

DSSC - CVPR

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Introduction

This project requires the implementation of an image classifier based on convolutional neural networks. It's divided in three parts which I'll cover one at time. The data-set is given and has been already split into training and test sets. I used MATLAB.

Common Setup

For all steps and scripts there are some common features like:

- Input resizing: to match different CNN 1st layer proprieties (in all three dimensions), I used "imresize", "repmat" and "augmentedImageDatastore" options.
- Input normalization: is almost always automatically done by 1st layer.
- Data augmentation: to avoid overfitting and improve performance; I used translations, rotations, shear and reflection along vertical axe.
- Early stopping criteria: also to avoid overfitting, I used "MaxEpoch"(> 10 for my NN, 4 for transfer learning) and/or "Patience" (usually 6-8 iteration) on Validation Set Loss.
- Train-Validation split: 85%-15%.

Part 1

Just followed given instruction, only interesting part is recognize that (without using data augmentation) after a couple of epoch Validation Loss start to increase while Training Loss is still decreasing (same but reversed on accuracy score), meaning that the CNN is no more learning features but just overfitting on the Training Set.

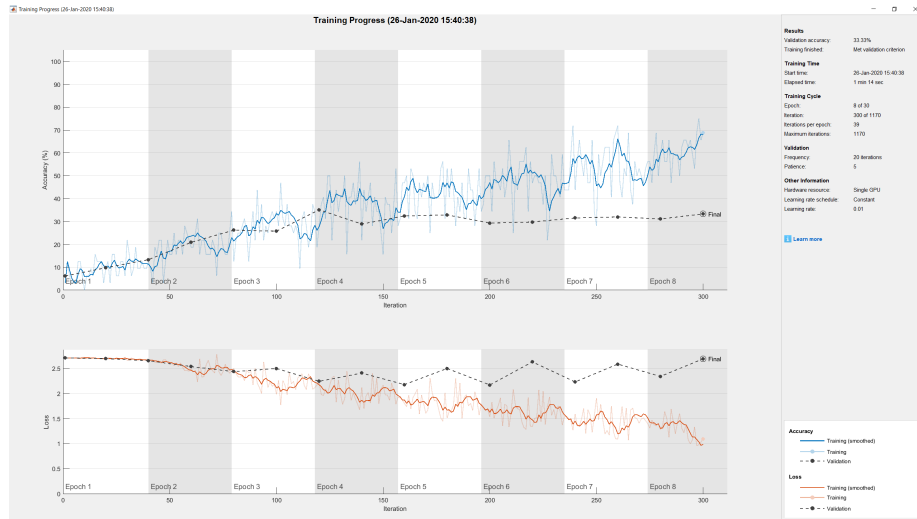


Figure 1: Shallow NN

		Confusion Matrix																	
Output Class	Bedroom	21 0.7%	8 0.3%	6 0.2%	3 0.1%	9 0.3%	1 0.0%	5 0.2%	8 0.3%	24 0.8%	7 0.2%	6 0.2%	0 0.0%	1 0.0%	4 0.1%	16 0.5%	17.6% 82.4%		
	Coast	2 0.1%	109 3.7%	6 0.2%	7 0.2%	0 0.0%	0 0.0%	0 0.0%	0 0.0%	10 0.3%	2 0.1%	55 1.8%	0 0.0%	0 0.0%	0 0.0%	1 0.0%	2 0.1%	56.5% 43.5%	
	Forest	0 0.0%	2 0.1%	28 0.9%	3 0.1%	2 0.1%	7 0.2%	1 0.0%	2 0.0%	5 0.2%	4 0.1%	11 0.4%	3 0.1%	1 0.0%	1 0.0%	3 0.1%	38.4% 61.6%		
	Highway	2 0.1%	49 1.6%	0 0.0%	116 3.9%	6 0.2%	1 0.0%	0 0.0%	0 0.0%	1 0.0%	8 0.3%	1 0.0%	32 1.1%	0 0.0%	0 0.0%	0 0.0%	2 0.1%	63.0% 37.0%	
