Object based classification using Deep Learning

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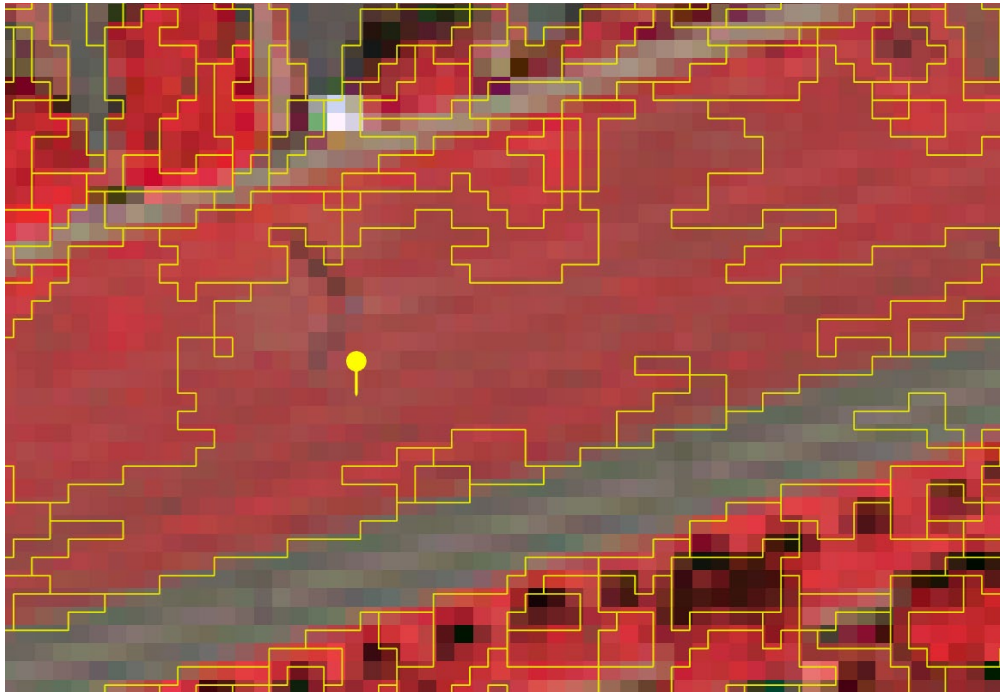
Introduction

Remote Sensing Images – High resolution

Object based Image Classification

Machine Learning – Deep Learning



Data

A total of 10 data channels will be used in the classification process.

8 bands belong to WorldView-2 dataset

1 band belong to NDVI dataset calculated from WorldView-2

1 band is the Canopy Height Model

Study Area

The area is in Dallas metropolitan area, Texas

It is characterized by diverse classes like water, buildings, roads, trees, and grassland.

Data Preprocessing

Calculate NDVI: using Image Analysis tools (B7 and B5)

Calculate Elevation Layer: Canopy Height Model

- Using LiDAR dataset from Texas Natural Resources Information System (TNRIS)
- Digital Terrain Model (DTM) - Digital Surface Model (DSM)

