	4.2857e-5, -6.5714e-5	0.16198, -0.24845
4.86447, 52.33386	4.2857e-5, -4.5714e-5	0.16198, -0.17283
4.86456, 52.33386	1.32857e-4, -4.5714e-5	0.50229, -0.17283
4.86456, 52.33386	1.32857e-4, 1.44286e-4	0.50229, 0.54550
4.86423, 52.33405	-1.97143e-4, 1.44286e-4	-0.74534, 0.54550
4.86423, 52.33405	-1.97143e-4, -6.5714e-5	-0.74534, -0.24845
4.86447, 52.33384	4.2857e-5, -6.5714e-5	0.16959, -0.24845

(b)

### Tensor representation

[0.16198, -0.24845, 1, 0, 0],  
 [0.16198, -0.17283, 1, 0, 0],  
 [0.50229, -0.17283, 1, 0, 0],  
 [0.50229, 0.54550, 1, 0, 0],  
 [-0.74534, 0.54550, 1, 0, 0],  
 [-0.74534, -0.24845, 1, 0, 0],  
 [0.16959, -0.24845, 0, 0, 1]

## Literature Review

1. Related Work
2. Existing Framework
3. Our Framework
4. Comparisons

- 2D CNN on images



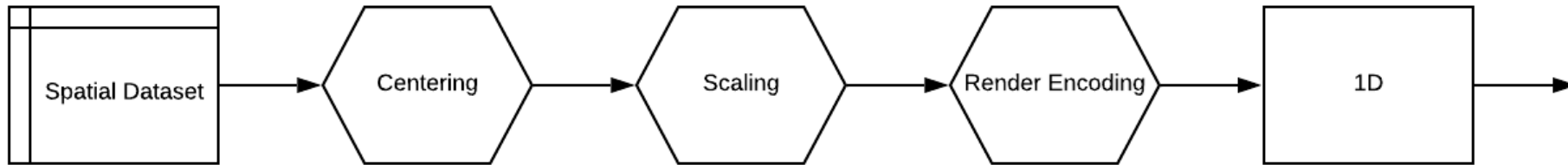
## Literature Review

1. Related Work
2. Existing Framework
3. **Our Framework**
4. Comparisons

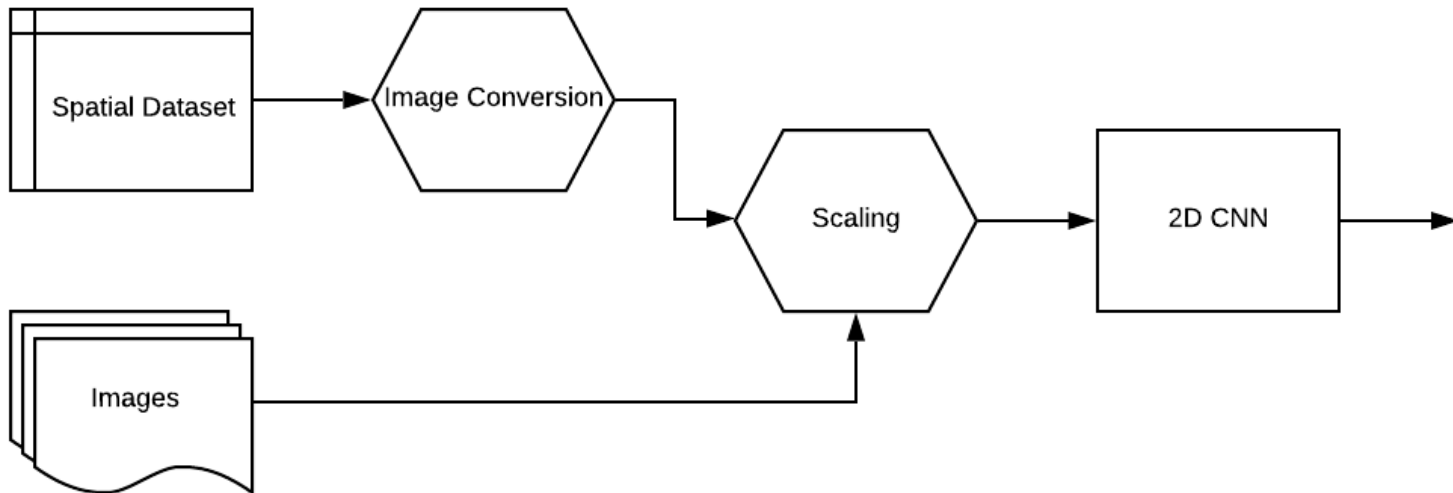




### Existing 1D CNN Approach



### New 2D CNN Approach



### Literature Review

1. Related Work
2. Existing Framework
3. Our Framework
4. **Comparisons**

## Data

1. **Benchmarks**
2. Dataset Descriptions
3. Dataset Preprocessing

Method	Task (no. of classes)	
	Neighbourhood inhabitants (2)	Building types (9)
Majority class	0.514	0.142
k-NN	0.671	0.377
Logistic regression	0.659	0.328
SVM RBF	<b>0.683</b>	0.365
Decision tree	0.682	0.389
CNN	0.664 $\pm$ 0.005	<b>0.408 <math>\pm</math> 0.003</b>

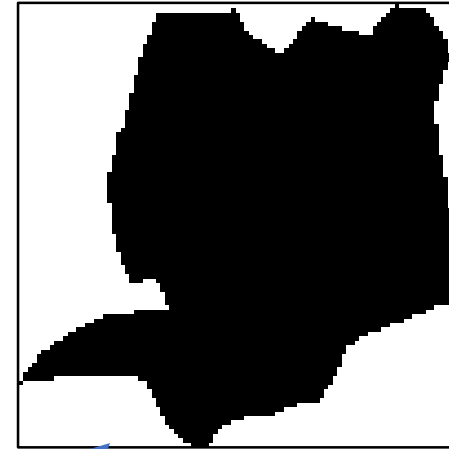
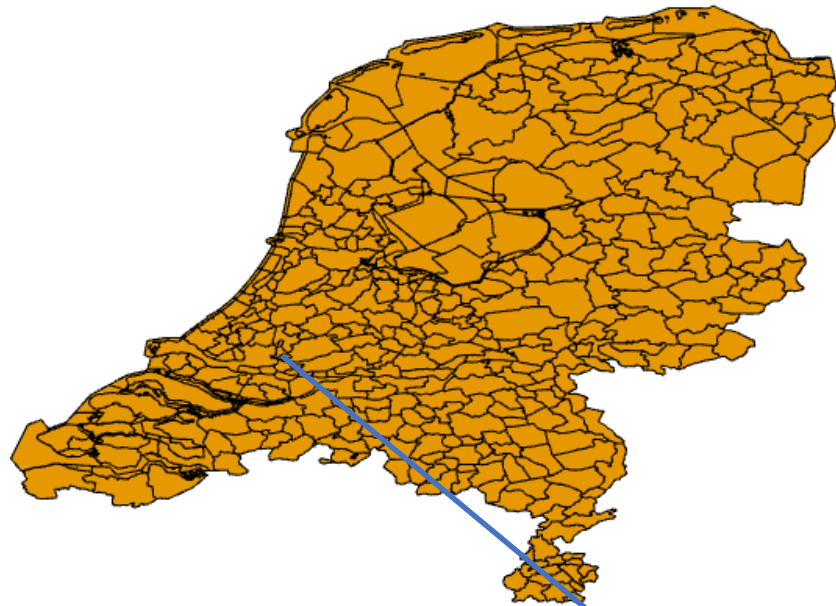
Neighbourhood inhabitants		Buildings	
Class	frequency	Function	frequency
$\geq$ median	6,610	Habitation	23,000
$<$ median	6,598	Industrial	23,000
Total	13,208	Lodging	23,000
		Shopping	23,000
		Gatherings	22,007
		Office	21,014
		Education	10,717
		Healthcare	7,832
		Sports	6,916
		Total	160,486

