A Deep Neural Network Slope Reduction Model on Sentinel-1 Images for Water Mask Extraction

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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 or events.

- Focus: Emergency Management applications (managerial function that copes with hazards and disasters)
  - Problem: Highly sloped areas should be indiscriminately excluded from water masks that derive from SAR imagery?

- Introduction of a water estimation method that takes into consideration the morphology of the ground and automatically generates the water bodies mask

Related work

The effect of elevation information at the water bodies extraction task:

- (Hong et al., 2015): Problem: filtering of occluded areas tend to erase actual water reservoirs residing at high altitudes ⇨slope information performed better vs direct elevation information
- (Čotar et al., 2016): Assumption: Water bodies do not lie on steep terrain and high in the mountains ⇨ 1) Removal of geometric and radiometric errors, and airports that SAR resembles to water, 2) Use of region growing technique to retrieve miss-removed and rough water pixels
- (Acharya et al., 2018): Assumption : a single water index does not perform well in a big scene with varying altitudes ⇨ Segmenting the test scene for specific elevations & use of NDVI and NDWI for detecting water

Related work

Networks are being used to facilitate the execution of imagery related application:

- (Michail et al., 2018) : Target: Create accurate flood mask ⇨ Combines Mahalanobis Distance-based classification where four-dimensional classification features derived directly from the image pixels (R, G, B and Near-Infrared channel)

  Issue: Small non-flooded areas inside flooded area i.e. probable false negatives ⇨ Apply image dilation and erosion
- (Zhang et al., 2019): Issue: Difficulty in discriminating water and shadows from SAR images + noise ⇨ Use of deep neural network model for tackling noisy information: 1) Use of 2 Multi-level Features Extraction and Fusion (MFEF) networks for generating separate score maps, 2) fusion with different weights for producing final score map

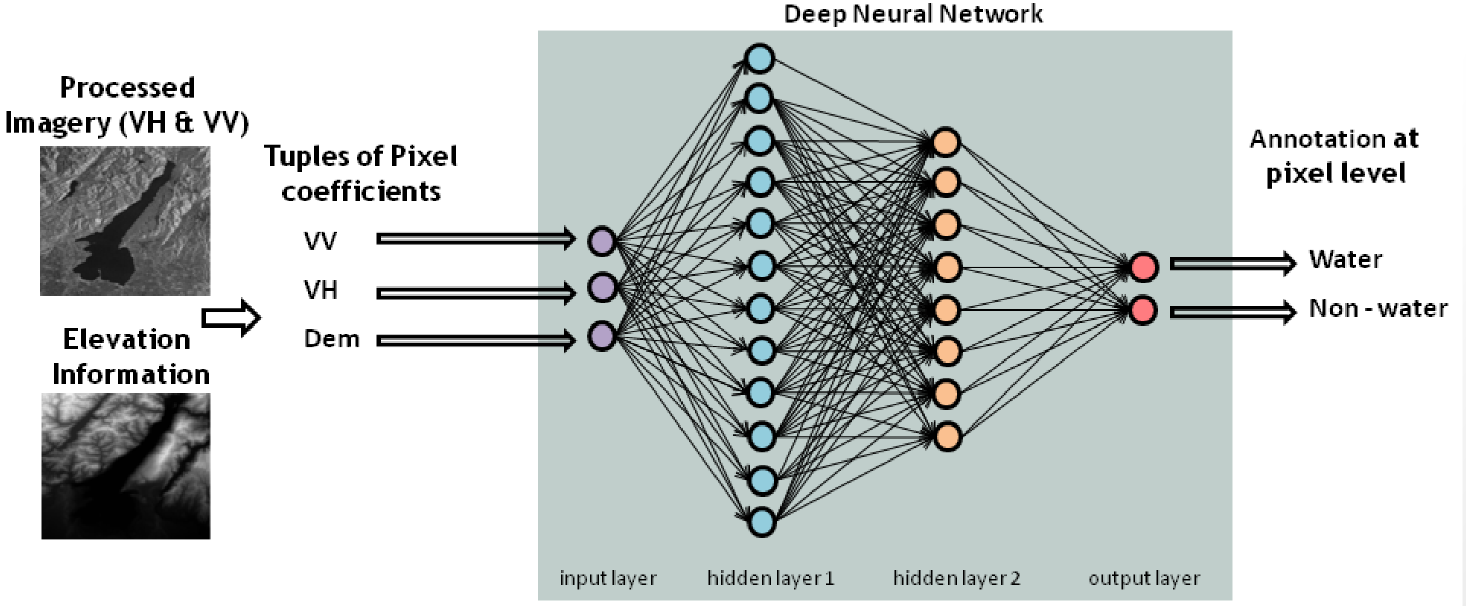
Methodology (1)

Method: Train a Deep Neural Networks (DNN)

- Build a custom model by using a DNNs
- Train from scratch using a dataset with tuples of input data
- Experimented with two different input versions of 3 layers DNNs:
  - **VV-VH**: artificial network considering for each image pixel the tuple of the processed VV and VH polarisation bands in decibel (dBs)
  - **VV-VH-Dem**: artificial network considering for each image pixel the tuple of processed VV and VH polarisation bands (in dBs) and the elevation information
- Compared with a remote sensing approach:
  - **VV or VH histogram thresholding:** The deep valley of the histogram was used to separate water from non-water areas

Methodology (2)

- Model analysis:
  - Fully connected neural network, involves 3 layers
  - Tuples of pixels values are inserted to input layer
  - Two hidden layers with 12 and 8 neurons
  - Each of the initial tuples is classified as flooded or not