Composite Bands

Normalize the data: Min Max normalizing

Methodology

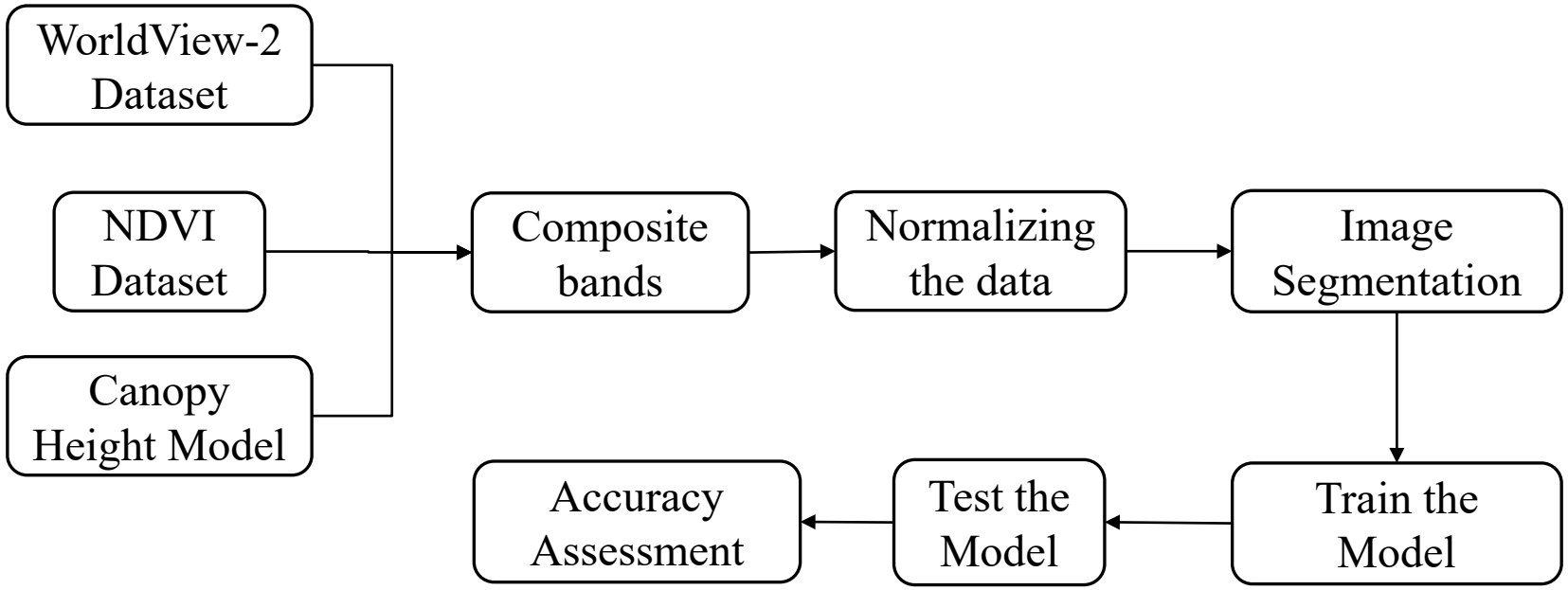
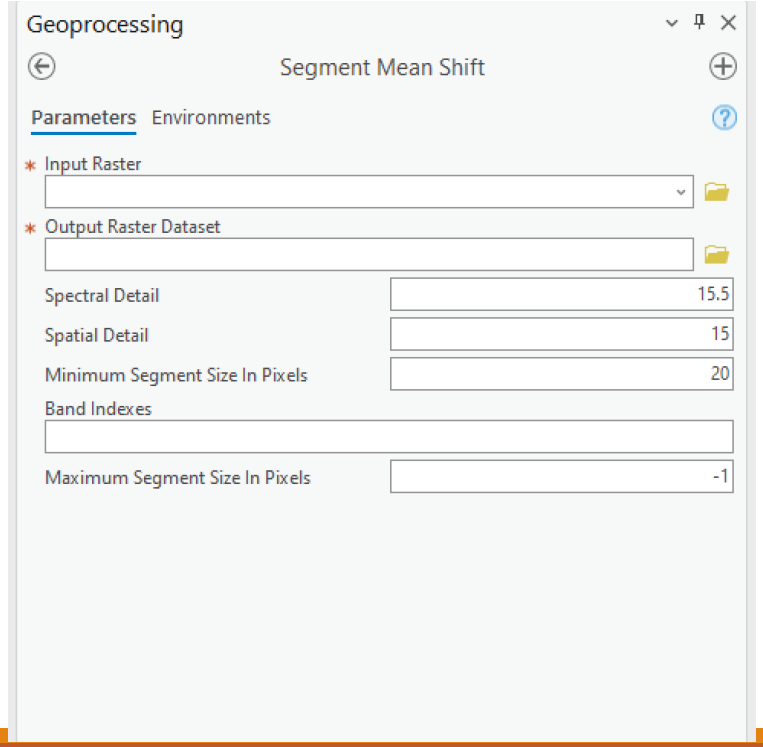