## Data

1. Benchmarks
2. **Dataset Descriptions**
3. Dataset Preprocessing

## Data

1. Benchmarks
2. Dataset Descriptions
3. **Dataset Preprocessing**



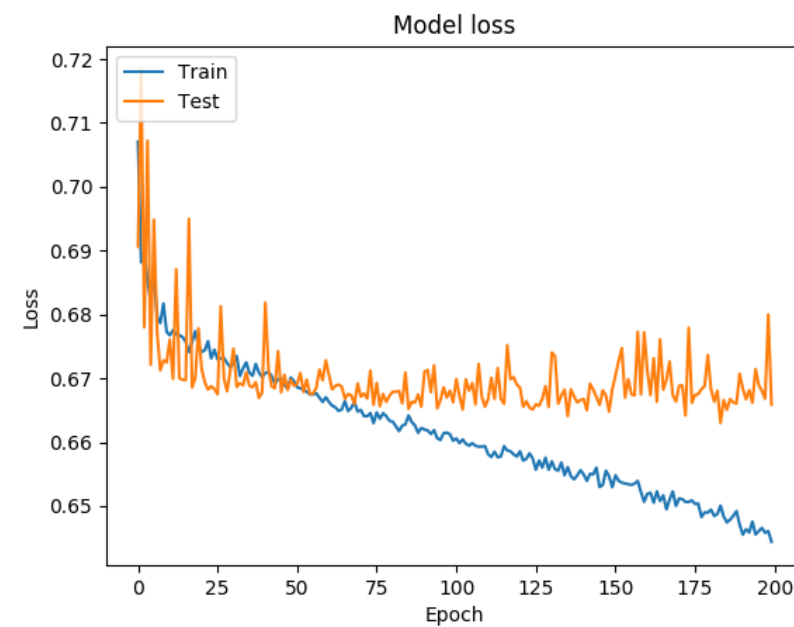
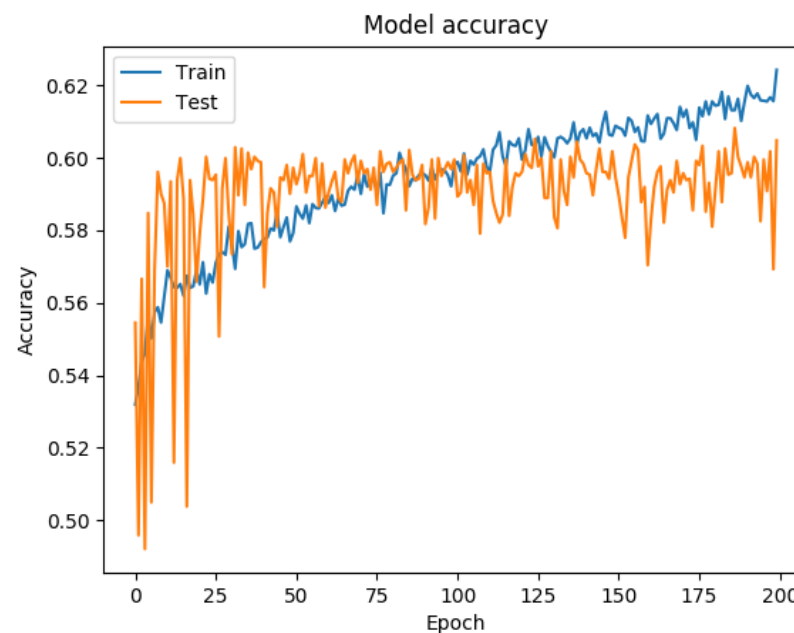
100x100

Scaling

MULTIPOLYGON (((6.490848046163124 52.77088348471561, 6.490982951822918 52.77087899922233,  
6.490998928293062 52.77087846443353, 6.491122124970168 52.77088414443787, 6.491215279514428  
52.770888439578925, 6.491272190126054 52.77089106676583, 6.4920275320370235  
52.77092589893195, 6.4923542897349655 52.770946675142994, 6.492480266246836  
52.7709561924976, 6.49253288950031....

# Network Architecture: Neighborhoods- Baseline Paper Comparison

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 100, 100, 32)	832
activation_1 (Activation)	(None, 100, 100, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 34, 34, 32)	0
conv2d_2 (Conv2D)	(None, 34, 34, 65)	52065
activation_2 (Activation)	(None, 34, 34, 65)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 65)	0
dense_1 (Dense)	(None, 32)	2112
activation_3 (Activation)	(None, 32)	0
dropout_1 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 2)	66
activation_4 (Activation)	(None, 2)	0
Total params: 55,075		
Trainable params: 55,075		
Non-trainable params: 0		



