Meta-Learning for Instance Segmentation on Satellite Imagery

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***Abstract*—In the last decade, remote sensing and geospatial intelligence are areas in which computer vision and deep neural network(DNN) algorithms are becoming very prominent in applications. Some powerful applications of analyzing satellite imagery with deep learning include weather forecasting, disaster relief [5] and cartography.**

Despite the early success, applying deep learning and computer vision algorithms in these domains require currently very large volumes of data to detect objects and classify features robustly. There are also many challenges for machines to adapt to features across different geographic areas. In addition some deep learning tasks, such as instance segmentation, require pixel annotations on satellite imagery that is expensive and time consuming. Time consuming data collection and labeling limits the ability for deep learning to be deployed in practice.

The National Geospatial-Intelligence Agency (NGA), a government geospatial intelligence (GEOINT) organization, created a challenge [1] to advance more progress by providing a segmentation dataset for researchers and practitioners to segment circular objects in satellite imagery across different geographic regions. Some examples of these circular features in the satellite imagery dataset included: circular irrigation areas, fuel storage tanks, traffic circles, fountains and more.

Applying semantic segmentation to circular features in satellite imagery is very challenging since circular objects vary by size (3m to 300m in diameter), geographic region, composition (vegetation and steel) and settings (circular irrigation areas, buildings, agriculture, fountains, etc.). Circular features might not be perfectly circular - limited sensor resolution can result in some portions of circular features being jagged, edges that are otherwise part of a circular or disrupted by cross-cutting objects at greater height and other anomalies.

Inspired by the NGA challenge and the current drawbacks of applying deep learning in remote sensing applications, our project focuses on exploring few-shot based systems for instance segmentation to detect circular objects on satellite images. Our project is important because very little work has been done in the area of few-shot satellite image segmentation and our solution could reduce the requirement of large volumes of data and allow deep learning segmentation systems to be deployed in real-world constraints.

In this work, first we propose a simple and quick low-shot circular feature detection model using transfer learning from a pretrained off-the-shelf model on the COCO dataset, achieving satisfactory results. Second, we formulate a few-shot circular feature segmentation as a meta-learning problem and develop a MAML UNet algorithm for low/few-shot segmentation.

We ran analyses and experiments to better understand our dataset, validate whether our models can achieve our project goal, and evaluated our few-shot systems under different settings. We started our experiments by analyzing a satellite imagery segmentation dataset provided by the NGA. We processed the data (3903 images in total), created a training set with images in grayscale color format, and the labels converted from geospatial coordinates to binary segmentation masks.

We then conducted data analysis to better understand the geographical distribution imagery. We processed the GPS coordinates and conducted reverse geocoding to extract the geographic region of the data. We noticed that our dataset was sampled from 11 different countries across the world and that the circular structures vary in size and number from region to region significantly. This allowed us to better understand the complexities of our dataset and filter examples (i.e. remove outliers) to prepare our dataset for few-shot learning experiments.

We validated our initial assumption, that we can segment circular structures/features using DNN-based image segmentation techniques, by creating a baseline image segmentation model using the popular UNet architecture using ResNet34 as a backbone feature extractor. We achieved a 0.97 mIoU on training our model on all examples in the dataset and validated our baseline segmentation architecture would be suitable for few-shot system.

To address the challenge of using as few data as possible for our instance segmentation task, we first developed an independent few-shot detection algorithm using transfer learning. Using a pretrained ResNet50 model and initializing and finetuning RetinaNet on a novel class of few labelled satellite images with circular features we created a quick and simple 5-shot detection algorithm, achieving 78.12% accuracy.

We then continued with creating a few-shot semantic segmentation model by adapting our baseline UNet model into a few-shot setting using the MAML framework. We call our model MAML-UNet. We conducted a few-shot segmentation experiment, where our model (under a 2-shot segmentation task setting) achieved a mIoU=0.485 after 200 epochs of training.

We also experimented with how constructing meta-learning datasets in different ways could impact few-shot learning performance. More specifically we wanted to see what was the best method to construct dataset that maximises the knowledge shared between segment circles across all geographic regions. We constructed a Clustered-Split and a Random-Split dataset, in which for the former, the images were sampled based on unsupervised clustering method. Our experiments concluded that few shot segmentation performed better on the Clustered-split dataset across many k-shot settings than when using the Random-split dataset. This will be useful for practioners applying few-shot segmentation on their own datasets.

