Semi-Supervised Classification and Segmentation on High Resolution Aerial Images

Sahil Khose Abhiraj Tiwari Ankita Ghosh

Manipal Institute of Technology, Manipal

2021

• Why do we need visual scene understanding of disaster images?

- Why do we need visual scene understanding of disaster images?
 - Vital for quick response and large scale recovery.

- Why do we need visual scene understanding of disaster images?
 - Vital for quick response and large scale recovery.
- Challenges related to gathering visual data.

- Why do we need visual scene understanding of disaster images?
 - Vital for quick response and large scale recovery.
- Challenges related to gathering visual data.
 - Cost of labeling the data.
 - Time for labeling the data.

- Why do we need visual scene understanding of disaster images?
 - Vital for quick response and large scale recovery.
- Challenges related to gathering visual data.
 - Cost of labeling the data.
 - Time for labeling the data.
- Unsupervised and Semi-supervised learning is the solution!

FloodNet Dataset

The dataset consists of 1450 train images (2343 total) taken from a UAV after hurricane Harvey. Out of this dataset 400 images are labeled while 1050 images are unlabeled.

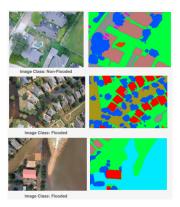


Figure: Few samples from the FloodNet dataset

Semi-Supervised Methodology

Input: Sample image

Output: Class of the given image

for
$$epoch \leftarrow 0$$
 to E do

if
$$epoch < E_i^{\alpha}$$
 then $\alpha \leftarrow \alpha_i$

else if
$$epoch < E_f^{\alpha}$$
 then

$$\alpha \leftarrow \frac{\alpha_f - \alpha_i}{E_f^{\alpha} - E_i^{\alpha}} * (epoch - E_i^{\alpha}) + \alpha_i$$

else

$$\alpha \leftarrow \alpha_f$$

end if

Run the model on train set

$$loss \leftarrow \textit{BCE}(\textit{I}, \hat{\textit{I}}) + \alpha * \textit{BCE}(\textit{u}_{\textit{epoch}}, \textit{u}_{\textit{epoch}-1})$$

Generate the pseudo labels for unlabeled data

Evaluate the model on validation set

end for

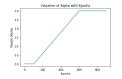


Figure: Change of alpha over epochs

Models Used

- Classification
 - ResNet18 with a binary classification head
- Segmentation
 - DeepLabV3+
 - ResNet34 backbone

Classification Results

Model	Training	Test	#params	
	Accuracy	Accuracy		
InceptionNetv3	99.03%	84.38%	23.8M	
ResNet50	97.37%	93.69%	25.6M	
Xception	99.84%	90.62%	22.9M	
ResNet18 (our)	96.69%	96.70%	11.6M	

Table: Classification models comparison

Segmentation Results

Method		Building NF				Water	Tree	Vehicle	Pool	Grass	mIoU
UNet	0.	0.	0.34	0.	0.45	0.49	0.47	0.	0.	0.64	0.239
PSPNet	0.04	0.45	0.66	0.32	0.73	0.61	0.71	0.14	0.18	0.82	0.4665
DLV3+	0.16	0.49	0.69	0.45	0.76	0.72	0.76	0.14	0.18	0.85	0.5204
DLV3+ (SSL)	0.17	0.48	0.69	0.48	0.75	0.72	0.76	0.15	0.18	0.85	0.5223

Figure: Segmentation models comparison

Segmentation Samples

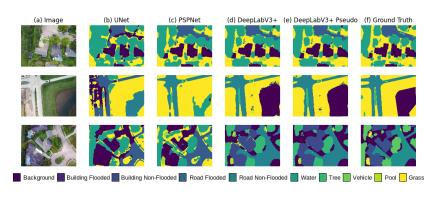


Figure: Visual comparison on FloodNet dataset for semantic segmentation

Conclusions and Future Work

- Explored semi-supervised classification and segmentation methods
- Handled class imbalance
- Increase of 0.19% mIoU on using pseudo labels, provides wide scope for improvement on increasing unlabeled data.

Conclusions and Future Work

- Explored semi-supervised classification and segmentation methods
- Handled class imbalance
- Increase of 0.19% mIoU on using pseudo labels, provides wide scope for improvement on increasing unlabeled data.
- Self-supervised pretraining, attention based models, addition of discriminative loss and vision transformers

Contact Us!

- Sahil Khose sahil.khose@learner.manipal.edu
- Abhiraj Tiwari abhiraj.tiwari1@learner.manipal.edu
- Ankita Ghosh ankita.ghosh1@learner.manipal.edu
- GitHub Repository https://github.com/sahilkhose/FloodNet