## Modeling

1. **2D CNN**
2. Pre-Trained Models

## Network Architecture: Neighborhoods- Baseline Paper Comparison

### Modeling

1. **2D CNN**
2. Pre-Trained Models

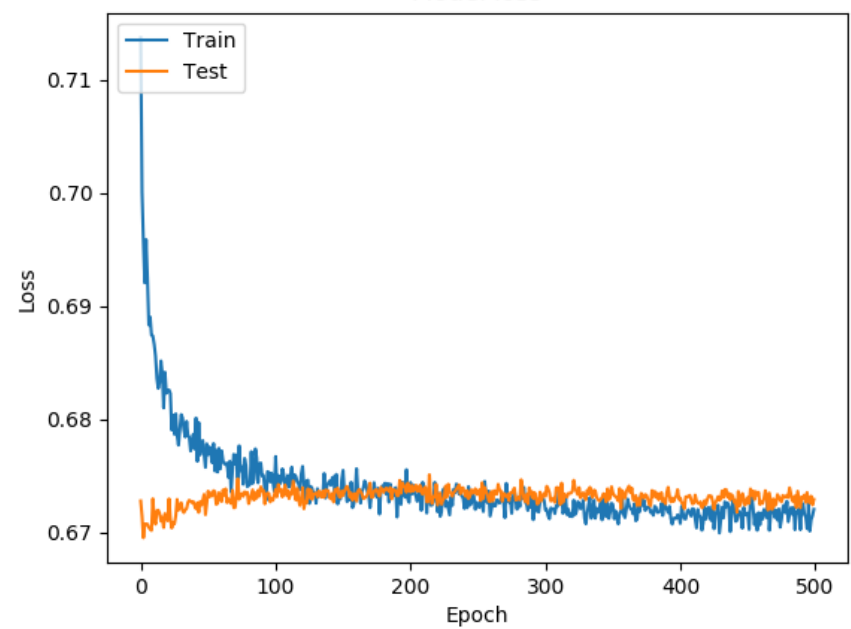
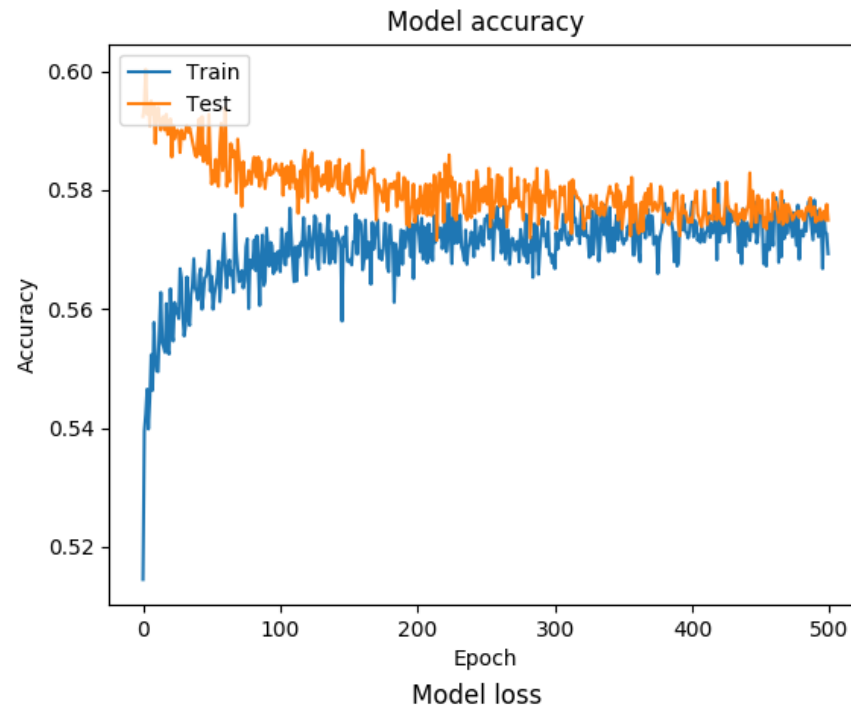
#### Classification Report

	precision	recall	f1-score	support
0	0.54	0.61	0.57	487
1	0.62	0.55	0.59	570
accuracy			0.58	1057
macro avg	0.58	0.58	0.58	1057
weighted avg	0.58	0.58	0.58	1057

Acc: 0.5795  
Loss: 0.6744

# Network Architecture: Neighborhoods

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 96, 96, 32)	832
batch_normalization_1 (Batch Normalization)	(None, 96, 96, 32)	128
activation_1 (Activation)	(None, 96, 96, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 32, 32, 32)	0
spatial_dropout2d_1 (Spatial Dropout)	(None, 32, 32, 32)	0
conv2d_2 (Conv2D)	(None, 28, 28, 64)	51264
batch_normalization_2 (Batch Normalization)	(None, 28, 28, 64)	256
activation_2 (Activation)	(None, 28, 28, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 10, 10, 64)	0
spatial_dropout2d_2 (Spatial Dropout)	(None, 10, 10, 64)	0
conv2d_3 (Conv2D)	(None, 6, 6, 128)	204928
batch_normalization_3 (Batch Normalization)	(None, 6, 6, 128)	512
activation_3 (Activation)	(None, 6, 6, 128)	0
spatial_dropout2d_3 (Spatial Dropout)	(None, 6, 6, 128)	0
global_average_pooling2d_1 (Global Average Pooling2D)	(None, 128)	0
dense_1 (Dense)	(None, 700)	90300
activation_4 (Activation)	(None, 700)	0
dropout_1 (Dropout)	(None, 700)	0
dense_2 (Dense)	(None, 2)	1402
activation_5 (Activation)	(None, 2)	0
Total params: 349,622		
Trainable params: 349,174		
Non-trainable params: 448		



## Modeling

1. **2D CNN**
2. Pre-Trained Models

## Network Architecture: Neighborhoods

### Modeling

1. **2D CNN**
2. Pre-Trained Models

#### Classification Report

	precision	recall	f1-score	support
0	0.49	0.91	0.64	487
1	0.71	0.19	0.29	570
accuracy			0.52	1057
macro avg	0.60	0.55	0.47	1057
weighted avg	0.61	0.52	0.45	1057

