DEEP LEARNING APPROACHES FOR FLOOD DETECTION

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Abstract

To effectively mitigate flood damage, satellite imagery proves invaluable for assessing affected areas due to its extensive coverage capabilities. Unlike optical satellite images, which may be hindered by adverse weather conditions such as heavy rain or storms, synthetic aperture radar (SAR) imagery remains resilient.

However, interpreting SAR images conventionally poses challenges compared to optical imagery due to their unique characteristics. Deep learning has emerged as an efficient method for image segmentation and recognition, with numerous studies leveraging this technique in recent years.

In this project, we propose creating 9-channel images by stacking VH, VV, and auxiliary input bands. The VV and VH bands are clipped, and all values are scaled to 0-255. Additional flipped and rotated augmentations are concatenated to enhance the dataset.

Subsequently, three randomly initialized U-Net convolutional neural networks (CNNs) are trained using different train-test splits while employing a consistent loss function of dice loss with a squared denominator. Ensemble predictions are generated by averaging the outputs from the trained models.

By integrating deep learning methodologies with SAR image analysis, this approach aims to provide more accurate and robust assessments of flood-affected areas, ultimately enhancing flood damage mitigation effort.

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Chapter 1

Introduction

1.1 What is flooding?

Flooding occurs when water inundates land that is usually dry. It can happen due to various reasons like heavy rainfall, snowmelt, river overflow, storm surges, or dam failure. Flooding can cause extensive damage to infrastructure, homes, agriculture, and ecosystems, posing significant risks to human life and well-being.

1.2 What are the causes and impacts of floods?

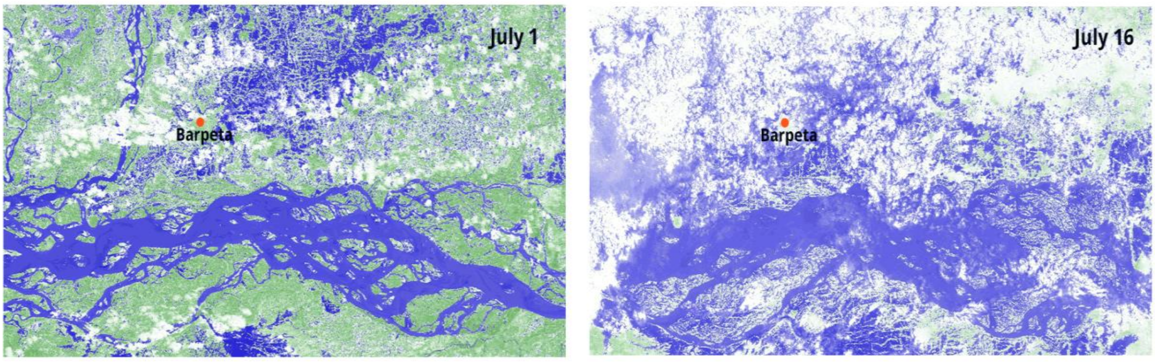
Floods result from environmental factors like heavy rainfall, snowmelt, storm surges, and deforestation, altering natural drainage patterns. Human activities such as urbanization, infrastructure development, and alterations to land use exacerbate flooding risks. Climate change intensifies flooding through altered weather patterns and rising sea levels.

Flooding causes loss of life, property damage, and economic disruption, leading to displacement and health risks for affected communities. Environmental consequences include habitat destruction, soil erosion, and contamination of water sources, exacerbating the overall impact.

Effective flood management requires addressing both environmental and human factors to mitigate risks such as disaster preparedness, efficient flood monitoring techniques, infrastructure improvements, and sustainable land use planning are essential for reducing the severity of these impacts on communities and ecosystems., enhancing community resilience.

1.3 Case Study: 2022 Assam Floods

Assam Floods 2022 is one of the worst floods ever seen in Assam in the decade which lasted for almost 7 Months (From April 2022 to October 2022) in a series of waves.



