Land Use Classification

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Goals

- Classify land by using satellite images for various land-use types by leveraging state-of-the-art CNN architectures and transfer learning approach
- Demonstrate how size of dataset affects the accuracy of CNN models trained from scratch and CNN models trained by employing transfer learning

Motivation

- Infrastructure Planning
- Resource Planning
- Disaster Management

Datasets

- NWPU-RESISC45
  - 31500 satellite images, 45 land-use classes, 700 images per class
- UC Merced
  - 2100 satellite images, 21 land-use classes, 100 images per class

Data Preparation

- Divided the 2 datasets into train (.8), validation (.1) and test (.1) sets individually
- Extracted only the 19 common classes between NWPU-RESISC45 and UC Merced

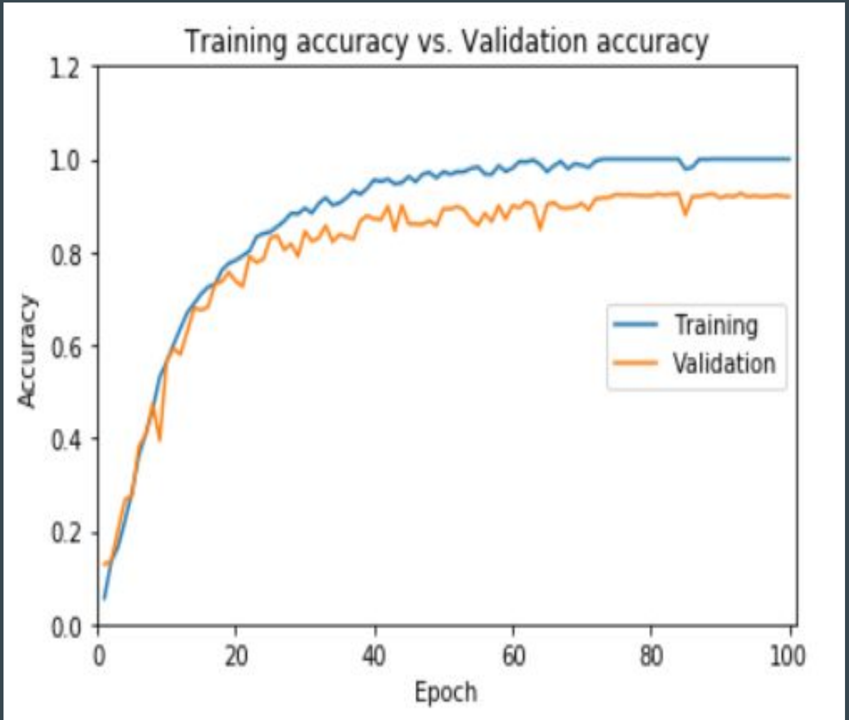
Proposed Approach

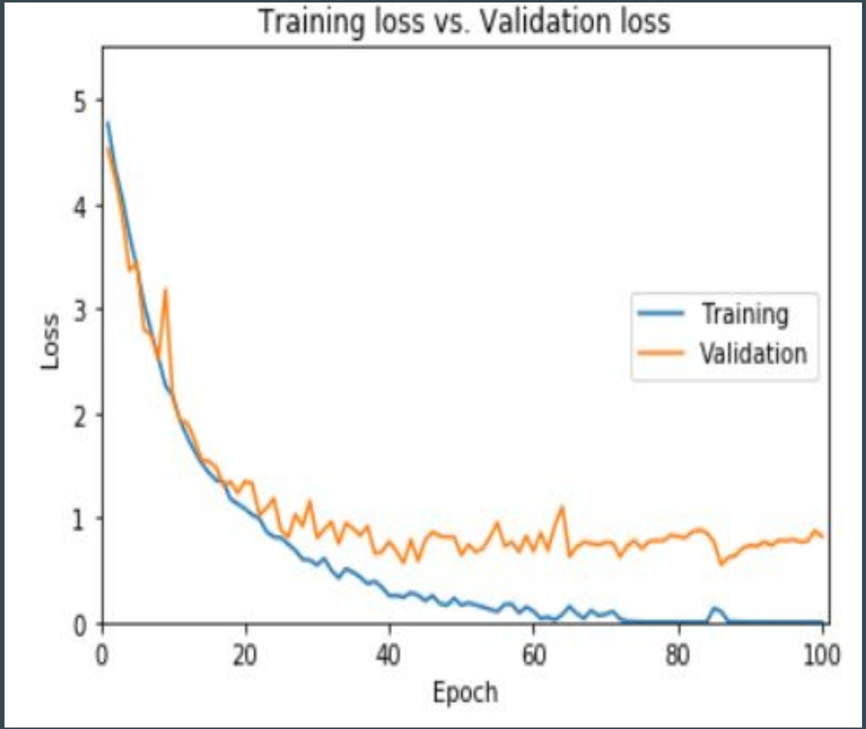
- Transfer Learning
  - Using a pre-trained CNN and repurpose it to the task of interest
  - Output of the penultimate layer of a pre-trained network which is trained on ImageNet Data is used as a feature vector for classification
  - Idea behind it - Optical remote sensing images have strong low level similarities with general purpose optical images
  - Reduces model training time and lends a higher generalizability to the model predictions
- Evaluation Metric - Accuracy
  - Accuracy = number of correct predictions made divided by the total number of predictions made
  - Employing accuracy as a measure for performance of the models as the class sizes are equal

CNN Architectures

- GoogLeNet
  - Inception Modules
  - Fewer Parameters therefore less prone to overfitting and model can be deeper
  - Different sized filters can be used at each layer therefore retaining spatial information
- VGG
  - High number of trainable parameter therefore has promise of higher accuracy