Acc: 0.5199  
Loss: 0.6854



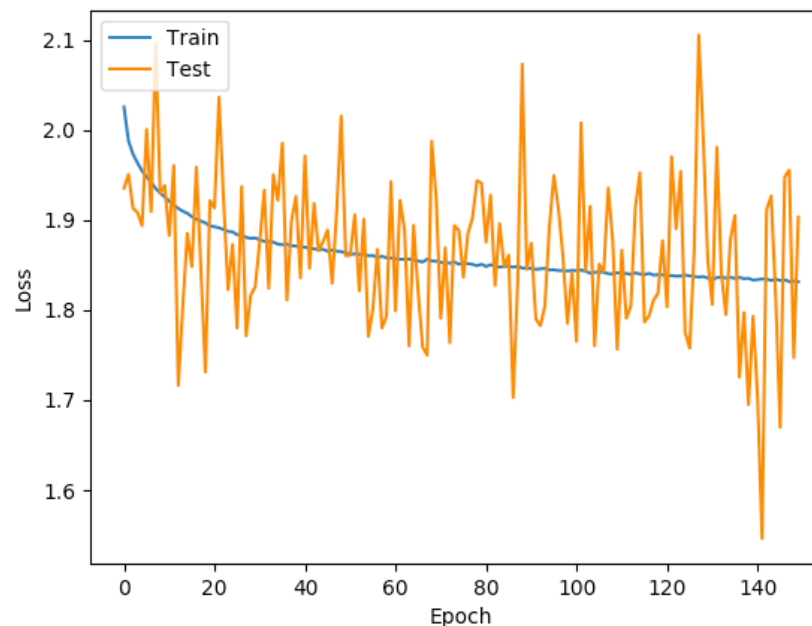
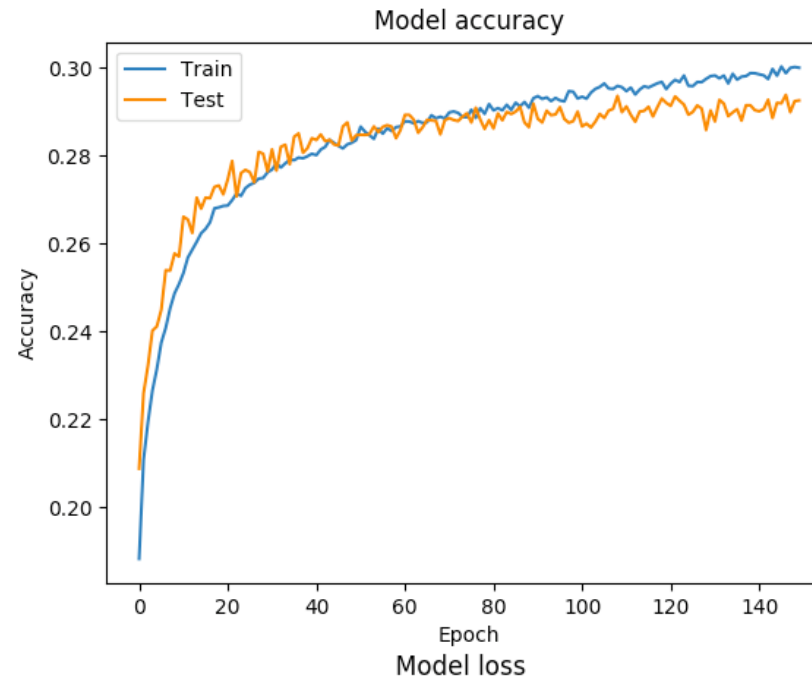
# Network Architecture: Buildings Dataset

conv2d_1 (Conv2D)	(None, 96, 96, 16)	416
batch_normalization_1 (Batch Normalization)	(None, 96, 96, 16)	64
activation_1 (Activation)	(None, 96, 96, 16)	0
max_pooling2d_1 (MaxPooling2D)	(None, 19, 19, 16)	0
spatial_dropout2d_1 (Spatial Dropout)	(None, 19, 19, 16)	0
conv2d_2 (Conv2D)	(None, 15, 15, 32)	12832
batch_normalization_2 (Batch Normalization)	(None, 15, 15, 32)	128
activation_2 (Activation)	(None, 15, 15, 32)	0
average_pooling2d_1 (Average Pooling2D)	(None, 3, 3, 32)	0
spatial_dropout2d_2 (Spatial Dropout)	(None, 3, 3, 32)	0
flatten_1 (Flatten)	(None, 288)	0
dense_1 (Dense)	(None, 700)	202300
activation_3 (Activation)	(None, 700)	0
dropout_1 (Dropout)	(None, 700)	0
dense_2 (Dense)	(None, 8)	5608
activation_4 (Activation)	(None, 8)	0
Total params: 221,348		
Trainable params: 221,252		
Non-trainable params: 96		

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## Modeling

1. 2D CNN
2. Pre-Trained Models



## Results: Buildings Dataset

Classification Report				
	precision	recall	f1-score	support
0	0.32	0.63	0.42	830
1	0.34	0.09	0.14	1789
2	0.34	0.49	0.40	1802
3	0.10	0.13	0.11	637
4	0.25	0.31	0.28	1845
5	0.30	0.47	0.36	1820
6	0.19	0.03	0.06	1698
7	0.31	0.22	0.26	1884
accuracy			0.29	12305
macro avg	0.27	0.30	0.25	12305
weighted avg	0.28	0.29	0.26	12305

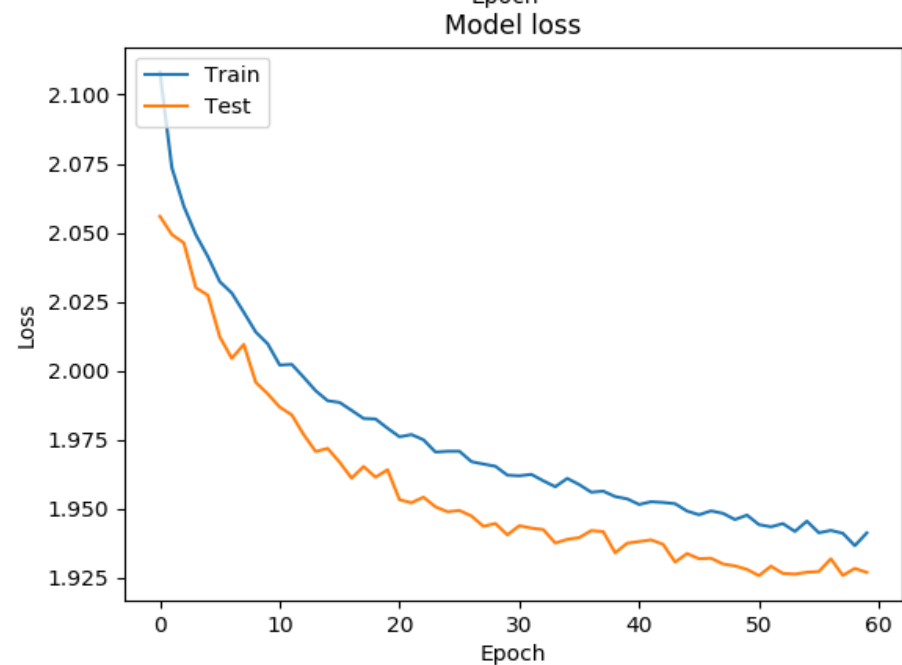
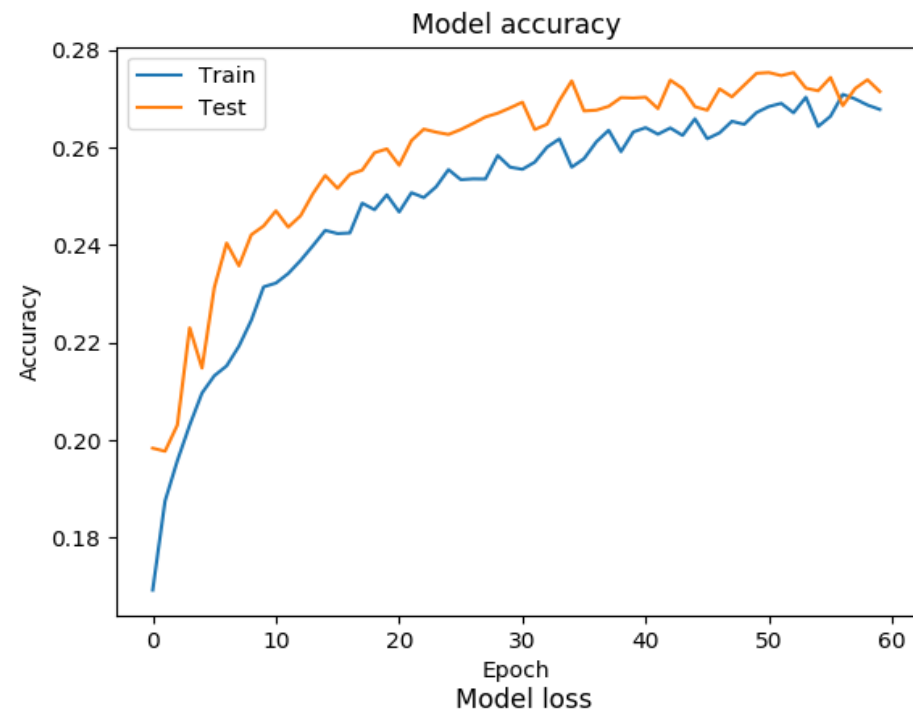
acc: 0.2879  
loss: 1.8293

