SEMANTIC SEGMENTATION OF DEFORESTATION ON SATELLITE IMAGES IN THE KHARKIV REGION

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Deforestation is a crucial problem nowadays. It can cause climate change, soil erosion, flooding, and increase greenhouse gases in the atmosphere. And such activity as illegal forest logging is one of the main reasons for deforestation. The process of finding these clearcuts consists of downloading images from satellite, preprocessing the bands, image analysis and labeling by a person. So there is a lot of manual routine work that can be automated using Deep Learning.

To solve this problem there has been a solution developed that automatically downloads new images from the satellite storage, preprocesses and prepares data for clearcuts segmentation. Then a deep learning model converts images to binary masks of clearcuts and polygonizes them to vector objects that can be displayed on the map. End users are then able to check each detected clearcut and get statistical information about area changes over time. The service consists of Image processing, Web application back- and frontend. As mentioned before, the process of finding clearcuts is a computer vision task. Each clearcut has its own shape and area. So the goal is not only to find the position of a clearcut (object detection) but also determine which pixels belong to it (semantic segmentation).

The Dice score was used as a algorithm performance metric.The Dice score or F score is very similar to IoU but is not as strict. Similarly to how L2 can penalize the largest mistakes more than L1, the IoU metric tends to have a "squaring" effect on the errors relative to the F score. While the F score measures an average performance, the IoU score measures something closer to the worst-case performance. So in our case, it is a more appropriate metric:

$$dice = \frac{2 \cdot TP}{2 \cdot TP + FP + FN}$$

Fig 1.1 - Dice score formula

The first thing we have to do is to download raw images from the satellite. In our case, we are working with Sentinel-2 and L2A products. L2A data is atmospherically corrected, with filtered reflectances, so you get a clearer image without additional noise. For downloading you can use ScihubCopernicusAPI. After downloading you have to prepare the data before putting it into your model. In the downloaded archive, you have a number of different bands, so we have to filter them. Then create NDVIchannel from B4 and B8 bands, scale all bands, convert it into 8-bit images (values of pixel 0-255) and merge them all into a single image. TIFF format is perfectly suitable for storing satellite images. The original size of the downloaded images with resolution 10 meters per pixel is approximately 10K*10K. We can't work with such big images, so the next step is to cut the whole image onto the small pieces with size 224*224. As the segmentation models, ResNets architectures was used, wrapped into the U-Net and FPN models. We used different ResNet options (ResNet-50 and ResNet-101), with different initial learning rates and optimizers.

As a conclusion , that there is *almost* no dependency of the dice score on the season (for all of the models) and the area of deforestation (except the largest regions, which were almost ideally segmented with our models). But the models in use (U-Net and FPN) show a little disagreement in the seasonal segmentation quality; these models could be used in an ensemble, to take the seasonal errors of each other into account. To analyze the reason for false segmentation better, we need also to include image analysis (distribution of NDVI for false segmentation, etc.).

References

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