Mapping Floodwater from Radar Imagery

Tashin Ahmed

August 3, 2022

Mapping Floodwater from Radar Imagery

Tashin Ahmed
AriSaf Tech
Yokohama, Kanagawa, Japan
tashin@arisaftech.co.jp

Abstract

Flooding is aggravating every year as global warming exacerbating causing sea level rising. Recent flood in Bangladesh in 2022 broke all previous records of flooding in that area. Simultaneously, it submerged areas that have seen no flood in the last 100 years. As the situation is getting much worse year to year and sudden flooding occurring regularly throughout the world, it is becoming a necessity to forecast flood warning so that casualties can be lessened.Sentinel-1 mission has been launched to collect earths surface data and Microsoft's new Planetary Computer made the data available for researchers. This short paper is based on the outcomes of a competition - "STAC Overflow: Map Floodwater from Radar Imagery", hosted by DrivenData and Microsoft AI for Earth, where the goal was to detect flood coverage areas in near real-time. Here, participants generated predictions as single-band 512×512 pixel images whether there is water or no water in every pixel. Jaccard index has been used as the performance metric and top performing models have achieved over 0.80.

Introduction

Image segmentation with AI based system is widely used in medical image analysis nowadays, but it is also producing compelling outcome in satellite image analysis thus, floodwater detection can be an important application. Here, we have demonstrated the dataset from Sentinel-1 [10] via Microsoft Planetary Computer and discussed the top outcomes produced by the top three teams.

Almost all top performers have used UNet [7] as their primary segmentation model. Turning point for the winners is basically the adjustments they have included with the UNet model that we will discuss in the upcoming section.

Dataset

Feature of the dataset are radar images consisting one image per band and two bands per chip. Images are 512×512 in size and file format is GeoTIFF [4] for every data. Every pixel of images shows energy reflected to the satellite measure in decibels (db). Pixel values could be negative, positive and zero, where zero marks missing data.

Sentinel-1 can transmit and receive a signal in both horizontal and vertical polarizations. Data for this challenge consists of 2 microwave frequency readings, (1) VV (vertical transmit and vertical receive) and VH (vertical transmit and horizontal receive) [3].

For each chip, participants had to use one or both bands to detect floodwater. Missing data from the images had been excluded during scoring.

Train set comprises 542 chips (1084 images) of 13 flood incidents. Every chip corresponds with a single chip indicating pixels containing water where '1' indicates presence of water, '0' indicates absence and '255' indicates missing data.

Methodologies

The baseline solution that the host has initially provided was created using UNet decoder and ResNet-34 [2] as encoder. That means in this case, the initial encoder of UNet has been switched to ResNet-34. It achieved an IoU [6] of 0.44.

Evaluation Metric

Evaluation metric for this competition was Jaccard index, also known as Generalized Intersection over Union (IoU) [6]. This evaluation metric is a similarity measure between two sets of label. Here, it is the size of the interaction divided by the size of the union of non-missing pixels. Through this, we can exclude predictions on missing data.

Applied Strategies

Top leaderboard position holders used a combination of UNet and UNet++ [12], Convolutional Neural Networks (CNN) [5] and gradient boosted decision trees [8]. Also, they have experimented with different sampling strategies, adversarial training schemes and image augmentation techniques to handle label imbalances and to enhance the train dataset.

Evaluation and Results

Winning model of the competition was a UNet model where EfficientNet-B0 [9] was used as the backbone (encoder). Pixel by pixel classification by translating images into tables has been performed next. Both techniques did not fill in the flooding rather than predict the excess. So, winning participants combined the two outcome from two approaches rather than taking the averages. They utilized Nasadem band [1] along with polarization band. Winning solution achieved IoU of 0.8094.

Second position on the leaderboard performed different augmentation techniques like random rotations, vertical and horizontal flips. The approach was created by splitting IDs into a train and a test set. Three different splits allowed to train three different models. This participant used Dice Loss square (Dice loss [11] with denominator squared) as the loss function. This approach secured IoU of 0.8072 on the private leaderboard.

Third position approach was a kind of unique one as the participant focused on generalizable ensemble instead of cross validations. This strategy scored 0.8036 on the private leaderboard.

Conclusion

This short paper discussed the competition outcome from an online AI competition [1]. Top participants have tried different techniques to find an optimal solution. Top solutions and neccessary documents can be found from DrivenData GitHub [2] repository.

References

[1] Crippen, R.; Buckley, S.; Belz, E.; Gurrola, E.; Hensley, S.; Kobrick, M.; Lavalle, M.; Martin, J.; Neumann, M.; Nguyen, Q.; et al. 2016. NASADEM global elevation model: Methods and progress.

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

[3] Jensen, J. R. 2009. *Remote sensing of the environment: An earth resource perspective 2/e*. Pearson Education India.

[4] Mahammad, S. S.; and Ramakrishnan, R. 2003. GeoTIFF-A standard image file format for GIS applications. *Map India*, 28–31.

[5] O'Shea, K.; and Nash, R. 2015. An introduction to convolutional neural networks. *arXiv preprint arXiv:1511.08458*.

[6] Rezatofighi, H.; Tsoi, N.; Gwak, J.; Sadeghian, A.; Reid, I.; and Savarese, S. 2019. Generalized intersection over union: A metric and a loss for bounding box regression. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 658–666.

[7] Ronneberger, O.; Fischer, P.; and Brox, T. 2015. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, 234–241. Springer.

[8] Saberian, M.; Delgado, P.; and Raimond, Y. 2019. Gradient boosted decision tree neural network. *arXiv preprint arXiv:1910.09340*.

[9] Tan, M.; and Le, Q. 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. In *International conference on machine learning*, 6105–6114. PMLR.

[10] Torres, R.; Snoeij, P.; Geudtner, D.; Bibby, D.; Davidson, M.; Attema, E.; Potin, P.; Rommen, B.; Floury, N.; Brown, M.; et al. 2012. GMES Sentinel-1 mission. *Remote sensing of environment*, 120: 9–24.

[11] Wang, L.; Wang, C.; Sun, Z.; and Chen, S. 2020. An improved dice loss for pneumothorax segmentation by mining the information of negative areas. *IEEE Access*, 8: 167939–167949.

[12] Zhou, Z.; Rahman Siddiquee, M. M.; Tajbakhsh, N.; and Liang, J. 2018. Unet++: A nested u-net architecture for medical image segmentation. In *Deep learning in medical image analysis and multimodal learning for clinical decision support*, 3–11. Springer.

[1] https://www.drivendata.org/competitions/81/detect-flood-water/

[2] https://github.com/drivendataorg/stac-overflow/