### Modeling

1. 2D CNN
2. Pre-Trained Models

# Network Architecture: Buildings Dataset

conv2d_1 (Conv2D)	(None, 91, 91, 32)	3232
batch_normalization_1 (Batch Normalization)	(None, 91, 91, 32)	128
activation_1 (Activation)	(None, 91, 91, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 18, 18, 32)	0
spatial_dropout2d_1 (Spatial Dropout)	(None, 18, 18, 32)	0
conv2d_2 (Conv2D)	(None, 14, 14, 64)	51264
batch_normalization_2 (Batch Normalization)	(None, 14, 14, 64)	256
activation_2 (Activation)	(None, 14, 14, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
spatial_dropout2d_2 (Spatial Dropout)	(None, 7, 7, 64)	0
conv2d_3 (Conv2D)	(None, 5, 5, 128)	73856
batch_normalization_3 (Batch Normalization)	(None, 5, 5, 128)	512
activation_3 (Activation)	(None, 5, 5, 128)	0
average_pooling2d_1 (Average Pooling2D)	(None, 1, 1, 128)	0
spatial_dropout2d_3 (Spatial Dropout)	(None, 1, 1, 128)	0
flatten_1 (Flatten)	(None, 128)	0
dense_1 (Dense)	(None, 700)	90300
activation_4 (Activation)	(None, 700)	0
dropout_1 (Dropout)	(None, 700)	0
dense_2 (Dense)	(None, 9)	6309
activation_5 (Activation)	(None, 9)	0
Total params: 225,857		
Trainable params: 225,409		
Non-trainable params: 448		