Lastly we wanted see if our MAML-Unet segmentation model can adapt to unseen geographic regions. We chose a geographic region with the most images and the most diversity in circular features and trained our model in a 3-shot setting (where images were examples in that geographic region only). We then compared our trained model against a baseline model (without MAML) to

see if few-shot learning performance would be higher or lower in segmentation performance. The result was that our MAML-UNet model can adapt to several unseen geographic regions and perform better for regions which their circular features have some shared structure with the initially trained region.

We believe our work in attempting to develop a few shot instance segmentation system, by constructing and experimenting with an independent few shot detection and segmentation system, can enable instance segmentation to adapt to various settings quickly and enhance applications in remote-sensing and geospatial intelligence, without the requirement of large amount of labelled training data.

Software for our implementation and experiments can be found here: https://github.com/gsarm78/MetaSegmentation/

Index Terms—**Meta-learning, few-shot learning, few-shot segmentation**

I. Introduction

Earth Observation (EO) satellites are used by many organisations and agencies for a range of applications and in many diverse fields, ranging from cartography to climate studies and disaster relief. One such organisation is The National Geospatial-Intelligence Agency (NGA) the nation's primary source of geospatial intelligence (GEOINT). The NGA provides GEOINT in support of U.S. national security and defense, as well as disaster relief. GEOINT is the exploitation and analysis of imagery and geospatial information that describes, assesses and visually depicts physical features and geographically referenced activities on the Earth.

Modern deep learning techniques and models have made huge progress in the field of computer vision, in some cases outperforming humans. Many of these techniques are used or can be used for geospatial intelligence. One such use case is the identification of where circles or circular structures in the world are and how big they are.

In a recent challenge [1], NGA is seeking for novel approaches to segmentation of satellite imagery to detect, delineate, and describe circular shaped features. These features come in a variety of sizes (from 3m to 300m) and compositions (from vegetation to steel). Examples include agriculture, circular irrigation areas, fuel storage tanks, buildings, traffic circles and fountains.

What makes this challenging is that circular features might not be perfectly circular - portions might be jagged edges that are otherwise part of a circular or disrupted by cross-cutting objects at greater height. In addition, computer vision algorithms currently require large volumes of data to define a single discrete object. While gaining success, it is still difficult for machines to search geographic areas and accurately segment specific shapes within those areas with limited ground truth labels.

At the same time, these circular features share characteristics in remote sensed imagery no matter where on Earth they are taken. This raises two question a) whether detection and segmentation can be done with few data samples and b) whether segmentation of label-scarce regions could be improved by leveraging the knowledge gained in the model trained in regions with plenty of data.

Recent progress in semi-supervised and few-shot algorithms help alleviate this challenge. One simple method to follow in a situation where training data is scarce while using knowledge gained while solving one problem to aid the solving of another is known in machine learning as *transfer learning* [2].

In several computer vision tasks, transferring knowledge from one task or domain to another by fine-tuning models pre-trained on the related datasets has shown to perform well when the problems are different but related, even with small amount of data. In our case we argue that the diverse nature of circular features in satellite images is a good example of different-but-related tasks. We illustrate this in Fig. 1 using representations of circular features from different countries.

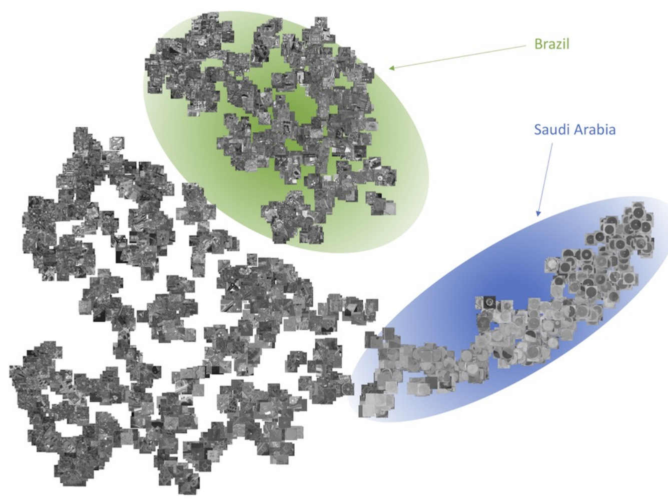

Fig. 1. A t-SNE analysis based on VGG16 features of sample NGA satellite images containing circular structures from different countries. Only a random of 1000 samples are shown in the figure.

Circular structures across the world are distinct from each other e.g in Saudi Arabia circular structures are mainly agricultural farms, while in Kenya are water tanks, yet they share common characteristics. Transfer learning allows models to adapt to each distribution individually and share knowledge across the domains. Thus far, transfer learning on satellite remote sensing data has been focused on fine-tuning pre-trained models from other remote-sensing tasks and performing domain adaptation.