	Industrial	12 0.4%	3 0.1%	4 0.1%	4 0.1%	78 2.6%	25 0.8%	7 0.2%	7 0.2%	21 0.7%	28 0.9%	18 0.6%	12 0.4%	13 0.4%	9 0.3%	4 0.1%	13 0.4%	28.2% 71.8%	
	InsideCity	5 0.2%	2 0.1%	18 0.6%	0 0.0%	4 0.1%	45 1.5%	1 0.0%	0 0.0%	1 0.0%	5 0.2%	1 0.0%	5 0.2%	18 0.6%	9 0.3%	4 0.1%	6 0.2%	36.3% 63.7%	
	Kitchen	23 0.8%	10 0.3%	21 0.7%	4 0.1%	15 0.5%	21 0.7%	25 0.8%	35 1.2%	25 0.9%	35 1.2%	7 0.2%	11 0.4%	23 0.8%	8 0.3%	10 0.3%	19 0.6%	93.7% 106.3%	
	LivingRoom	38 1.3%	13 0.4%	40 1.3%	5 0.2%	35 1.2%	38 1.3%	36 1.2%	93 3.1%	66 2.2%	28 0.9%	33 1.1%	63 2.1%	38 1.3%	49 1.6%	57 1.9%	147.6% 85.3%		
	Mountain	3 0.1%	11 0.4%	3 0.1%	3 0.1%	3 0.1%	1 0.0%	1 0.0%	1 0.0%	21 0.7%	1 0.0%	15 0.5%	0 0.0%	0 0.0%	0 0.0%	2 0.0%	1 0.0%	30.4% 69.6%	
	Office	1 0.0%	10 0.3%	50 1.7%	4 0.1%	12 0.4%	11 0.4%	9 0.3%	6 0.2%	14 0.5%	38 1.3%	11 0.4%	4 0.1%	3 0.1%	0 0.0%	1 0.0%	30 1.0%	81.3% 18.7%	
	OpenCountry	0 0.0%	40 1.3%	3 0.1%	8 0.3%	6 0.2%	2 0.1%	2 0.1%	0 0.0%	24 0.8%	0 0.0%	103 3.5%	0 0.0%	2 0.1%	0 0.0%	0 0.0%	1 0.0%	53.9% 46.1%	
	Store	6 0.2%	0 0.0%	26 0.9%	0 0.0%	12 0.4%	29 1.0%	8 0.3%	11 0.4%	8 0.3%	0 0.0%	4 0.1%	72 2.4%	19 0.6%	15 0.5%	9 0.3%	7 0.2%	32.7% 67.3%	
	Street	1 0.0%	0 0.0%	7 0.2%	0 0.0%	5 0.2%	15 0.5%	4 0.1%	1 0.0%	5 0.2%	0 0.0%	5 0.2%	6 0.2%	95 3.2%	8 0.3%	6 0.2%	9 0.3%	60.1% 39.9%	
	Suburb	0 0.0%	1 0.0%	1 0.0%	1 0.0%	1 0.0%	3 0.1%	2 0.1%	2 0.1%	3 0.1%	0 0.0%	1 0.0%	1 0.0%	6 0.2%	35 1.2%	1 0.0%	1 0.0%	60.3% 39.7%	
	TallBuilding	2 0.1%	2 0.1%	7 0.2%	0 0.0%	23 0.8%	9 0.3%	4 0.1%	9 0.3%	18 0.6%	8 0.3%	6 0.2%	12 0.4%	0 0.0%	0 0.0%	0 0.0%	75 2.5%	42.6% 57.4%	
			18.1% 81.9%	41.9% 58.1%	12.3% 87.7%	72.5% 27.5%	37.0% 63.0%	21.6% 78.4%	22.7% 77.3%	49.2% 50.8%	7.7% 92.3%	33.0% 67.0%	33.2% 66.8%	33.5% 66.5%	49.5% 50.5%	24.8% 75.2%	29.3% 70.7%	32.0% 68.0%	
			Target Class																
			Bedroom	Coast	Forest	Highway	Industrial	InsideCity	Kitchen	LivingRoom	Mountain	Office	OpenCountry	Store	Street	Suburb	TallBuilding		

Figure 2: Shallow NN

The overall validation accuracy is around 33% vs. a training accuracy reaching the 60% (clearly overfitting). Test accuracy is around 32%.