  - Prone to overfitting
- InceptionResNet
  - Newer convolution network based on GoogLeNet and ResNet
  - Residual connections leads to dramatically improved training speed for the Inception architecture

Training Plot Example





Plots shown here pertain to training of GoogLeNet on NWPURESISC_45 train set from scratch
Left image shows accuracy plot as the model trains and right image shows loss plot as the model trains

Confusion Matrix Example

0.937593984962406

	precision	recall	f1-score	support
0	0.95	0.99	0.97	70
1	0.99	0.99	0.99	70
2	0.95	0.99	0.97	70
3	1.00	1.00	1.00	70
4	0.89	0.90	0.89	70
5	0.97	0.97	0.97	70
6	0.85	0.89	0.87	70
7	1.00	0.99	0.99	70
8	0.99	0.97	0.98	70
9	0.94	0.86	0.90	70
10	0.83	0.84	0.84	70
11	0.92	0.94	0.93	70
12	0.93	0.91	0.92	70
13	0.96	0.96	0.96	70
14	0.97	0.96	0.96	70
15	0.96	0.91	0.93	70
16	0.88	0.96	0.92	70
17	0.96	0.94	0.95	70
18	0.92	0.86	0.89	70
accuracy			0.94	1330
macro avg	0.94	0.94	0.94	1330
weighted avg	0.94	0.94	0.94	1330

- The image on the left shows the confusion matrix which pertains to prediction made by GoogLeNet on NWPURESISC_45 test set
- GoogLeNet model is trained from scratch on NWPURESISC_45 train set

Accuracy Results

- UC Merced Data

Model	Scratch	Transfer Learning
GoogLeNet	0.70	0.805
VGG	0.56	0.805
InceptionResNet	0.71	0.89

Accuracy Results

- NWPU-RESISC45 Data

Model	Scratch	Transfer Learning
GoogLeNet	0.93	0.82
VGG	0.81	0.85
InceptionResNet	0.88	0.878

Takeaway

- In general, increase in size of training dataset improves prediction accuracy of the deep learning model
- Transfer Learning can be leveraged when the dataset is smaller to provide gains in prediction accuracy
  - Increases generalizability of the model
  - Mitigates over fitting
- Training deep learning models from scratch is a good idea when the size of training set is adequately large

Thank you!