Road Passability Estimation using Deep Neural Networks and Satellite Image Patches

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Motivation

- High applicability of Artificial Intelligence (AI) in numerous fields among them remote sensing
- Application of deep learning techniques on satellite images for automatic identification of concepts.
- Focus: Emergency Management applications
  - Problem: Starting from a point A to a point B, is a road passable or not due to a flood?
  - Introduction of a road passability method that automatically decides whether a roadway depicted in a satellite image is clear

Related work

Road extraction

- (Babu et al., 2016): extraction of road components from satellite images using Laplacian of Gaussian operator. Combine panchromatic and multispectral images to obtain more details. Objects are identified using HSY color models components.
- (Henry et al., 2018): considers 3 different pre-trained Fully-Convolutional Neural Networks (FCNNs): FCN-8s with a VGG-19, Deep Residual U-Net0 and DeepLabv3+ for semantic segmentation. Different nature of SAR images compared to optical ⇨ performance drop. Roads may be disconnected at intersections due object awareness in FCNN.
- (Shi et al., 2018): propose the Generative Adversarial Networks (GAN). “Segnet” generates a pixel-wise classification map. GAN defines two models; the generative model for stimulating the data probability distribution, and the discriminative model for finding whether a sample is coming from the generative model or the ground truth map.

Related work

Flood detection

- (Kang et al., 2018): use the Fully-Convolutional Network (FCN) on Gaofen-3 SAR images for flood mapping. FCN is robust to speckle noise in SAR. To make the model less complex, 7 x 7 kernels are replaced with 3 x 3 kernels reducing conv6 parameters.
- (Kia et al., 2012): considers set of criteria performances (coefficient of determination (R2), sum squared error (SSE), mean squared error (MSE), root mean squared error (RMSE)) to optimize the performance of Artificial Neural Network (ANN). Considers 7 input nodes that represent flood causative parameters. Main factor in training is the *rainfall*. Main factor for flood susceptibility mapping is the *elevation*.
- (Skakun, 2012): segments single SAR image using self-organizing Kohonen maps (SOMs) and uses auxiliary information on water bodies derived from optical satellite images for image classification. Uses a moving window for image processing.

Methodology

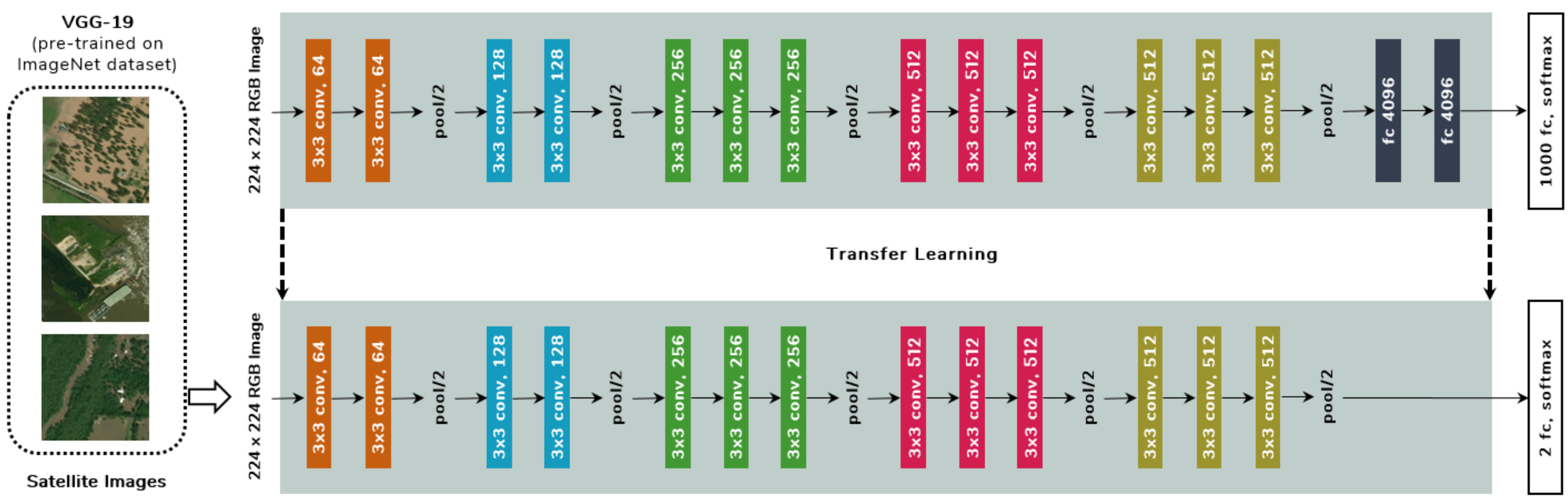
- **Method: Transfer learning on pre-trained Deep Convolutional Neural Networks (DCNNs)**