Causes and Impact

The main causes for the floods are the Pre-Monsson rains which were started from 6 April 2022 across the state and the Monsoon Season thereafter.

In total around 5.6 million people got affected, 4.7 million people got displaced, Crop land of 108,308 Hectares got damaged, 3,660,173 animals got affected and 32 districts in the state.

In May 2022, flooding struck 27 districts, affecting 670,000 people, with extensive soil erosion reported across the state. The subsequent floods from June to September, driven by the monsoon season, saw major rivers overflowing, destroying 1,100 houses, partially damaging 7,000 others, and impacting over 90,000 individuals.

Additionally, landslides occurred in six districts, exacerbating the situation. The October 2022 floods further inundated low-lying areas near riverbanks, affecting 70,000 people.

These floods also led to a surge in Japanese encephalitis cases, raising concerns about the spread of waterborne diseases. Notably, Assam's second-largest city, Silchar, experienced six days of inundation, and railway lines were disrupted due to flooding and landslides.

A flooded railway station during the floods

A rescue boat transporting people to safer places

A flooded village submerged under floodwater

IRCS volunteers distributing relief material in Bongaigaon district, Assam

Response

In response to the floods, the Union Government of India formed an Inter-Ministerial Central Team (IMCT), which conducted surveys in flood-affected areas from May 26 to May 29, 2022, and from June 30 to July 3, 2022.

After effects

In June, heavy rains led to flooding and landslides in Assam and Meghalaya, causing 20 and 18 deaths, respectively. Cherrapunji and Mawsynram recorded record rainfall levels. Arunachal Pradesh also faced casualties and missing persons due to landslides, while flooding displaced 12,000 people in Tripura.

By June 21, over 130 deaths were reported in northeast India, with significant damage to Kaziranga National Park and widespread impacts in Meghalaya. In August, floods claimed 36 lives in Himachal Pradesh and resulted in casualties and missing persons in Uttarakhand.

1.4 Motivation: Problem and Approaches

1.4.1 Conclusions from the case study

The case study paints a vivid picture of the recurring and severe nature of flood events in the region, spanning multiple states and impacting communities differently. From Assam to Uttarakhand, the toll of flooding is evident in the loss of lives, displacement of thousands, and extensive damage to property and infrastructure.

This narrative underscores the pressing need for robust flood monitoring systems that can provide early warnings, facilitate timely evacuations, and inform targeted response efforts to mitigate the impacts of future flood events. Such systems not only safeguard lives and livelihoods but also play a crucial role in preserving the delicate balance of ecosystems in flood-prone regions.

By leveraging machine learning algorithms and diverse data sources like satellite imagery and weather forecasts, predictive models can be developed to identify early warning signs of floods. These models enable timely alerts, efficient resource allocation, and real-time monitoring, ultimately enhancing flood resilience and protecting vulnerable communities. Embracing this challenge presents a unique opportunity for researchers to make a tangible difference in disaster mitigation.

1.4.2 Data Representation and SAR imagery

Conventional data for flood monitoring typically includes ground-based measurements from river gauges, rainfall stations, and weather forecasts.
While valuable, conventional data has limitations in terms of coverage, especially in remote or inaccessible areas, and may be limited by weather conditions. Additionally, conventional data may not provide real-time information and often lacks spatial detail.