Part 2

For that part the goal was to improve the CNN with some different techniques.

Data-augmentation

For data augmentation I decided to use Shear, Rotation, Reflection and Translations, with following parameters:

```
1 imageAugmenter = imageDataAugmenter( ...
2     'RandXShear',[ -6,6], ...
3     'RandYShear',[ -6,6], ...
4     'RandRotation',[ -10,10], ...
5     'RandXReflection', true, ...
6     'RandXTranslation',[-6 6], ...
7     'RandYTranslation',[-6 6]);
8
9 augimds_Train = augmentedImageDatastore(imageSize,
    imdsTrain, 'DataAugmentation',imageAugmenter);
```

Given the tiny input size i thought was better to limit the parameters to a 10% of the images dimensions and keep rotations small (intuitively to kind of the match human error on taking pictures and to emphasize the fact that in our problem the orientation is quite important).



Figure 3: Augmented bedroom batch

More Layers

I added some layers:

- Convolutional: to improve the capability of features extraction.
- Batch-Normalization after every CL: Speed-up the training by normalizing activators and mitigate sensitivity to initialization randomness.
- Dropout: improve generalization and prevent overfitting by randomly setting to zero values with the given probability.

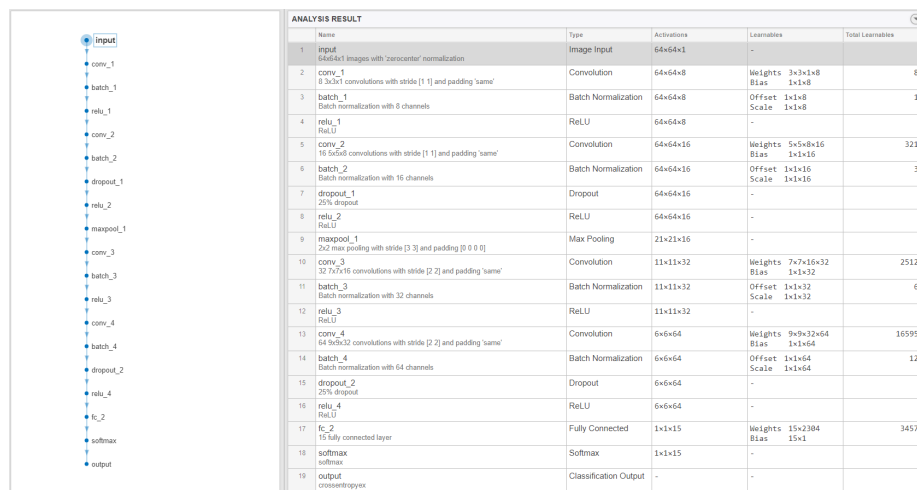


Figure 4: Improved NN Structure

Results

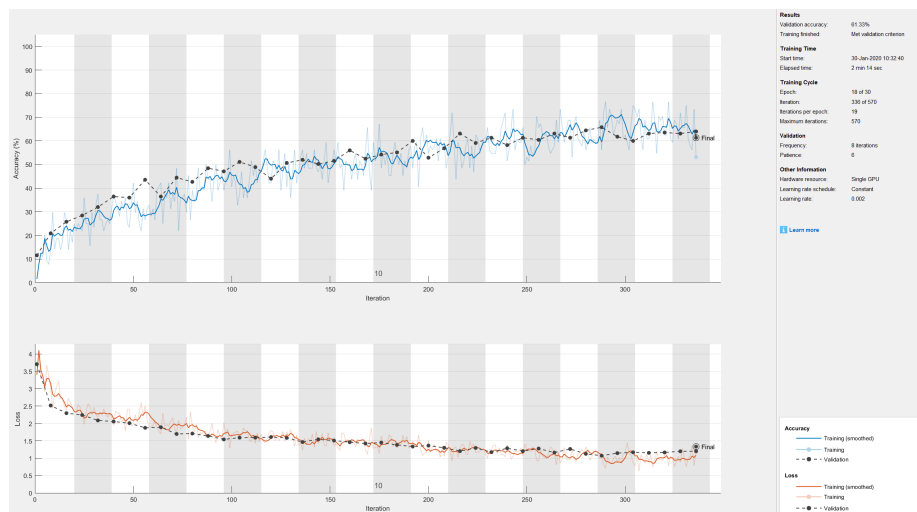


Figure 5: Improved NN

True Class	Bedroom	28	2	2	5	5	3	49		6	5	5	2	2	2	
	Coast		119	1	31					5		103		1		
	Forest			173		4				13		1	30	6	1	
	Highway		18	4	113	2	1	1		2		16	2		1	
	Industrial	5	1	11	10	69	11	13		5	6	19	36	11	3	11
	InsideCity	1	4	15	7	18	64	20		2	4	10	42	16	2	3
	Kitchen	3		3	4	2	2	75	1	1	5	2	4	6		2
	LivingRoom	9	1	5		10	3	90	17	4	7	6	19	7	6	5
	Mountain		10	14	5	1		1		178		56	4	5		
	Office	5		13		8	2	10	2	7	49	2	2	8	2	5
	OpenCountry		20	11	17	3		1		11	1	242	1	3		
	Store		1	9	3	3	3	8		3	1		178	2	3	1
	Street			6	7	4	5	5		1		6	10	147	1	
	Suburb		1		1	2	12	1	1	1		3	16	5	98	
	TallBuilding			10		22	1	26	2	6	7	2	16	5		159
		Bedroom	Coast	Forest	Highway	Industrial	InsideCity	Kitchen	LivingRoom	Mountain	Office	OpenCountry	Store	Street	Suburb	TallBuilding