In this work the objective is two-fold. First we propose a simple and quick low-shot circular feature detection model using **transfer learning** from a pretrained (not remote-sensing related) model on the COCO dataset, achieving satisfactory results. Second, the few-shot learning problem can be formulated as a **Meta-Learning** problem in which a model not only learns from data to perform tasks but *learn how to learn* to perform tasks through experiencing tasks on a variety of datasets which share some common structure. We explore the use of **Model Agnostic Meta-Learning (MAML)** [12] for the problem of inductive transfer learning where the generalization is induced by a few labeled examples (few-shot learning) in the target domain. A schematic of MAML is shown in Fig.2.

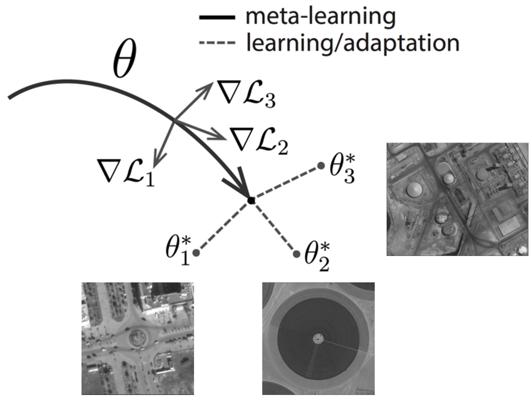

Fig. 2. The MAML algorithm finds initial weights θ from which a model can adapt to a new circular structure and geographic region θ_τ^* with few data samples.

II. Related Work

There is lots of research done in the subdomain of image segmentation in computer vision. The task requires dense pixel-level predictions, given an input image. There are several architectures for image segmentation as mentioned in [3]. Encoder-decoder architectures among others are very commonly used for this task with great performance.

The U-Net is one such architecture and is common and popular for image segmentation. It improves over vanilla encoder-decoder architectures by incorporating skip connections between the encoder and decoder, allowing deep models to be trained. Standard CNN architectures like Resnet [4] are often used as encoders in U-Net based architectures. We use the U-Net architecture and adapt it to the few-shot learning setting for image segmentation.

Meta-learning is beginning to be explored for satellite remote sensing applications. Alajaji and Alhichri in [5] describe the use of MAML on few-shot UC Merced, OPTIMAL-31 and AID RS classification.

Li, H. [9] in RS-MetaNet raises the level of learning from the sample to the task by organizing training in a meta way, and it learns to learn a metric space that can well classify remote sensing scenes from a series of tasks. They propose a new loss function, called Balance Loss, which maximizes the generalization ability of the model to new samples by maximizing the distance between different categories, providing the scenes in different categories with better linear segmentation planes while ensuring model fit. Their experimental results on UCMerced LandUse, NWPU-RESISC45, and Aerial Image Data, demonstrate that their method achieves state-of-the-art results in cases where there are only 1 to 20 labelled samples.

Another recent work by Deng J. et.al [8] deal with the problem of object detection in remote sensing. Since CNN-based methods mostly require a large number of annotated samples to train deep neural networks and tend to have limited generalization abilities for unseen object categories, Deng J. et.al use the YOLOv3 architecture and develop a multi-scale object detection frame- work. Their model contains three main components: a meta feature extractor that learns to extract feature representations from input images, a reweighting module that learn to adaptively assign different weights for each feature representation from the support images, and a bounding box prediction module that carries out object detection on the reweighted feature maps. They experiment on two public benchmark datasets demonstrating that their method for detecting objects from novel classes in 5 to 60-shot setting achieve better performance than vanilla YOLOv3.

The above mentioned work and other work in few-shot learning in computer vision relate to classification and object detection [6]. In [7], Z. Cao et.al propose a generalized meta-learning framework, named Meta- Seg, for image segmentation. It consists of a meta-learner and a base-learner. Specifically, the meta-learner learns a good initialization and a parameter update strategy from a distribution of few-shot semantic segmentation tasks. The base- learner is based on FCN8 architecture and trained on PASCAL5 dataset, achieving satisfactory multi-class segmentation results.

In general, very limited work has been done, at the time of writing this report, with few-shot image segmentation on satellite images and in particular identifying and segmenting circular structures. That makes the work described in this report unique.

III. Methods and Models

This chapter describes the main data pre-processing steps and the neural network architectures used.