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## Modeling

1. 2D CNN
2. Pre-Trained Models

## Network Architecture: Buildings Dataset

### Modeling

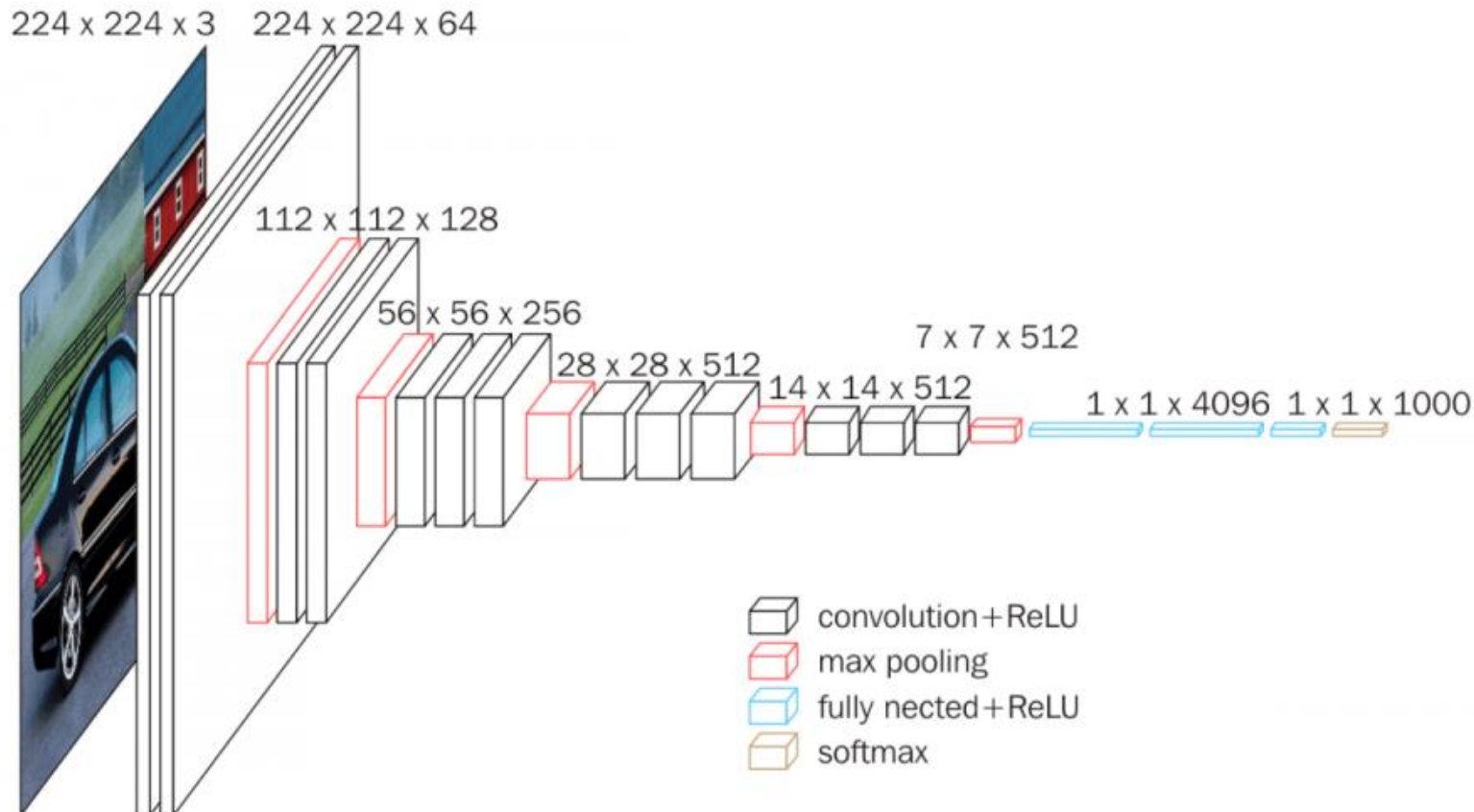
1. 2D CNN
2. Pre-Trained Models

loss: 3.1383  
acc: 0.2734

	precision	recall	f1-score	support
0	0.38	0.52	0.44	830
1	0.23	0.19	0.21	1789
2	0.34	0.42	0.37	1802
3	0.73	0.01	0.02	637
4	0.23	0.38	0.29	1845
5	0.27	0.41	0.32	1820
6	0.21	0.06	0.09	1698
7	0.26	0.22	0.24	1884
8	0.00	0.00	0.00	531
accuracy			0.27	12836
macro avg	0.29	0.25	0.22	12836
weighted avg	0.28	0.27	0.25	12836

## Modeling

1. 2D CNN
2. **Pre-Trained Models**



VGG is a convolutional neural network model proposed by K. Simonyan and A. Zisserman from the University of Oxford in the paper “Very Deep Convolutional Networks for Large-Scale Image Recognition” . The model achieves 92.7% top-5 test accuracy in ImageNet, which is a dataset of over 14 million images belonging to 1000 classes.

1. Prepare data

2. Extract features from the convolutional base

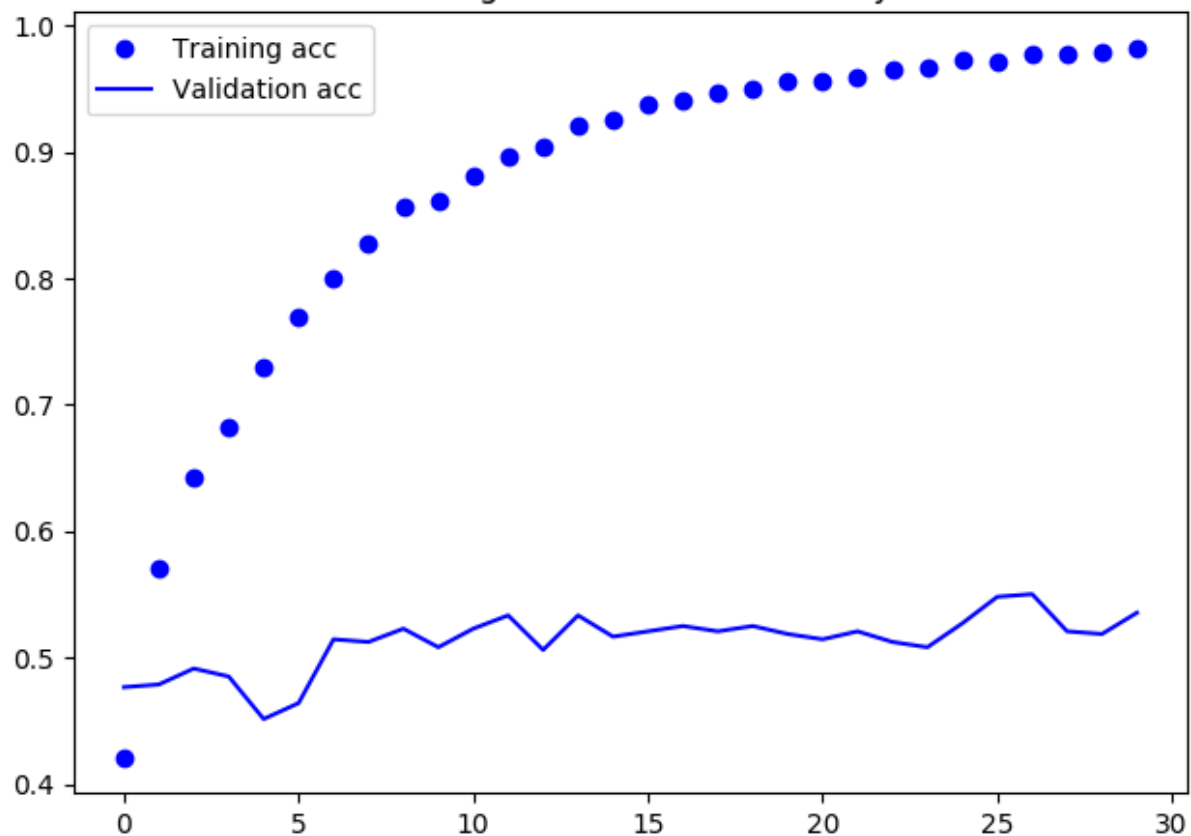
3. Fully-connected layers

Layer (type)	Output Shape	Param #
input_1 ( <u>InputLayer</u> )	(None, 100, 100, 3)	0
block1_conv1 (Conv2D)	(None, 100, 100, 64)	1792
block1_conv2 (Conv2D)	(None, 100, 100, 64)	36928
block1_pool1 (MaxPooling2D)	(None, 50, 50, 64)	0
block2_conv1 (Conv2D)	(None, 50, 50, 128)	73856
block2_conv2 (Conv2D)	(None, 50, 50, 128)	147584
block2_pool1 (MaxPooling2D)	(None, 25, 25, 128)	0
block3_conv1 (Conv2D)	(None, 25, 25, 256)	295168
block3_conv2 (Conv2D)	(None, 25, 25, 256)	590080
block3_conv3 (Conv2D)	(None, 25, 25, 256)	590080
block3_pool1 (MaxPooling2D)	(None, 12, 12, 256)	0
block4_conv1 (Conv2D)	(None, 12, 12, 512)	1180160
block4_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block4_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block4_pool1 (MaxPooling2D)	(None, 6, 6, 512)	0
block5_conv1 (Conv2D)	(None, 6, 6, 512)	2359808
block5_conv2 (Conv2D)	(None, 6, 6, 512)	2359808
block5_conv3 (Conv2D)	(None, 6, 6, 512)	2359808
block5_pool1 (MaxPooling2D)	(None, 3, 3, 512)	0
Total params: 14,714,688		

