Semi-Supervised Classification and Segmentation on High Resolution Aerial Images

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Abstract

FloodNet is a high-resolution image dataset acquired by a small UAV platform, DJI Mavic Pro quadcopters, after Hurricane Harvey. The dataset presents a unique challenge of advancing the damage assessment process for post-disaster scenarios using unlabeled and limited labeled dataset. We propose a solution to address their classification and semantic segmentation challenge. We approach this problem by generating pseudo labels for both classification and segmentation during training and slowly incrementing the amount by which the pseudo label loss affects the final loss. Using this semi-supervised method of training helped us improve our baseline supervised loss by a huge margin for classification, allowing the model to generalize and perform better on the validation and test splits of the dataset. In this paper, we compare and contrast the various methods and models for image classification and semantic segmentation on the FloodNet dataset.

1. Introduction

The frequency and severity of natural disasters threaten human health, infrastructure and natural systems. It is extremely crucial to have accurate, timely and understandable information to improve our disaster management systems. Rapid data collection from remote areas can be easily facilitated using small unmanned aerial systems which provide high-resolution images. Visual scene understanding of these collected images is vital for quick response and large scale recovery post-natural disaster. Classification and segmentation tasks are fitting in such situations as they can provide scene information to help the task force make decisions.

One of the major challenges with generating a vision dataset is the cost of labeling the data, especially for semantic segmentation. This often leads to labels only for a small percentage of the data which gives rise to the need for semi-supervised methods that can produce results that are at par with supervised methods. Another challenge that we face apart from the lack of labeled dataset is the heavy class imbalance. Lack of labeled data coupled with class imbalance makes it a very challenging task to solve. Through our approach, we try to tackle these problems and produce creditable results.

Our contribution in this paper is two folds: semi-supervised classification and semi-supervised semantic segmentation. We discuss the existing literature in these fields based on which we have crafted our approach in Section 2. The subsequent sections throw light upon the pipeline of classification 3 and segmentation 4 respectively. Our paper describes the preprocessing and augmentation techniques used on the dataset, the methodology followed, the models and hyperparameters we have experimented with and the results obtained. Finally, we conclude by summarizing our results and discussing the scope of improvement in future 5.

2. Related Works

Supervised Classification: Classification has been one of the earliest undertakings in the deep learning domain. Over the years, several architectures and methods have emerged which have leveraged extensive datasets like ImageNet [5] to produce state of the art results using supervised learning. The architectures that our paper makes use of are ResNet [6] and EfficientNet [14].

ResNet proposes residual connection architecture which makes it feasible to train networks with a large number of layers without escalating the training error percentage. Using the technique of skip connections, it resolves the issue of vanishing gradient.

EfficientNet proposes a simple but highly effective scaling method that can be used to scale up any model architecture to any target resource constraints while maintaining model efficiency. They observed the effects of model scal-
The labeled dataset was heavily augmented to get more images for training the model under supervision. The image samples were randomly cropped, shifted, resized and flipped along the horizontal and vertical axes.

We downsized the image from $3000 \times 4000$ to $300 \times 400$ dimensions to strike a balance between processing efficiency gained by the lower dimensional images and information retrieval of the high-resolution images.

### 3.2. Methodology

ResNet18 with a binary classification head was used for semi-supervised training on the dataset. The model was trained for $E$ epochs out of which only the labeled samples were used for $E_1^{\alpha}$ epochs after which pseudo labels were used to further train the model. $\alpha$ has an initial value of $\alpha_i$ that increases up to $\alpha_f$ from epoch $E_1^{\alpha}$ to $E_f^{\alpha}$ as described in Algorithm 1.

A modified form of Binary Cross-Entropy (BCE) was used as the loss function as shown in line 10 in Algorithm 1 where $l$ is the label of a sample, $\hat{y}$ is the predicted class for labeled sample and $u_{\text{epoch}}$ is the predicted class for an unlabeled sample in the current epoch. This loss function was optimized using Stochastic Gradient Descent (SGD) [12].

#### Algorithm 1: Semi-supervised classification train loop

| Input: Sample image | Output: Class of the given image |
|---------------------|----------------------------------|
| $\text{for epoch } \leftarrow 0 \text{ to } E$ | |
| $\text{if epoch } \leq E_1^{\alpha}$ | $\alpha \leftarrow \alpha_i$ |
| $\text{else if epoch } \leq E_f^{\alpha}$ | $\alpha \leftarrow \frac{\alpha_i - \alpha_f}{E_f^{\alpha} - E_1^{\alpha}} \cdot (\text{epoch} - E_1^{\alpha}) + \alpha_i$ |
| $\text{else}$ | $\alpha \leftarrow \alpha_f$ |
| $\text{end if}$ | |
| $\text{Run the model on train set}$ | |
| $loss \leftarrow BCE(l, \hat{y}) + \alpha \cdot BCE(u_{\text{epoch}}, u_{\text{epoch}-1})$ | |
| $\text{Generate the pseudo labels for unlabeled data}$ | |
| $\text{Evaluate the model on validation set}$ | |
| $\text{end for}$ | |

### 3.3. Experiments

We used ResNet18 as it is computationally efficient. We experimented with Adam [8] optimizer and SGD. Optimizing using SGD was much more stable and the optimizer was less susceptible to overshooting. Different values of $\alpha$ were experimented with and it was found that a slow and gradual increase in alpha was better for training the model. Our best performing model uses $\alpha_i = 0$ and $\alpha_f = 1$. The value of 

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**3.1. Data and Preprocessing**

In the given dataset 398 sample images were labeled out of which 51 samples were flooded and 347 were non-flooded. The large class imbalance prevents the model from achieving a good F1 score while training with the labeled dataset. To prevent this we used a weighted sampling strategy while loading the data in the model as inspired from [10]. Both the classes were sampled equally during batch generation.
\(\alpha\) increases from epoch \(E^\alpha_i\) = 10 to \(E^\gamma_f = 135\). The model was trained on batch size of 64.

| Model                | Training Accuracy | Test Accuracy | #params |
|----------------------|-------------------|---------------|---------|
| 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 1. Classification models comparison

### 3.4. Results

Our system performed significantly better than all the classification baseline results mentioned in the FloodNet paper while having a considerably smaller architecture (half the number of parameters) as shown in Table 1. Our best model achieves **98.10%** F1 and **96.70%** accuracy on the test set.

