Electrical Substation Extraction from Images using Machine Learning

Aarsh Chaube
dept. of Computer Science Engineering
SRM Institute of Science and Technology
Kattankulathur, India
ac5973@srmist.edu.in

Ved Dubey
dept. of Computer Science Engineering
SRM Institute of Science and Technology
Kattankulathur, India
vd8413@srmist.edu.in

Naman Garg
dept. of Computer Science Engineering
SRM Institute of Science and Technology
Kattankulathur, India
ng7739@srmist.edu.in

Soumya Snigdha Kundu
dept. of Computer Science Engineering
SRM Institute of Science and Technology
Kattankulathur, India
sk7610@srmist.edu.in

***Abstract*—This paper presents a solution of our approach for the Virtual Competition in association with RRSC-Central, NRSC, ISRO, Nagpur on 'Machine learning based feature extraction of Electrical Substations from Satellite data using Open-Source tools'. The primary goal of the challenge is to develop a machine learning-based software using open source tools to extract electrical substations from high resolution satellite data. Our approach comprises of utilising a variant of U-Net++ and a special data augmentation pipeline specifically adhering to segmentation pipelines. Our solution placed third out of all the entries with the accuracy being comparable to the first two places.**

***Index Terms*—Machine Learning, satellite imagery, segmentation**

I. Introduction

Satellite imagery is readily available to humanitarian organizations, but translating images into maps is an intensive effort. Maps are produced by specialized organizations or in volunteer events such as mapathons, where imagery is annotated with roads, buildings, farms, rivers etc. In the case of electrical substations, there needs to be specialised settings to collect such data which has made the field quite new with very few prior approaches. The combination of availability of recent datasets and advances in computer vision made through machine learning paved the way toward automated satellite image translation [1]. Although there are existing methods which tackle a myriad of satellite vision problems, feature extraction of the power infrastructure is a new challenge since much attempts have not been done in this domain.

In this paper, we describe and analyze the above mentioned challenges for a specific satellite imagery dataset from a IEEE-ICETCI 2021 competition [2] (Sample segmentation seen in fig 1). We explore the challenges faced due to the small size of the dataset, the specific character of data, and supervised machine learning algorithms that are suitable for this kind of problems.

We thank DS Community SRM for gathering the team.

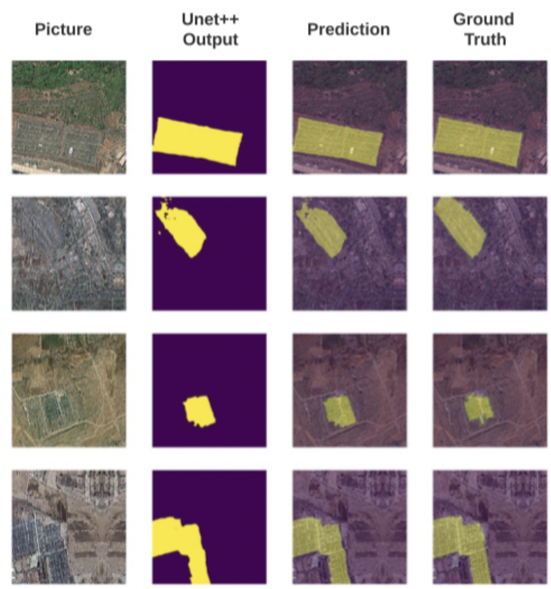

Fig. 1. Sample testing results from validation set.

The major boundary which had to be overcome was the lack of prior approaches to the data. Our contributions are as followed:

- This paper proposes Unet++ [3] segmentation module combined with a custom Dice loss variant to produce accurate segmentation masks for electrical substation extraction.
- The custom loss function helps prevent the complex Unet++ model from overfitting on the small dataset.
- We implement a custom data augmentation pipeline consisting of GridDistortion and CropNonEmptyMaskIfExists functions to extend the dataset and overcome the class imbalance problem.