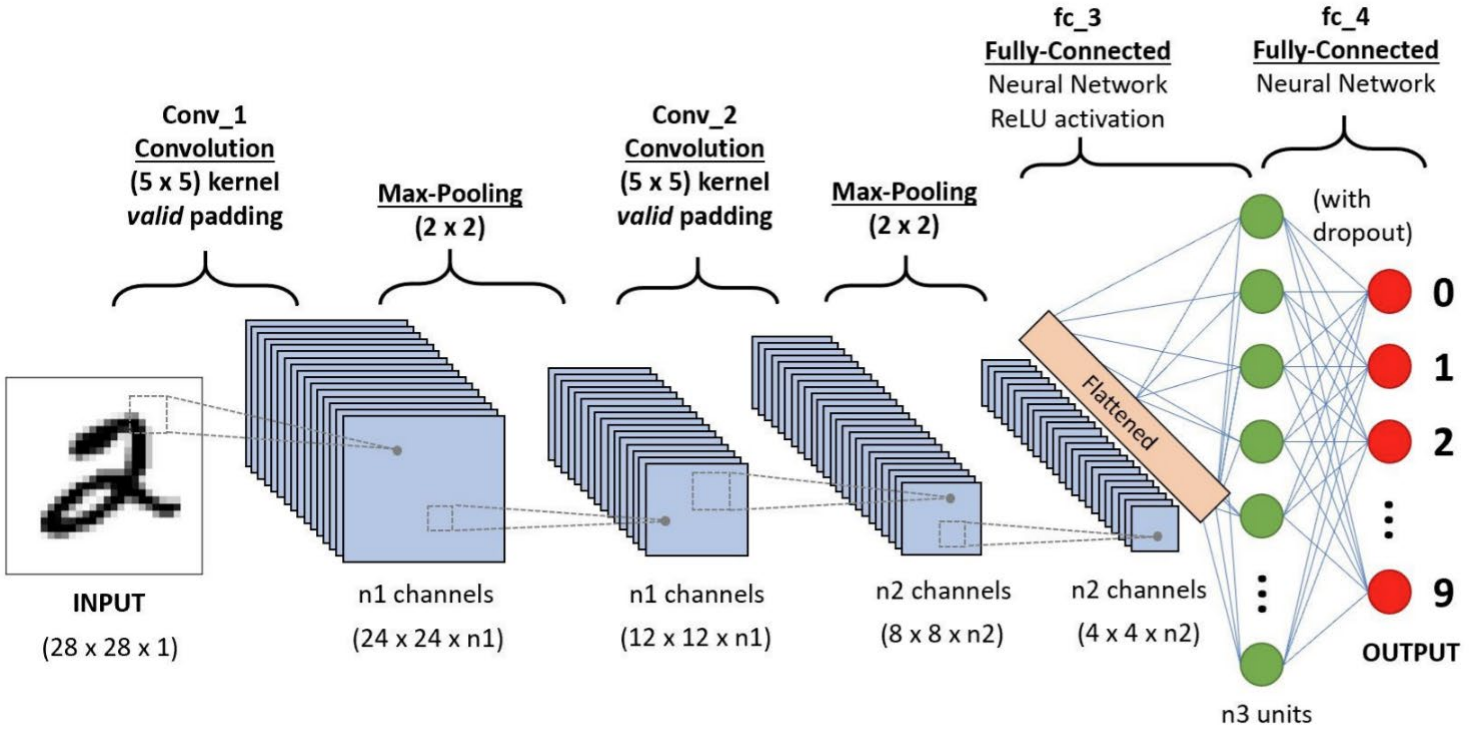
Image Segmentation

Mean shift Image Segmentation: ArcGIS Pro/arcpy library

Spatial detail; Spectral detail



Convolution Neural Networks



Source: [Convolutional Neural Network Architecture | CNN Architecture (analyticsvidhya.com)]

The Problem..

Incompatibility of the shape and size between image objects and training image chips for deep learning.

- The image objects generated for object-based image classification vary in shape and size
- The shape and size of the training image chips for CNN require to be fixed

Generating multiple image chips to cover a single image object and used these image chips to train the DL model.

- An image object of ‘grassland’ class is often bigger than an image object of ‘building’ class.

Therefore…

In this paper, we propose to generate image objects with a fixed size by setting a small segmentation scale for the image.

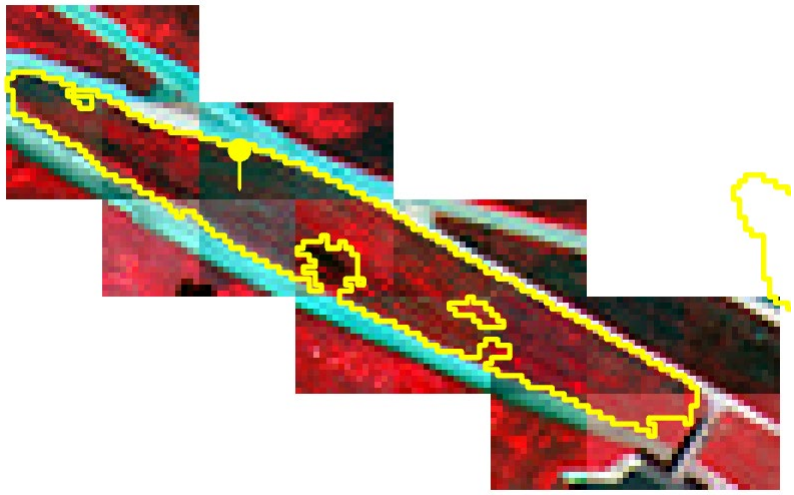
As a result, large features such as rivers will be over-segmented into multiple images objects.