## Modeling

1. 2D CNN
2. **Pre-Trained Models**

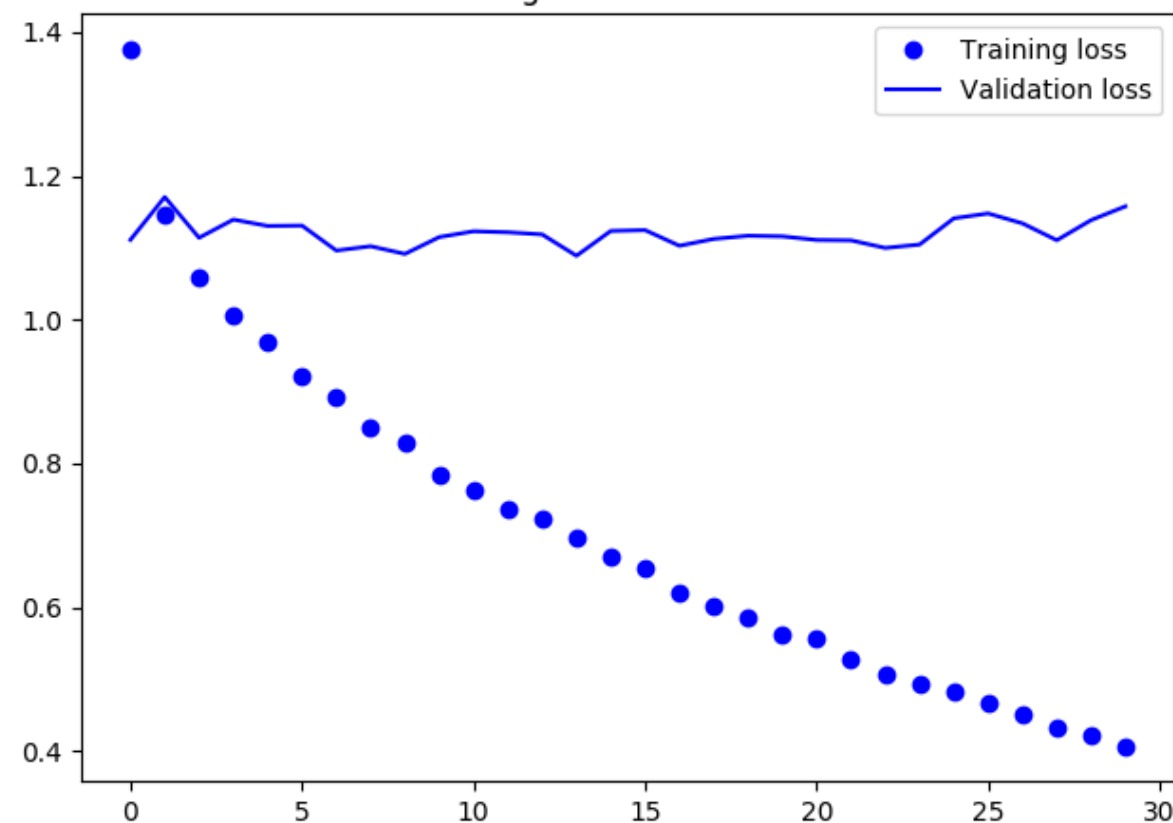
Training and validation accuracy


$$0.408 \pm 0.003$$

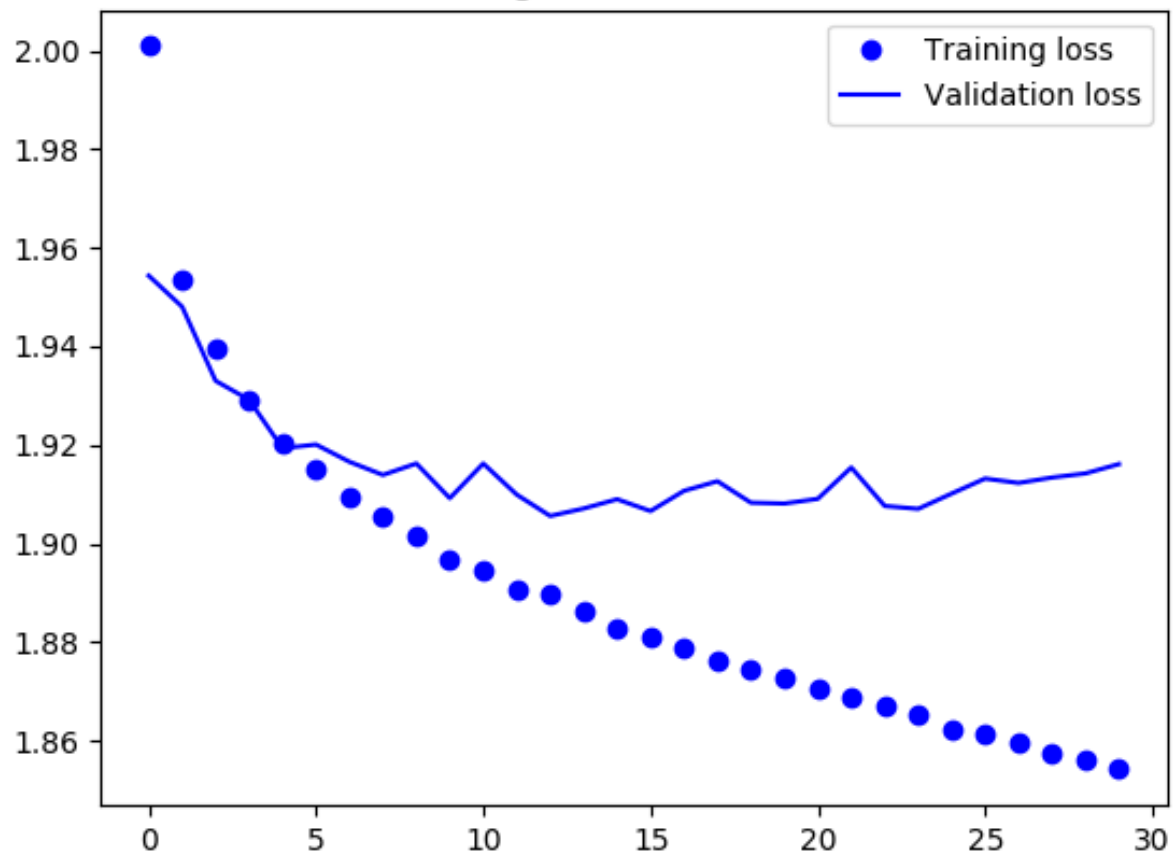
## Modeling

1. 2D CNN
2. **Pre-Trained Models**

Training and validation loss



Training and validation loss



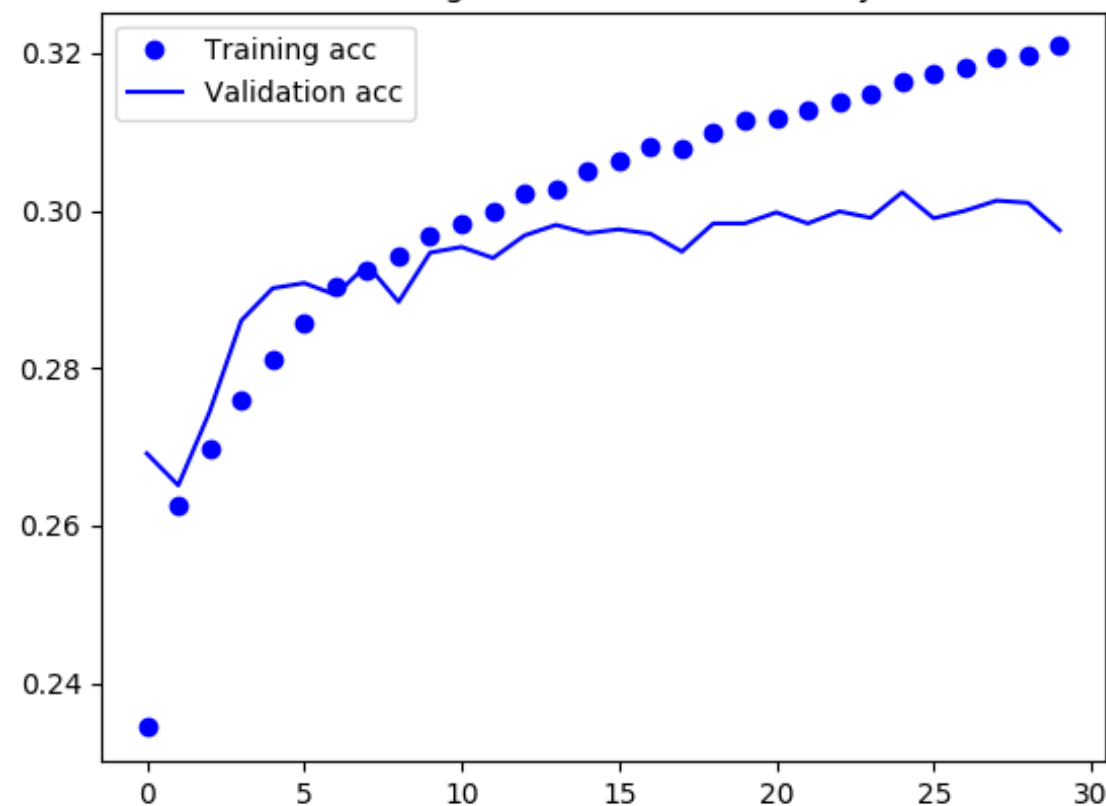
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$$0.408 \pm 0.003$$

## Modeling

1. 2D CNN
2. **Pre-Trained Models**

Training and validation accuracy





## Conclusion

### 1. **Take-Aways**

### 2. Future Work

- Flexible, Light-Weight, Accurate