A. Dataset

For this work, we evaluate the proposed detection and segmentation methods using the dataset provided by the NGA Circle Finder Marathon Challenge in [1]. The training data set has 3903 satellite images which can be downloaded from the Topcoder.com forum after a simple registration. All the images are in TIFF format and typically have a square-like shape. All these images have their own unique ImageIDs. Each image may have 1 to 1000 individual circles. The circles vary in proximity and size and number. The circles represent circular man-made structures for example fountains, fuel storage tanks, buildings, irrigation areas, agriculture and traffic circles. Each image is associated with four files: a) a panchromatic only bands of the image that has the highest resolution (0.3m), b) a multi-spectral bands of the image, Red, Green, Blue, Yellow, NIR,NIR2, RedEdge, Coastal. For our project, we utilized the panochromatic band image to train our segmentation model.

The annotation files are based on polygon annotations in geo-json format. The GeoJSON format included the coordinate reference system and the geospatial coordinates that define the circle. To load the satellite imagery data and project the geospatial polygon annotations into binary pixel masks, we leveraged the python library rasterio [11].

B. Pre-processing

We processed the dataset to create our training set suitable for binary segmentation. We processed the Panochromatic band imagery to be in grayscale pixel format. We then converted labels from GPS coordinates to binary masks, in which black indicates background and white region indicates the labeled region of the image (in our case circular structure(s)), as shown in Fig. 3 below

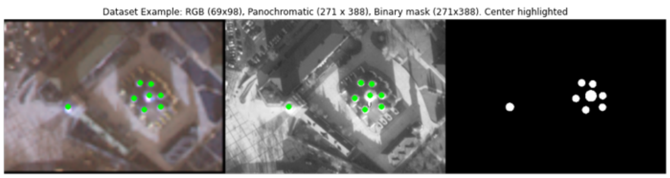

Fig. 3. Sample image after the processing. RGB (left), Panochromatic (center), binary masks (right)

To better understand the geographical distribution of the dataset we plotted the location of the images as parsed by the GeoJSON file associated with each image, as shown in Fig.4:

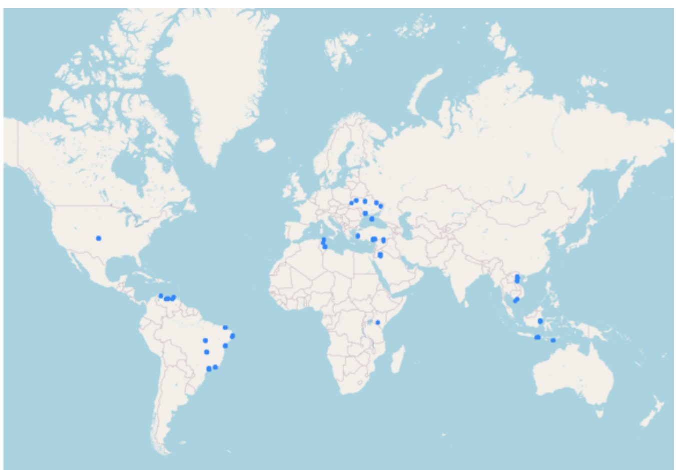

Fig. 4. Geographic distribution of images

From the analysis We notice that our dataset was sampled from 11 different countries and spans worldwide, Fig.5.

Brazil	930 images
Saudi Arabia	673 images
Ukraine	474 images
Venezuela	472 images
Turkey	350 images
Tunisia	310 images
Indonesia	296 images
Viet Nam	192 images
United States	163 images
Kenya	40 images
Syria	3 images

Fig. 5. Distribution of images across 11 countries

Our next steps was to formulate the binary segmentation task in a few-shot segmentation setting, where there are limited number of examples of images and labels that vary across geographic regions. We performed unsupervised clustering on the dataset based on circular composition to develop a few-shot setting on the dataset which is suitable for few-shot segmentations. Our assumption is that circular features have shared characteristics or shared structure among themselves based on their composition, but can slightly vary based on geographic region. For instance, some regions have more agricultural circular structures while other regions have more fountains or water tanks.

To group images by their circular composition (agriculture vs. fountains vs. water tanks etc.) we used a pre-trained VGG16 model to extract 4096 vector embeddings from the images in the dataset. To reduce the embeddeding space we further run Principal Component Analysis (PCA) and reduced the embeddings to two components, as in Fig.6.