		Predicted Class														

Figure 6: Improved NN

The overall validation accuracy is around 61%, almost equal to training one, test accuracy is around 57%. Notice how all the new features prevent the CNN to overfit the training set, reaching a kind of plateau with train and validation losses lines really close to each over.

Ensemble of NN

I've also tried to use an ensemble of 10 of the previous NN.

True Class	Bedroom	61	2	2	2	4	1	13	19	5	2		1	1	1	2
	Coast		171	2	25		1			2		59				
	Forest			203		2				19			2	2		
	Highway		12	4	122	1	2			4		10	2	3		
	Industrial	7	4	19	8	83	12	5	2	15	4	13	19	6	2	12
	InsideCity			16	4	5	108	5	1	4	4	8	28	20	3	2
	Kitchen	11		1	4	5	4	54	5	2	5	1	9	6		3
	LivingRoom	29	1	2		17	4	45	48	6	4	3	13	8	1	8
	Mountain		9	17	3					214		28		2		1
	Office	10	1	5		8	9	7	7	3	51		2			12
	OpenCountry		19	18	16					34		223		1	1	
	Store			64		4	7	2		4			144	5	2	3
	Street			14	3	2	5			2		5	7	102		2
	Suburb			9	1	2	7		2	4		4	6	15	91	
	TallBuilding	1		12		23	5	1	3	8	1	1	10	2		160
		Bedroom	Coast	Forest	Highway	Industrial	InsideCity	Kitchen	LivingRoom	Mountain	Office	OpenCountry	Store	Street	Suburb	TallBuilding
		Predicted Class														

Figure 7: Ensemble of improved NN

I've reached a test accuracy a bit over 64% using the arithmetic means of the output classification score from each CNN.

Part 3

Lastly was required to adopt a Transfer Learning approach importing using trained CNNs. I used almost the same data augmentation techniques as before, I just added the gray2rgb option to match imported networks input size. There are two approach for this task:

- Replace last Full-Connected layer with another one (with the right dimension for our classification problem) and then fine-tune the derived CNN.
- Get activators from a Convolutional, ReLU or Pooling layer and then train a SVM to get classification.

Replace

I tried first approach with AlexNet and VGG, for AlexNet I tried both freezing all layers except the new one and no freeze but with 0.1x of learning rate and 20x LearnFactor on last layer. For VGG the only possible option due HW limitation was the first one.

