Mapping Floodwater from Radar Imagery

Tashin Ahmed

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

Abstract

Every year, flooding gets worse as a result of the sea level rise brought on by exacerbated global warming. All previous records for flooding in that region were broken by the recent floods in Bangladesh in 2022. At the same time, it flooded areas that had not experienced flooding in the previous 100 years. Forecasting flood warnings is becoming essential in order to reduce casualties since the situation worsens year after year and abrupt flooding occurs frequently all over the world. Microsoft's new Planetary Computer has made the data from the Sentinel-1 mission, which was deployed to collect data on the surface of the globe, available to researchers. This brief document is based on the results of a competition called "STAC Overflow: Map Floodwater from Radar Imagery," which was sponsored by DrivenData and Microsoft AI for Earth and aimed to identify flood coverage areas in almost real-time. Here, participants predicted whether or not there is water in every single pixel using single-band 512×512 photos. Top performing models have achieved over 0.80 on the Jaccard index, which has been utilized as a performance criterion.

Introduction

Floodwater detection could be a key application because image segmentation with AI-based systems is now often utilized in medical image analysis and also produces impressive results in satellite image analysis. Here, we have used Microsoft Planetary Computer to demonstrate the dataset from Sentinel-1 [10] and discussed the top results obtained by the top three teams.

As their main segmentation model, nearly all top performers have utilized UNet [7]. The UNet model adjustments that the winners have made, which we will discuss in the next section, are essentially the turning point for them.

Dataset

Radar images with one image per band and two bands per chip are a key component of the dataset. Images are 512×512 pixels in size, and each piece of data contains a GeoTIFF file [4]. Every image pixel displays energy that was reflected to the satellite and is expressed in decibels (db). There are three possible pixel values: negative, positive, and zero, where 0 denotes missing data.

Both horizontal and vertical polarizations of a signal can be transmitted and received by Sentinel-1. Two microwave frequency readings—VV (vertical transmit and receive) and VH—make up the data for this task (vertical transmit and horizontal receive) [3].

Participants had to use one or both bands for each chip to find floodwater. Missing information from the photos was disregarded while scoring.

542 chips (1084 photos) from 13 flood occurrences make up the train set. The number "1" denotes the presence of water, "0" denotes its absence, and "255" denotes missing data. Each chip corresponds to a single chip that signals pixels containing water.

Methodologies

The ResNet-34 [2] encoder and UNet decoder were used to produce the baseline solution that the host initially offered. That indicates that ResNet-34 has been used in place of UNet's original encoder in this instance. It obtained an IoU [6] of 0.44.

Evaluation Metric

The Jaccard index, also known as Generalized Intersection over Union (IoU) [6], served as the competition's evaluation metric. This assessment metric compares the similarity of two collections of labels. Here, the interaction size is calculated by dividing it by the total size of the non-missing pixels. This allows us to rule out predictions based on missing data.

Applied Strategies

Top leaderboard position holders combined UNet and UNet++, Convolutional Neural Networks (CNN), and gradient-boosted decision trees [12, 5, 8]. In order to deal with label imbalances and improve the train dataset, they have also experimented with various sampling strategies, adversarial training schemes, and picture augmentation techniques.

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.

The person in second place on the leaderboard used several augmentation methods, such as random rotations and vertical and horizontal flips. By separating IDs into a train and a test set, the technique was developed. It was possible to train three separate models using three different splits. Dice Loss Square (Dice Loss [11] with denominator squared) was used by this participant as the loss function. IoU of 0.8072 was obtained using this strategy on the private leaderboard.

The participant's third-place strategy was somewhat distinctive because it focused more emphasis on generalizable ensemble than cross validations. On the private leaderboard, this approach received a score of 0.8036.

Conclusion

This short essay covered the results of an online AI competition[1]. Top competitors have experimented with many methods in search of the best result. Readers can get the best result and necessary documents in the DrivenData GitHub[2] repository.

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

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