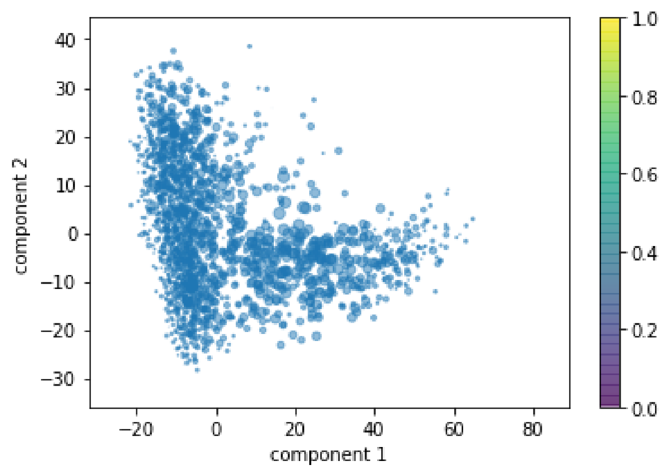

Fig. 6. Dimensionality reduction of the dataset using PCA

C. MAML

MAML (Model Agnostic Meta Learning) aim to find good initial network parameters θ that can efficiently adapt to new problems with a single or small number of stochastic gradient descent steps. The parameters found are not for any specific problem, but instead used to directly optimize the performance of the network when the parameters are fine-tuned via SGD steps on a small amount of training data for a particular problem. In our case, we try to learn initial parameters that allow us to successfully train an image segmentation model when only a few number of images are presented.

Finding these initial parameters can be done as normally with SGD. In the equation below, α is the predefined constant.

$$\theta' = \theta - \alpha.\nabla\mathcal{L}_{train(\mathcal{T})}(\theta)$$

The meta-learner is trained to improve its initialization of learner weights using the query set or test set of training tasks.

$$\theta = \theta - \beta.\nabla\mathcal{L}_{test(\mathcal{T})}(\theta')$$

Here, β is the learning rate for the meta-learner and can be trained using normal optimization algorithms like Adam.

D. Segmentation Architecture

We implemented our baseline and few-shot semantic segmentation model using the UNet segmentation architecture [10]. UNet is an fully convolutional segmentation model consisting of a series of convolutional layers to learn features relevant to segmentation, and a series of decoding layers to output a tensor, where each pixel corresponds to a class probability. We modified the UNet architecture by replacing the convolution layers with Depthwise separable 2D convolution. This enabled our segmentation model to be memory efficient and reduce the amount of GPU memory when training under the expensive MAML framework.

IV. Experiments

Below describes the experiments we conducted in our project. We completed a series of experiments to validate that our baseline segmentation and baseline few-shot segmentation could segment on our dataset. We then experimented with how examples for meta-datasets should be sampled, i.e. a random-split or clustered-split scheme, and assessed how it would impact few-shot segmentation performance. Finally, we conducted an experiment to see whether our few shot segmentation system can adapt to unseen geographic regions.

A. Baseline Segmentation

We conducted our baseline segmentation experiment to validate that our segmentation system was implemented correctly and that our model had enough capacity to segment circular features in our dataset. The goal from this experiment would be to use the baseline model and adapt it to few-shot segmentation (using the MAML framework). We conducted our experiment using our efficient UNet architecture - Fig.7, and did a 90/10 train/validation split on our entire dataset.

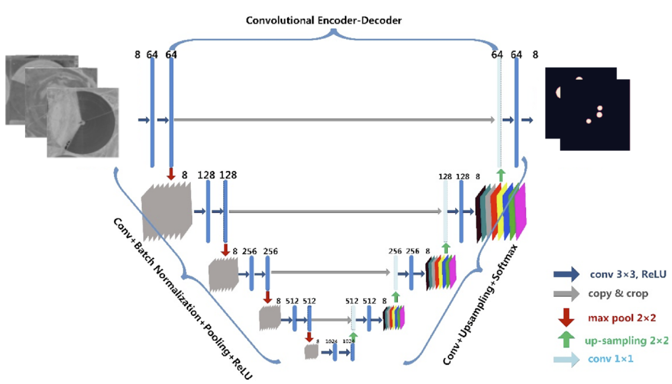

Fig. 7. Baseline UNet architecture

In Figure 8 we present our results. We achieved a 0.97 mIoU after 100 epochs, validating that our baseline architecture was implemented correctly and that our model had the ability to segment circular features on our dataset.