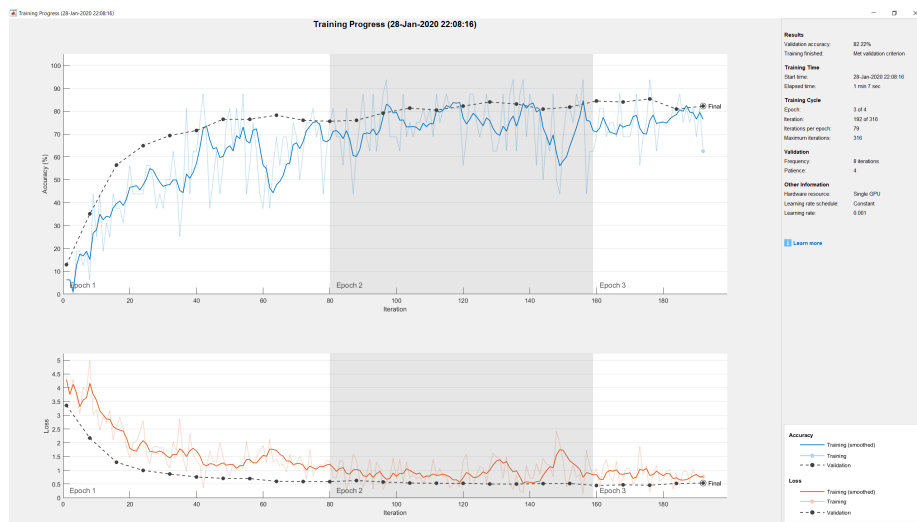


Figure 8: AlexNet Freeze

True Class	Bedroom	34					2	9	16		5						
	Coast		158	1	9					1		50				1	
	Forest			335						2		19				2	
	Highway		1		139	4	4		1			4	2	1	3	1	
	Industrial		1		1	144	41	2	1	1	1		1		9	9	
	InsideCity						156	2							1	6	
	Kitchen	2					3	100				4		1			
	LivingRoom	17				2	12	54	89		13						2
	Mountain		1	3	1					242		28				1	
	Office					2	19	5			89						
	OpenCountry									10		272				3	
	Store	2		1		15	37	12	2	4	2		136	1		3	
	Street				4	4	49	2	1			1		127	3	1	
	Suburb						4		1						138		
	TallBuilding				1		20	30			1					204	
		Predicted Class															