Fixed sized image chips are then derived by enclosing the resulting small image objects and fed into a fully connected CNN as training sample.

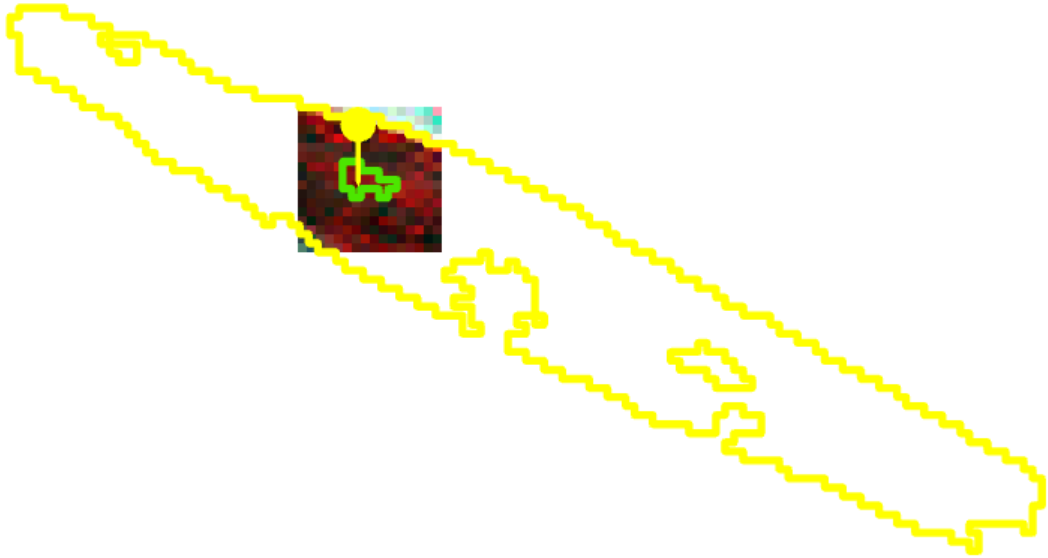
After the training, all small image objects are classified using the trained fully connected CNN.

Example:

Grassland:



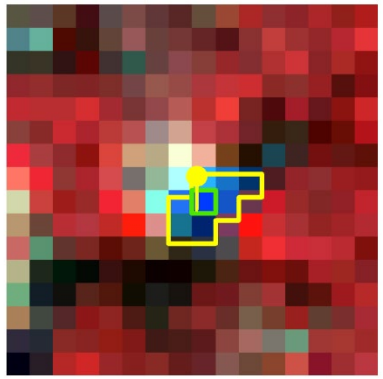
Default Segmentation

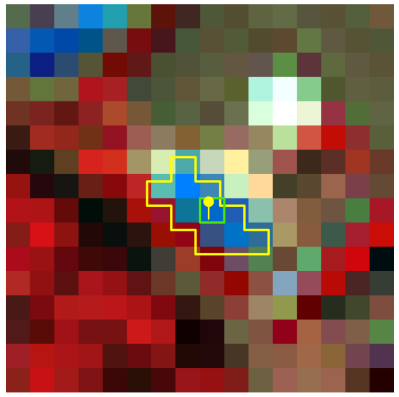


Small Scale Segmentation

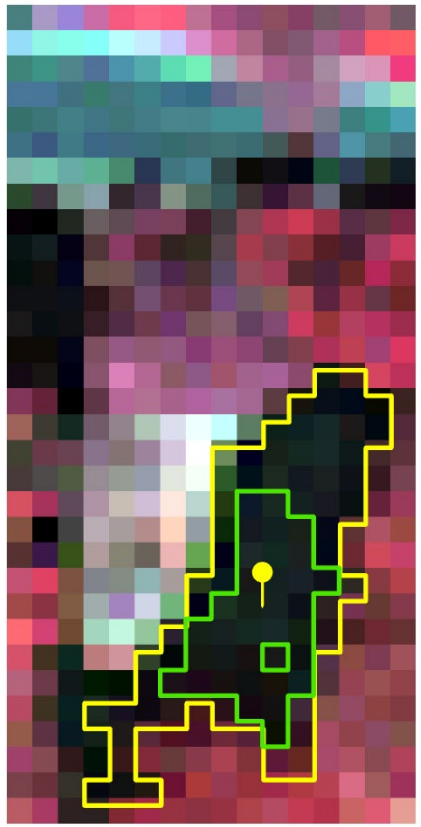
Example:

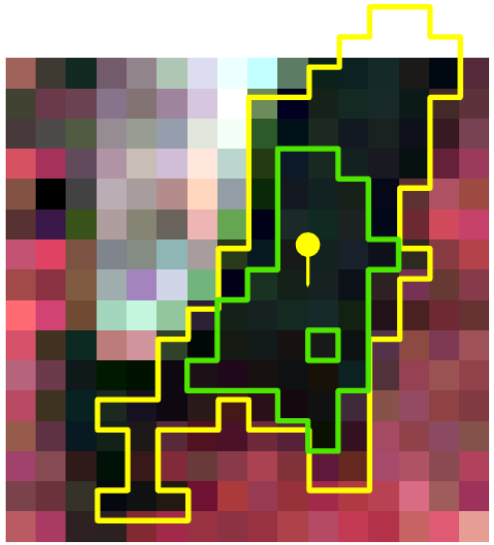
Swimming Pool:





River:





Results

7 training classes: building, grass, river, road, shadow, tree, swimming pools

Training and Testing for small segmentation scale (16x16):

Classes	Training Segments	Training Images	Testing Segments	Testing Images
Building	130	141	38	38
Grass	191	191	52	52
River	150	870	43	240
Road	214	214	34	34
Shadow	156	224	32	101
Tree	166	166	43	43
Swimming Pools	181	184	54	54

Results

Training and Testing for default segmentation scale:

Classes	Training Segments	Training Images	Testing Segments	Testing Images
Building	130	593	38	111
Grass	167	2192	47	533
River	108	2299	35	732
Road	182	6188	27	626
Shadow	157	803	32	240
Tree	147	171	41	44
Swimming Pool	138	157	42	42

Accuracy Assessment:

Small Segmentation Scale Results (16x16):

Predicted Actual	Building	Grass	River	Road	Shadow	Tree	Swimming Pool	Total
Building	36	0	2	0	0	0	0	38
Grass	0	50	2	0	0	0	0	52
River	1	0	36	3	0	3	0	43
Road	4	0	0	30	0	0	0	34
Shadow	1	0	0	0	30	1	0	32
Tree	0	0	8	0	0	35	0	43
Swimming Pool	0	0	0	0	0	0	54	54
Total	42	50	48	33	30	39	54	296

Accuracy Assessment:

Default Segmentation Scale Results:

Predicted Actual	Building	Grass	River	Road	Shadow	Tree	Swimming Pool	Total
Building	7	1	0	26	2	1	1	38
Grass	0	7	0	36	4	0	0	47
River	0	1	18	10	4	2	0	35
Road	0	0	0	20	7	0	0	27
Shadow	1	1	0	5	25	0	0	32
Tree	0	1	2	22	0	16	0	41
Swimming Pool	0	0	0	1	1	0	40	42
Total	8	11	20	120	43	19	41	262

Comparison:

Classes	Small Segmentation Scale (16x16)		Default Segmentation Scale	
	Precision	Recall	Precision	Recall
Building	0.86	0.95	0.88	0.18
Grass	1.00	0.96	0.64	0.15
River	0.75	0.84	0.90	0.51
Road	0.91	0.88	0.17	0.74
Shadow	1.00	0.94	0.58	0.78
Tree	0.90	0.81	0.84	0.39
Swimming Pool	1.00	1.00	0.98	0.95
Overall	**92%**		**51%**	

Limitations and Future Work

Confusion between road and building

Confusion between shadow and river

Future work:

- Improve segmentation
- Data Augmentation

Summary

The accuracy of classification using deep learning depends on the scale of segmentation.

The final accuracy of object-based classification using fully connected convolution layer is 92%.