- Build models by using pre-trained Convolutional Neural Networks (CNN).
- Pre-trained models are trained on an external dataset of millions of images

- Experimented with:
  - **VGG-19** (Simonyan and Zisserman, 2014): developed for ImageNet dataset by the Visual Geometry Group at the University of Oxford
  - **Inception-v3** (Szegedy, et al. 2016): developed by Google with emphasis on making scaling to deep networks computationally efficient
  - **ResNet** (He, et al. 2016): developed by Microsoft Research that uses residual functions for adding stability to deep networks

Methodology

- Performed fine-tuning:
    - remove the last pooling layer (for each network)
    - replace the layer with a new pooling layer
    - New pooling layer has softmax activation function with size 2 (2 classes to recognize – road passable or not)



Model Implementation

- TensorFlow [1]: Open source machine learning framework
- Keras [2] : Open source neural network Python package for developing models

- Keras simplifies CNN training by modifying easily network structure and pre-trained weights, freezing the weights in the imported network and eventually training the weights in the newly added layers
- combine existing knowledge from the imported weights with the gained knowledge from the domain-specific collection of satellite images with ground-truth annotation on road passability.

[1] https://www.tensorflow.org

[2] https://keras.io/

Experiments

Dataset:

- Taken from MediaEval 2018 Satellite Task “Emergency Response for Flooding Events” - “Flood detection in satellite images” [1]
- Information on satellite imagery:
  - WorldView Satellite[2]
  - captured event "Hurricane Harvey" in 2017
  - ground sample distance 30 cm (1 pixel = 30 cm).
- **1,437** satellite images
- Manually annotated satellite image patches of flooded areas with label indicating road passability or not due to floods
- Dataset was split to training and validation set
  - training set contained 1,000 images,
  - the validation set 437 images

[1] http://www.multimediaeval.org/mediaeval2018/multimediasatellite/

[2] https://www.satimagingcorp.com/satellite-sensors/worldview-3/

Experiments

Settings

- Tuning of set of parameters to achieve best accuracy:
  - learning rate values = 0.001, 0.01, 0.1
  - batch size values = 32, 64, 128
  - optimizer functions = Adam, Stochastic Gradient Descent (SGD)
- Keep stable set of parameters:
  - epoch was set to 35
  - loss function = sparse categorical cross-entropy

Results

- Experimentation with the batch size parameter

			Batch size 32		Batch size 64		Batch size 128	
DCNN	Learning rate	Optimizer	Dev. Set Acc.	Valid. Set Acc. Dev.	Dev. Set Acc.	Valid. Set Acc. Dev.	Dev. Set Acc.	Valid. Set Acc. Dev.
VGG-19	0,001	Adam	0,861	0,7666	0,8610	0,7666	0,8610	**0,7667**
VGG-19	0,001	SGD	0,876	0,7071	0,8630	0,7117	0,8740	0,7162
Inception_v3	0,01	Adam	0,788	0,6247	0,8610	0,5789	0,8990	0,5629
Inception_v3	0,001	SGD	0,792	0,5950	0,8330	0,6224	0,8480	0,5973
ResNet-50	0,01	Adam	0,833	0,4943	0,8640	0,6957	0,8720	0,7094
ResNet-50	0,001	SGD	0,804	0,6911	0,8310	0,7094	0,8390	0,7140
ResNet-101	0,1	Adam	0,86	0,5492	0,8710	0,5126	0,8850	0,5126
ResNet-101	0,001	SGD	0,789	0,5835	0,8260	0,5995	0,8380	0,5881

Conclusions:

- Increase of the batch size generally improves the accuracy
- Best accuracy for validation set: 76.67% for VGG-19 architecture, 128 batch size, 0.001 learning rate

Model Results Visualization

- Developed a Web user interface to showcase the applicability of developed road passability service
  - User is presented with a collection of satellite images, accompanied by their metadata
  - User clicks on image, which is partitioned to 16 smaller pieces and the classification is performed to every piece:
    - Passable roads are indicated with green border around the image segment
    - Non-Passable roads are indicated with red border around the image segment

Conclusion

Conclusions:

- Tweaking DCNN settings results in significant improvement in accuracy
- Lower values of the learning ratio ⇨ better accuracy
- Increasing batch size ⇨ better accuracy (up to certain level for avoiding over-fitting)

Future work

- Evaluation of the algorithm in alternative EO imagery and other resolutions
- Combination of existing approach with RCNN (Region CNNs) to perform semantic segmentation
- Extension to other extreme weather or crisis events in general

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