Figure 9: AlexNet Freeze

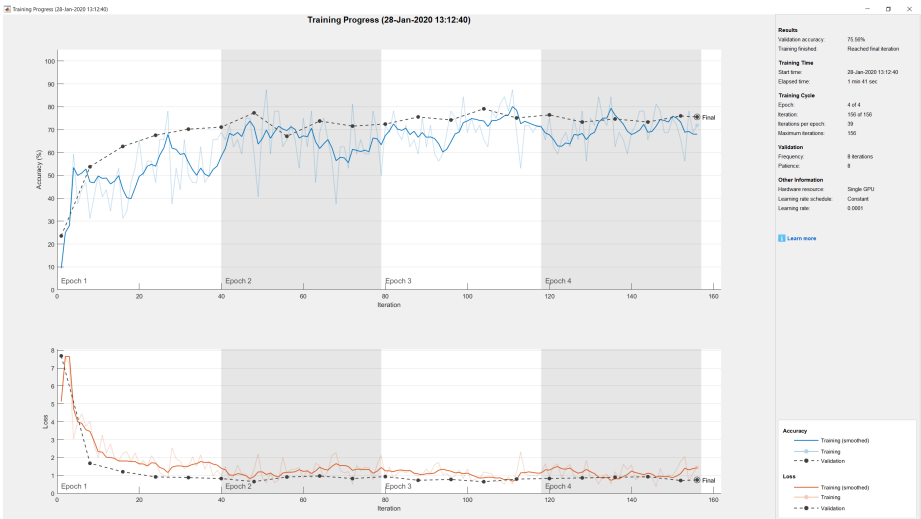


Figure 10: AlexNet No Freeze

True Class	Bedroom	75				1		2	36				1			1
	Coast	1	223	1	2	2	1			1		29				
	Forest		1	214						7		6				
	Highway		4		133	7	4	1	1			5	1	3		1
	Industrial	2			4	140	13	5	8	10		3	10	1		15
	InsideCity	3				19	176	7	2				1	2	2	2
	Kitchen	7					1	90	10			1				
	LivingRoom	31			1	3		14	130	1		1	3	1		4
	Mountain		7	5	2					146		14				
	Office	15						17	27		52		4			
	OpenCountry									17		239				
	Store	4		1	5	7	13	22	10	2			145	4		2
	Street				9	8	22	3		1				142		7
	Suburb	2		4		4	4		2	1		2			120	2
	TallBuilding			1		13	3			3			1	1		234
Predicted Class		Bedroom	Coast	Forest	Highway	Industrial	InsideCity	Kitchen	LivingRoom	Mountain	Office	OpenCountry	Store	Street	Suburb	TallBuilding

Figure 11: AlexNet No Freeze

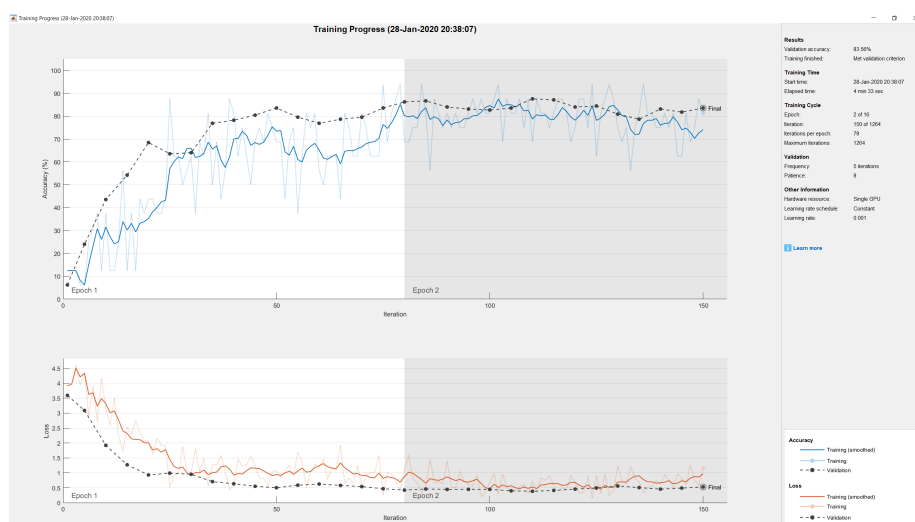


Figure 12: VGG

Supported Vector Machines

For second approach I used Resnet18 and Error-Correcting Output Codes Model for training the SVM classifier. Given the structure of this network I decide to extract the activators from last GlobalPooling layer which become the features vector of every image (512 dim. feature space).

True Class	Bedroom	95						2	19								
	Coast		297	1	3	1				1		17					
	Forest			214						1		13					
	Highway				147	5	1					1		6			
	Industrial				2	162	9					1	2	1	1	3	
	InsideCity					11	162	1			1			10	1	2	
	Kitchen	1					1	102	3		1		2				
	LivingRoom	22					1	16	145		2			1			
	Mountain		2	5	2					254		11					
	Office							2	3		110						
	OpenCountry		19	8	9					24		269					1
	Store					6	6	4	3		1		195				
	Street				2	4	6						1	107			2
	Suburb				1	1	5								134		
	TallBuilding			1		12	9								3		211
		Predicted Class															

Figure 13: SMV

Comment on results of part 3

All approaches went beyond 75% accuracy, with the SVM almost crossing 90% accuracy test score. Notice also that no overfitting is present (which can be a common problem when dealing with transfer learning due to the imbalance between the huge prior training set and the new one) this is mostly thanks to data augmentation applied on training set and early-stopping criterion on training routine.

For second approach i could also extract features form one of the last CL, but I'd get a 25k dimensions feature vector, which is too big for our problem in my opinion.