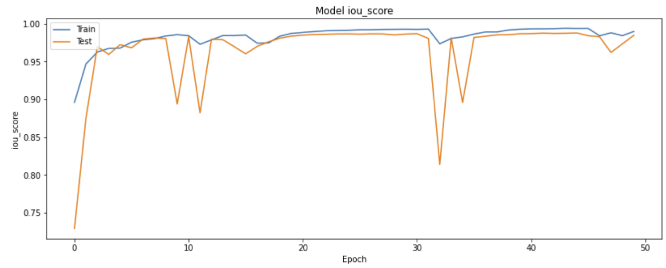

Fig. 8. Baseline UNet mIoU performance on image segmentation

B. Initial Few-Shot Segmentation

We conducted our initial few-shot segmentation experiment to validate if our segmentation system can adapt to few shot segmentation tasks. We adapted our segmentation system by using the baseline model and modifying it to learn using the MAML framework. We limited our MAML segmentation system to only have 1 inner gradient update, and set the inner update learn rate to 0.4, and meta-batch train size to 4.

In our experiment, we defined our few shot segmentation to a 2-shot segmentation task, where the image had two examples in the support set to segment 2 images in the query set. We also developed a few-shot dataloader to sample k-shot=2 examples using a random-split scheme. See Figure 9 for results. We can see that our model learns to conduct few-shot segmentation after 200 epochs, achieving a mIoU of 0.485.

We will also show qualitative results of our few shot segmentation system. The qualitative results were a result of training our MAML Unet, using a random split scheme and over 200 epochs, in a k-shot=4 setting. See Figure 10 for results. Here we see our few shot model able to segment the general area where the circular feature appear after running MAML over 200 epochs, compared to the baseline segmentation model that was not able to segment the area where the circular feature appear.

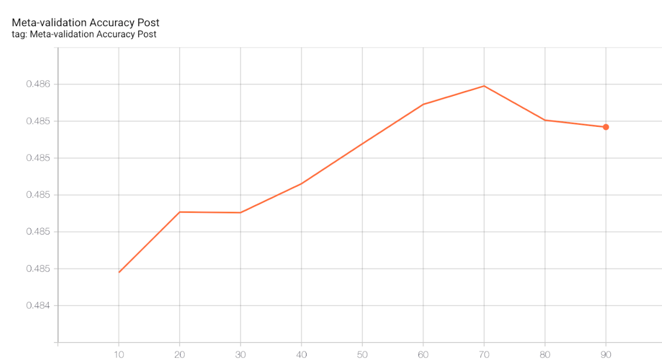

Fig. 9. Few Shot Segmentation experiment

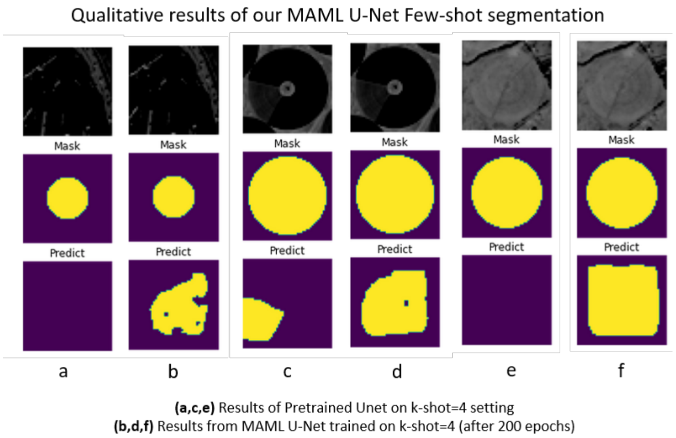

Fig. 10. Qualitative Results of Few Shot Segmentation (K-shot=4 setting)

C. Few-Shot Detection using Transfer Learning

One of our initial assumptions was whether using off-the-shelf pre-trained models on non-related datasets (not satellite images or remote-sensing data) could provide a simple, fast and satisfactory result in identifying the circular structures in the satellite images. We therefore created a few-shot object detection model using transfer learning, which aims to detect circular objects from very few training samples, in particular less than 5 examples. Initially we use the checkpoint of a pretrained ResNet50 model on the COCO dataset. COCO dataset is very different from the satellite images dataset of this work and very little shared structure exists, if at all.

Then we choose five random satellite images from our dataset with their respective annotation. The annotation in the case of this experiment done interactively within Google Colab, using its annotation functionality. We then added these annotations of the five examples, as a novel class. It is important to notice that the COCO dataset, which predicts 90 class slots by default, does not contain any class related to ”circular” features, so the circular structure will be one novel class that the model will have to predict. Also in our case the classes are set to one, by overriding the 90 classes of the COCO architecture, since there is only one class to detect, the Circular features.