- New benchmarks for 2D CNN trained on geometry coordinates

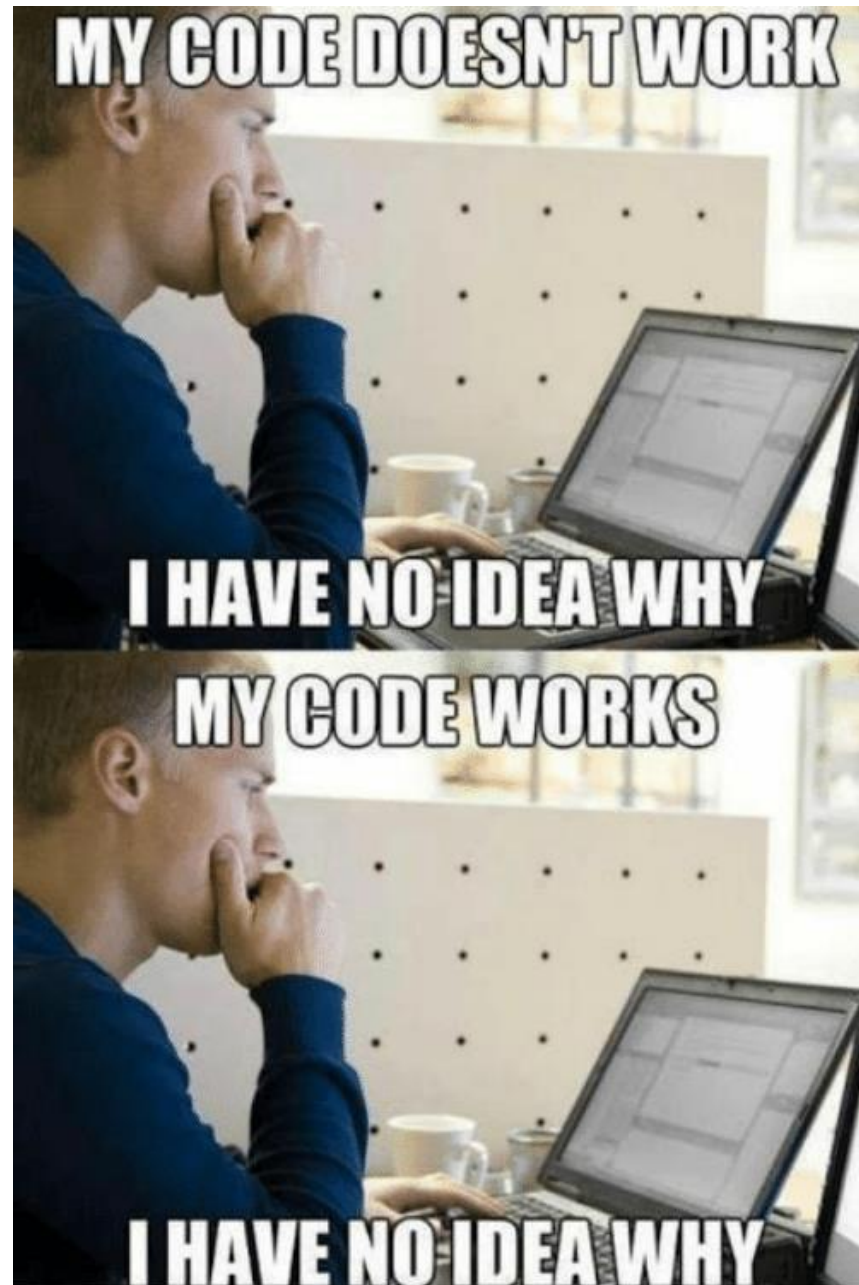
## Conclusion

1. Take-Aways
2. **Future Work**

- Combining other datasets to add more features for training

?

Questions



Term	GIS Definition
<i>Geometry</i>	spatial representation of an object comprised of one or more points
<i>Vector</i>	geometry defined by vertices and edges
<i>Feature</i>	geospatial object
<i>Shape</i>	geospatial object geometry
<i>Polygon</i>	sequence of three or more connected lines
<i>Multi-Polygon</i>	feature instance with two or more polygons