Model Implementation

- TensorFlow [1]: Open source machine learning framework
- Keras [2] :
  - Open source neural network Python package for developing models
  - Allows easy and fast prototyping of custom neural networks
  - Runs seamlessly on CPU and GPU
  - Simplified DCNN training by easily modifying network structure
  - Transfer knowledge with pre-trained weights, freezing the weights in the imported network and eventually training the weights in the newly added layers

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

[2] https://keras.io/

Experiments (1)

Dataset:

- Input
  - Tuples of VV-VH-DEM values for each pixel
  - DEM
- Source
  - For VV-VH:
    - Sentinel-1 Satellite[1] (GRD-IW)
    - Ground sample distance 10 m (1 pixel = 10 m)
  - For DEM: Use of Shuttle Radar Topography Mission data at 30m Global 1 arc second V003 elaborated by NASA and NGA
- Area:
  - Captured three lakes, Maggiore, Garda and Trasimeno (March 2019)

Experiments (2)

Dataset:

- Annotation
  - **~40 m tuples x 3 lakes**
  - Annotation file delineating lakes & water reservoirs provided by Alto Adriatico Water Authority (AAWA)
  - Use of Bing Maps high resolution images to make corrections
- Randomly splitting the dataset including tuples of all lakes to training & validation set:
  - Size of training set: 400.000 tuples
  - Size of validation set: 120.000 tuples

[1] https://sentinel.esa.int/web/sentinel/missions/sentinel-1

Experiments (3)

Settings:

- Tuning of set of parameters to achieve best accuracy:
  - learning rate values = 0.001, 0.01, 0.1
  - batch size value = 10,
  - optimizer functions = Adam, Stochastic Gradient Descent (SGD)
- Keep stable set of parameters:
  - epoch was set to 25
  - loss function = binary crossentropy

Experiments Results

- Overall best results obtained by Adam optimizer and 0.001 learning rate

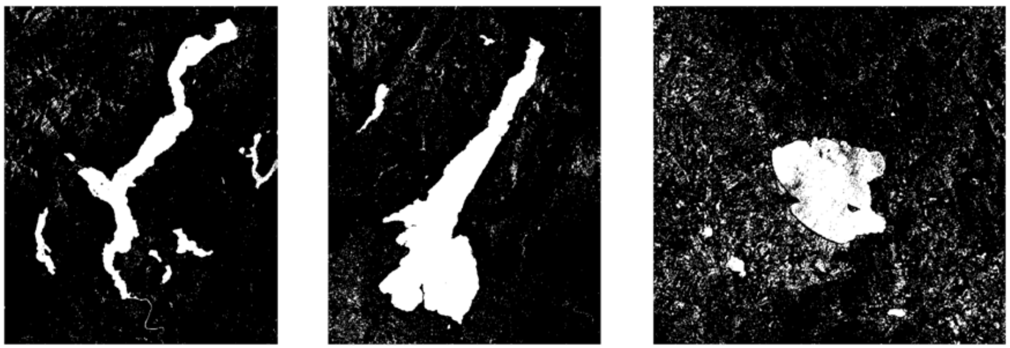
Lakes	Precision	Recall	Accuracy	F-score	Settings
Maggiore	98.29	87.84	93.15	**92.77**	Adam, 0.001
Maggiore	96.23	61.89	79.73	75.33	-22.0 dB (vh)
Garda	94.57	93.63	94.13	**94.10**	Adam, 0.001
Garda	95.55	70.45	83.58	81.10	-21.7 dB (vh)
Trasimeno	93.67	84.61	89.45	**88.91**	Adam, 0.001
Trasimeno	88.07	66.13	78.58	75.54	-13.9 dB (vv)

Conclusions:

- Accuracy improves for all cases comparing the Deep neural network model to the histogram thresholding method
- Maximum F-score of 94.10% for Garda lake with the DNN model

Model Results Visualization

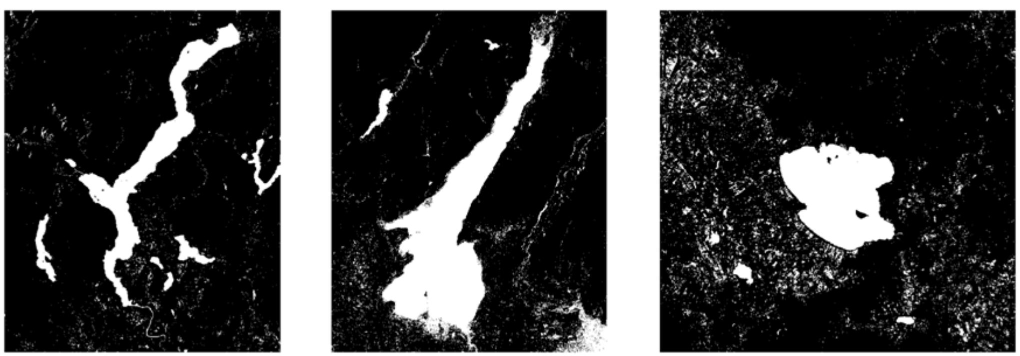
- Water masks generated with both RS and DNN methods
- DNN greatly reduces gaps in Trasimeno lake
- Reduces the false positives at the top of the surrounding mountainous areas



(a) (b) (c)

Histogram thresholding technique

a) Maggiore
b) Garda
c) Trasimeno



(a) (b) (c)

DNN approach

Conclusions & Future Work

Conclusions:

- Combining imagery with elevation data increases performance:
  - Reducing the false positives that are caused of the steep mountain slopes
- Lower values of learning ration ⇨ better accuracy
- Best results with Adam optimizer and learning rate of 0.001

Future work:

- Train a DCNN like VGG16, VGG19, ResNet50:
  - Using transfer learning of pretrained-models and train last layers of network
  - Train from scratch (full training) using large amount of annotated data
- Evaluation of alternative ways for fine-tuning pre-trained networks

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Thank you!

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