Then we build a single stage detection architecture, using the RetinaNet architecture. RetinaNet has two prediction ”heads”, one for classification and the other for ”box regression”. We restored the ”box regression” head and initialised the ”classification” head from scratch. As already mentioned we used a 5-shot setting, with a small number of batchsize=4 since our training set has 5 images only. We set the batch size = 4, learning rate = 0.01 and used 100 batches for 50 iterations.

We achieved a 78.12% accuracy which is very close to the current SoTA of Few-Shot Object Detection and the predictions based on the 5-shot setting are shown in Fig.11

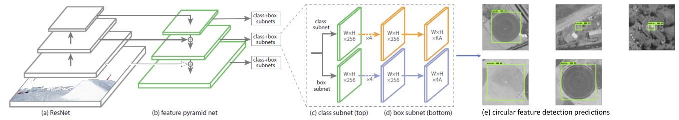

Fig. 11. Transfer-Learning based Few Shot Object Detection experiment

The experiment validates our assumption that transfer learning can give satisfactory results on new domains which are not related. That can have a direct application in image segmentation via reusing the existing off-the-self pretrained models and finetuning them on new detection or segmentation tasks related to remote sensing.

D. Experiment on Meta-dataset construction

We experimented with dataset construction to see how MAML UNet would perform based on how examples were sampled. This is an important consideration because we want to explore how to maximize the knowledge shared to segment circles across all geographic regions. We experimented if meta-learning dataset was constructed would effect performance from a random split scheme, or a clustered split scheme. In the random split scheme, examples were assigned randomly to meta-training, meta-val, and meta-test. In the clustered split setting, images were sampled based on their cluster assignment, where the cluster assignment was derived from running the k-Means algorithm on embeddings extracted from a pretrained VGG-16 model (pretrained from the ImageNet dataset). The cluster ids were then randomly assigned to the meta-train, meta-val, and meta-test. The results of this experiment are shown in Fig.12 in MAML. Our few-shot segmentation model resulted in higher performance across many k-shot settings than in comparison to few shot segmentation using the random assignment.

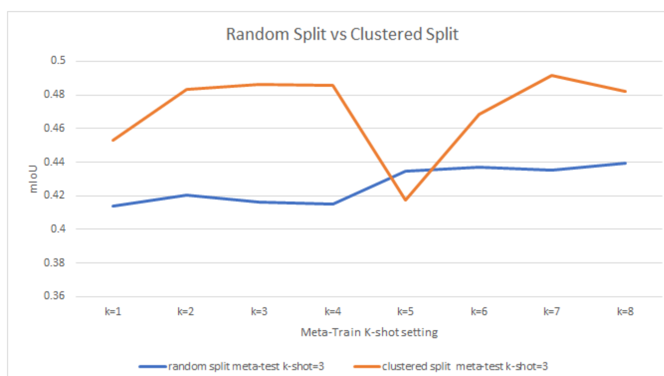

Fig. 12. Random Split vs Clustered Split for Few Shot segmentation

E. Experiment Few Shot Segmentation adapt to unseen regions

We completed an experiment to see if our few-shot segmentation model can adapt to unseen geographic regions. We conducted this experiment by geographic regions suitable to train our few shot segmentation model. We identified the geographic region with the largest number of examples and the most diversity in circular features the best region to train our system. We determined that images from Brazil met this criteria, as it had the most examples and varied in examples with different compositions (circular features from buildings, agricultural circles, etc.).

We then trained our model for 200 epochs from examples in the Brazil region, in a k-shot=3 setting, and then evaluated our model on meta-test k-shot=3 setting, where each meta-test dataset comprised of examples from different geographic regions. We compared the Meta-test accuracies in two settings, where one model was fine-tuned from the Brazil region, and the second model was a baseline few shot segmentation model. We created the few-shot baseline segmentation model where trained using vanilla SGD (and without using the MAML algorithm), and it was trained in the same few shot setting k-shot=3 as the finetuned model.

Fig 13. shows results of this experiment. Here we see that our segmentation model can adapt to several unseen geographic regions. Here we see that our model can adapt to unseen examples from Saudia Arabia and Venezuela, as the mIOU is higher for the model fine-tuned on the Brazil region compared to the baseline few shot segmentation model. We see that for other regions, our model fine-tuned on the Brazil region performed worse at the other unseen regions than the baseline model. We think this occurred because the other geographic regions contained examples that was not seen in the Brazil region.