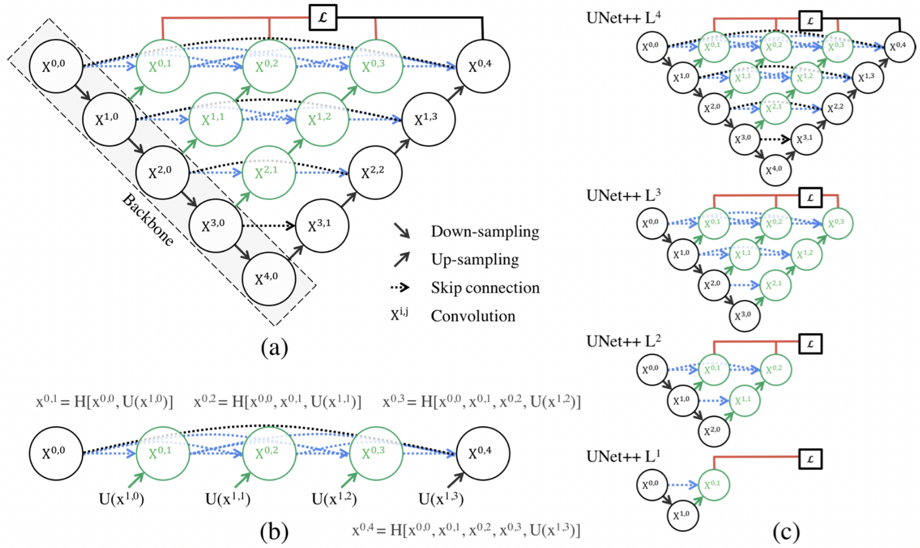

Fig. 2. Depiction of the UNet++ module utilised for the substation extraction.

II. Related Work

A. Machine Learning approaches to Satellite Imagery

While there has minimal work on electrical substation extraction, urban surroundings have been examined using other types of imagery information that have become available in recent times. F. Hu et al [4] has presented a resnet [5] model to perform multi-label classification of Amazon satellite images. This approach identifies the weather conditions and natural terrain features in the images as well as man-made developments.

B. UNet++ Module

UNet++ [3] consists of an encoder and decoder that are connected through a series of nested dense convolutional blocks. The main idea behind UNet++ is to bridge the semantic gap between the feature maps of the encoder and decoder prior to fusion. In fig 2., black indicates the original U-Net, green and blue show dense convolution blocks on the skip pathways, and red indicates deep supervision. Red, green, and blue components distinguish UNet++ from U-Net. The underlying hypothesis behind our architecture is that the model can more effectively capture fine-grained details of the foreground objects when high-resolution feature maps from the encoder network are gradually enriched prior to fusion with the corresponding semantically rich feature maps from the decoder network.

III. Materials and Methods

A. Data Augmentation

Along with the usual flipping and rotating of images, the segmentated data was also shown to $GridDistortion$ (varying magnification and radial appearance) and $CropNonEmptyMaskIfExists$ methods to overcome imbalance of classes.

IV. Experimentation and Results

We experimented with various encoder modules such as Resnet50, VGG11 and VGG16 but achieved the best results with Resnet50 owning to the residual connections present in the network and the batch normalisation layers preventing overfitting of the model. Sample test outputs are seen in fig 3. The experimentation also extended with other architectures and loss functions such as TernausNet 16 with Jaccard loss, UNet with ResNet50 and jaccard (IoU) loss and deeplabV3+. All the models saturated and prevented from gaining higher efficiency results.

The primary metrics used to decide the results in the competition is IOU (Intersection over Union). We achieved an IOU of 0.842381 which ranks third in the competition. As we have demonstrated that we can get good results using just the RGB channels, extending the same approach to a multi channel signal provides us with better results.

References

[1] S. P. Mohanty, J. Czakon, K. A. Kaczmarek, A. Pyskir, P. Tarasiewicz, S. Kunwar, J. Rohrbach, D. Luo, M. Prasad, S. Fleer *et al.*, "Deep learning for understanding satellite imagery: An experimental survey," *Frontiers in Artificial Intelligence*, vol. 3, 2020.

[2] "http://ietcint.com/user/electrical_substation_detection."

[3] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "Unet++: Redesigning skip connections to exploit multiscale features in image segmentation," *IEEE transactions on medical imaging*, vol. 39, no. 6, pp. 1856–1867, 2019.

[4] B. Zhou, A. Lapedriza, J. Xiao, A. Torralba, and A. Oliva, "Learning deep features for scene recognition using places database," 2014.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

Fig. 3. Example of segmented maps from the competition test data

Appendix

Calculation of IOU Value on Pytorch

```
def IoU(pred , true_pred , smooth =1e-10 , n_classes=2):
  with torch.no_grad():
    pred = torch.argmax(F.softmax(pred , dim =1) , dim=1)
    pred = pred.contiguous().view(-1)
    true_pred = true_pred.contiguous().view(-1)

    iou_class = []
    for value in range(0, n_classes):
      true_class = pred == value
      true_label = true_pred == value

      if true_label.long().sum().item()==0:
        iou_class.append(np.nan)

      else:

        inter = torch.logical_and(true_class)
```