Flood Level Estimation from Social Media Images

P. Chaudhary[1], S.D' Aronco[1], M. Moy de Vitry[2], J. P. Leitao [2], J. D. Wegner[1]
[1]**Photogrammetry and Remote Sensing, ETH Zurich;** [2]Eawag - Swiss Federal Institute of Aquatic Science and Technology;

1 Introduction

Due to global climate change, flood events are predicted to become more frequent and damaging[5,6]. Classical monitoring systems include stream gauge, remote sensing, and field data collection. These methods, however, reveal several limitations. On field data collection is instead usually expensive and dangerous as it requires to inspect the disaster area. A viable alternative source of information in this case comes from social media platforms. With this work, we aim at filling this gap, by proposing a deep learning framework to predict flood height.

2 Method overview

- We use Mask R-CNN[1] as base architecture which is a state-of-the-art solution for instance segmentation. The backbone of the architecture works as the main feature extractor. The lower layers detect low-level features like blobs, edges. As we move to higher layers, they start detecting full objects like cars, people, buses.
- The Region proposal network (RPN) is a neural network which scans over the image and gives scores based on whether there is an object or not in the scanned regions.
- The output from last stage are a set of Regions of Interest (RoIs) which are fed to the next stage for proposal classification. The proposal classification generates overall three outputs for each RoI: class, bounding box, flood level.

$$\mathcal{L} = \mathcal{L}_{\text{class}} + \mathcal{L}_{\text{bbox}} + \mathcal{L}_{\text{level}} + \mathcal{L}_{\text{mask}}$$

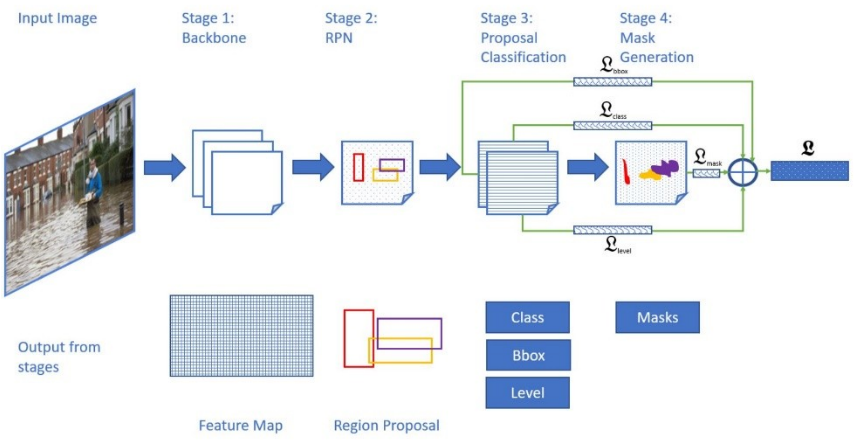
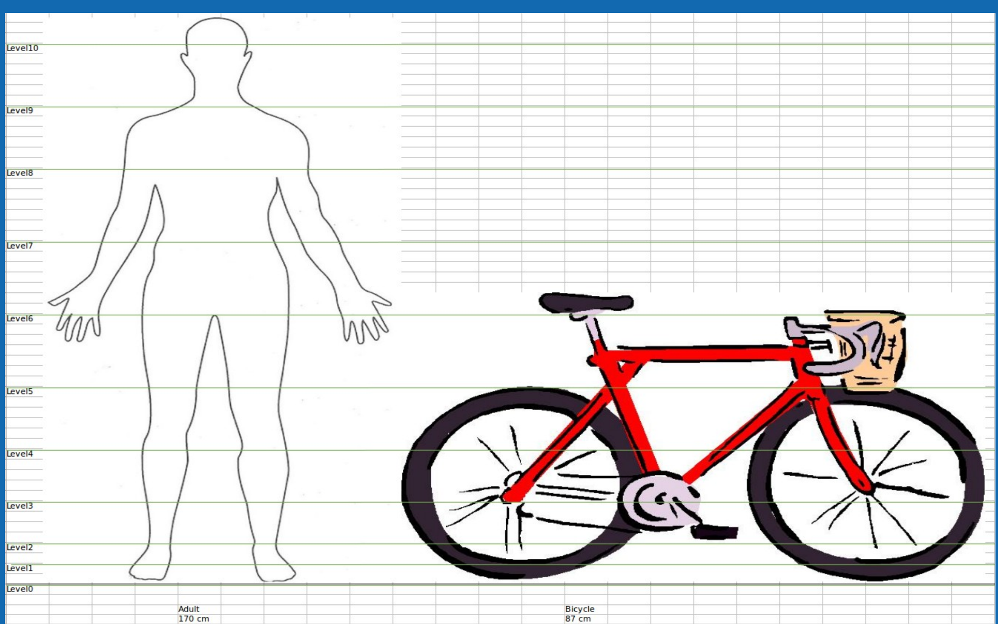


Figure. 1. Shows the overall architecture of our approach and respective output from each stages

3 Annotation Strategy



4 Experiments and Results

- **Experiment 1**: In this experiment, from each image's prediction and ground-truth level values, we remove the False Positive(FP) and False Negative(FN) cases.
- **Experiment 2**: For Experiment 2, we repeat the same steps as Experiment 1, but in this case we keep the FP and FN cases.
- **Experiment 3**: In the third experiment also, we do not remove any entries from prediction or ground-truth level values, but for every class prediction entry which has no match in ground-truth, i.e., FP case, we try to find a reference for level prediction.

		Exp 1	Exp 2	Exp 3
Error(cm) in standard model		7.32	9.47	9.47
Error(cm) in 5-fold cross validation(CV)	fold1	8.80	9.76	8.79
	fold2	7.25	7.40	6.82
	fold3	6.88	7.86	8.29
	fold4	7.91	9.60	8.70
	fold5	8.32	8.16	7.76
Mean error(cm) in 5-fold cross validation		**7.83**	**8.56**	**8.07**

Figure. 2. Summary of experiments

Figure. 3. Shows qualitative evaluation of test image

5 Conclusion

In this paper, we have presented a model to predict flood-water level from images gathered from social media platforms in a fully automated way.

- The prediction is done using a deep learning framework which is built on top of the Mask R-CNN architecture.
- We further provide a method to combine the multiple object instances level predictions and obtain a single water level prediction for the entire image.
- The conducted experiments proved the ability of the trained model to effectively predict water level from images within an acceptable error.

6 References

1. He, Kaiming et al. "Mask R-CNN." 2017 IEEE International Conference on Computer Vision (ICCV) (2017): 2980-2988.
2. He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep residual learning for image recognition. arXiv preprint arXiv:1512.03385.
3. Lin, T., Maire, M., Belongie, S. J., Bourdev, L. D., Girshick, R. B., Hays, J., Perona, P., Ramanan, D., Doll´ar, P. and Zitnick, C. L., 2014. Microsoft COCO: common objects in context. CoRR.
4. Hirabayashi, Y., Roobavannan, M., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H. and Kanae, S., 2013. Global flood risk under climate change. 3, pp. 816–821.
5. Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L. and Storlazzi, C. D., 2017. Doubling of coastal flooding frequency within decades due to sea-level rise. Scientific reports 7(1), pp. 1399.