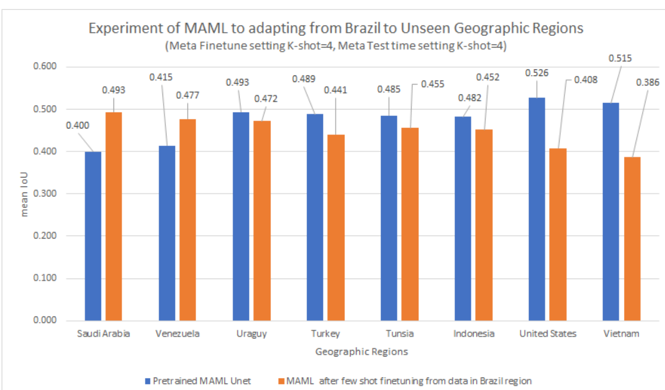

Fig. 13. Few Shot Segmentation adapting to Unseen Regions

V. Results and Discussion

In our project, we successfully applied key components of instance segmentation, namely object detection and segmentation, to work in a few shot setting. We experimented and saw that few-shot object detection on circular satellite features can be achieved with simple transfer learning. We also experimented and validated that the MAML algorithm can be applied successfully to segment circular features in satellite imagery. We also saw that few shot segmentation can adapt to unseen geographic regions.

A. Discussion and Future work

We discovered a lot of limitations with applying the MAML framework to a few shot segmentation task. We discovered that MAML consumes a lot of GPU memory as number of epoch increases. This is probably due to a limitation in the Tensorflow's GradientTape implementation, where GPU memory of temporary variables are not disposed, once temporary models are copied and used. Figure 14 shows how GPU utilization increases over the time period of one experiment. This limits the ability for MAML based few shot segmentation being applied in real world applications. Here we see that 70% GPU utilization is reached after 1 hour of training. We were

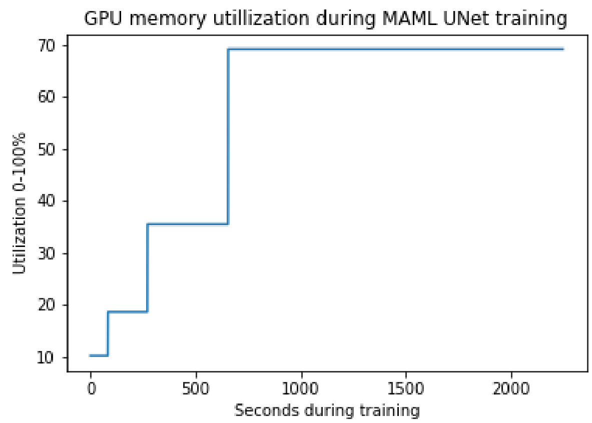

Fig. 14. GPU utilization over 1 experiment (2000 seconds = 100 epochs)

able to overcame this challenge by deploying many strategies. Our strategies to reduce GPU footprint included: reducing the batch size to be between 4-8 during trainig, reducing the number of parameters in our UNet segmentation system by using depthwise separable convolution layers rather than traditional convolution layers. We also reduced the image size of our dataset from 224x224 pixels to 48x48 to additionally reduce the number of parameters and GPU memory used over experiments. Unfortunately, applying the MAML framework to models, such as segmentation, limits the amount of epochs you can train using full size images. Reducing the image size made the GPU footprint small enough to train longer and train long enough to see improvements in mIoU.

Future directions to overcome these limitations, and apply MAML to real world segmentation settings, would be using iMAML [13] as the meta-learning framework for few shot segmentation. Using iMAML could significantly reduce the GPU memory usage, and allow researchers to do few shot segmentation on full size images.

We also include future work to experiment with Prototypical Networks [14] to implement few-shot detection and segmentation. We attempted developing few-shot segmentation using Protonets, but had challenges with adapting the network to a segmentation task. We recommend additional future work to experiment training object detection and segmentation in end-to-end manner.

VI. CONTRIBUTIONS

Andrew Mendez: Contributed to the Project Proposal, Milestone report, Final Presentation, and Final Report. Developed the Few-shot segmentation model using the MAML framework, completed the Few Shot Segmentation experiment, completed the Experiment on Meta-dataset construction, and completed the Experiment Few Shot Segmentation adapt to unseen regions.

George Sarmonikas: Contributed to the Project Proposal, Milestone Report, Final Presentation, Final Report, Developed Unsupervised clustering and t-SNE on dataset, developed Few-shot Object Detection Experiment using Transfer Learning, developed the Baseline UNet segmentation model, run experiments with 2-shot segmentation on MAML-Unet, and started experimenting on few-shot segmentation using ProtoNets.

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