### 4. Segmentation

In this section, we detail our approach for training a model which generates multi-class segmentation masks for given images. The semantic labels for the task is a 10 pixel-level class segmentation mask consisting of Background, Building-flooded, Building non-flooded, Road-flooded, Road non-flooded, Water, Tree, Vehicle, Pool and Grass classes. They are mapped from 0 to 9 respectively.

#### 4.1. Data and Preprocessing

To expedite the process of feature extraction for the deep learning model, we apply bilateral filter to the image, followed by two iterations of dilation and one iteration of erosion. For image augmentation we perform shuffling, rotation, scaling, shifting and brightness contrast. The images and masks are resized to \(512 \times 512\) dimensions while training as high-resolution images preserve useful information.

#### 4.2. Methodology

The dataset contains labeled masks of dimension \(3000 \times 4000 \times 3\) with pixel values ranging from 0 to 9, each denoting a particular semantic label. These are one-hot encoded to generate labels with 10 channels, where \(i^{th}\) channel contains information about \(i^{th}\) class.

We experiment with various encoder-decoder and pyramid pooling based architectures to train our model, the details of which are mentioned in Section 4.3. The loss function used is a weighted combination of Binary Cross-Entropy loss (BCE) and Dice loss as it provides visually cleaner results.

We apply a semi-supervised approach and generate pseudo masks for the unlabeled images. While training the model for \(E\) epochs, the labeled samples were used for \(E^\alpha_i\) epochs where Adam is used as an optimizer. After that pseudo masks were used to further train the model as described in Algorithm 1. \(\alpha\) has an initial value of \(\alpha_i\) that increases upto \(\alpha_f\) from epoch \(E^\alpha_i\) to \(E^\gamma_f\). SGD optimizer with 0.01 LR is used when pseudo masks are introduced to the model.

### 4.3. Experiments

We apply three state-of-the-art semantic segmentation models on the FloodNet dataset. We adopt one encoder-decoder based network named UNet, one pyramid pooling module based network PSPNet and the last network model DeepLabV3+ employs both encoder-decoder and pyramid pooling based module. We train all of them in a supervised fashion. For UNet, PSPNet and DeepLabV3+ the backbones used were ResNet34, ResNet101 and EfficientNet-B3 respectively.

For UNet the learning rate was 0.01 with step LR scheduler set at intervals \([10,30,50]\) and decay factor \(\gamma\) set to 0.1. For PSPNet the learning rate was 0.001 without any LR decay. For DeepLabV3+ the learning rate was 0.001 with step LR scheduler set at intervals \([7,20]\) and \(\gamma\) set to 0.1.

Adam optimizer and batch size of 24 was used for all the models with Mean Intersection over Union (MIOU) as the evaluation metric. We observed the best results when we weighed the BCE loss and Dice loss equally.

Once we recognized the best performing model on the task, we trained a DeepLabV3+ model with EfficientNet-B3 as the backbone and used SGD optimizer instead of Adam optimizer in a semi-supervised fashion. Due to computation and memory constraints we randomly sampled unlabeled data with the ratio of 1 : 10 for generating the pseudo masks.

### 4.4. Results

Table 2 showcases the comparison of the best models we achieved for each of the 3 architectures. The best test set result was achieved by a DeepLabV3+ architecture with EfficientNet-B3 backbone. A few example images of the predictions of the model against the ground truth are provided in Figure 1. It is evident from the table that small objects like vehicles and pools are the most difficult tasks for our models.

### 5. Conclusion

In this work, we have explored methods to approach semi-supervised classification and segmentation along with handling the class imbalance problem on high-resolution images. We have conducted a range of experiments to ob-
Method | Background Flooded | Building Flooded | Building Non-Flooded | Road Flooded | Road Non-Flooded | 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 |
DeepLabV3+ | 0.16 | 0.49 | 0.69 | 0.45 | 0.76 | 0.72 | 0.76 | 0.14 | 0.18 | 0.85 | 0.5204 |
DeepLabV3+ (pseudo-labels) | 0.17 | 0.48 | 0.69 | 0.48 | 0.75 | 0.72 | 0.76 | 0.15 | 0.18 | 0.85 | 0.5223 |

Table 2. Classwise segmentation results on FloodNet testing set

![Visual comparison on FloodNet dataset for semantic segmentation](image)

Our classification framework achieves laudable results with just 398 labeled images and also utilizes the entirety of the unlabeled data. Our segmentation framework shows an increase of 0.19% on using the unlabeled data as pseudo labels. This provides a wide scope of improvement. The amount of unlabeled data is approximately three times the amount of labeled data which if employed efficiently can produce superior results.

We foresee multiple opportunities for future research. Training the model in an unsupervised fashion and fine-tuning it with the labeled data followed by distillation as presented in SimCLRv2 [4] is a very promising method. Training with a contrastive loss [7] has been incremental at times. With the emergence of Visual Transformers, self-supervised Vision Transformers [1] could also be explored for this task.

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