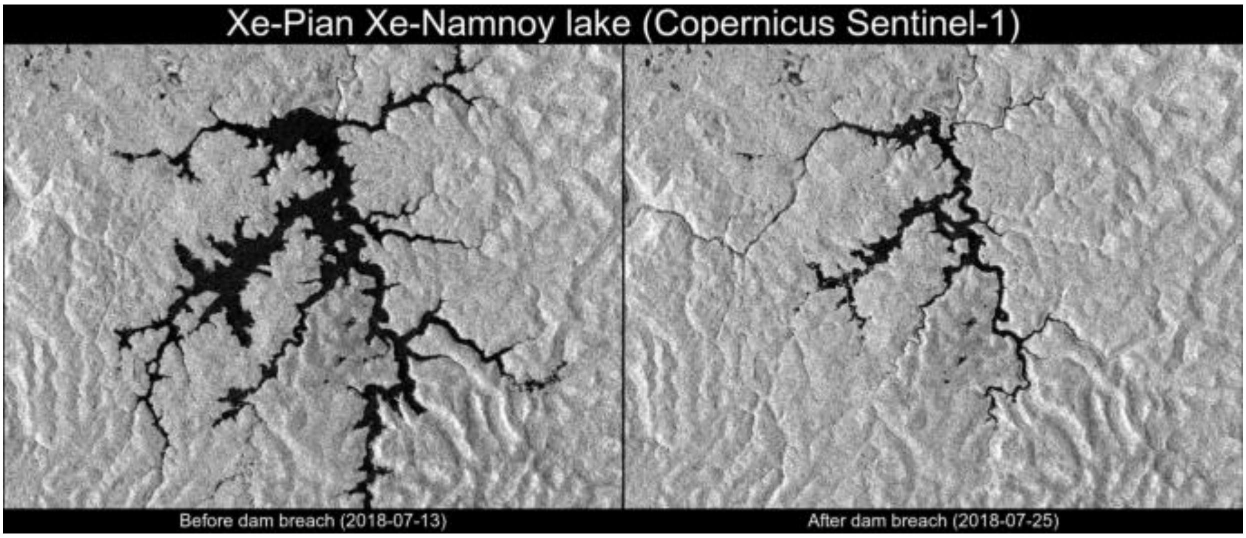
In contrast, **remotely sensed data** offers a transformative approach to flood monitoring. Remotely sensed data, such as satellite imagery, provides wide area coverage irrespective of geographical barriers or weather conditions.

It offers high temporal and spatial resolution, allowing for detailed monitoring and analysis of flood dynamics over time and space. Moreover, remotely sensed data can be integrated with conventional data sources to provide a comprehensive understanding of flood events.

The key features of remotely sensed data, including *wide area coverage, all-weather capability, high temporal and spatial resolution, and accessibility*, make it a compelling choice for flood monitoring applications, offering unprecedented insights and opportunities for effective decision-making and response efforts.

However, it's crucial to recognize that the accuracy and reliability of flood monitoring rely on the derivation and verification of ground truth from conventional data sources. Therefore, the synergy between conventional and remotely sensed data is essential.
By combining the strengths of both data types, we can enhance the accuracy, efficiency, and reliability of flood monitoring systems, ultimately improving our ability to mitigate the impacts of flood events and safeguard vulnerable communities.

Satellite-based Synthetic Aperture Radar (SAR) imagery, like that from the Sentinel program, is ideal for flood mapping due to its ability to provide near all-weather, day-night imaging independent of atmospheric conditions.



SAR sensors emit their own microwave radiation, ensuring continuous observation of the Earth's surface, even during intense precipitation or high wind speeds. This makes SAR imagery a preferred choice for accurate and reliable flood monitoring from space.

1.4.2 Analysis of existing approaches and domain choice

In recent years**, machine learning** (ML) methodologies have gained traction in the Synthetic Aperture Radar (SAR) community for object identification and classification tasks, including flood delineation.
Traditional ML (TML) techniques like *decision trees, gradient boosting, and support vector machines* (SVMs), as well as more **recent deep learning (DL) architectures**, have been applied to solve these problems.

TML approaches, mostly supervised, require training data for flood mapping, with *random forest classifiers and SVMs* being commonly utilized. These techniques have shown promise in delineating floods in various regions, including urban areas, and computing flood risk maps in inundation-prone areas.

DL architectures, on the other hand, *automatically learn* representations from data, allowing for complex classification tasks. While DL methodologies have shown potential for flood mapping using SAR data, their *application is hindered by the limited availability of training datasets.*

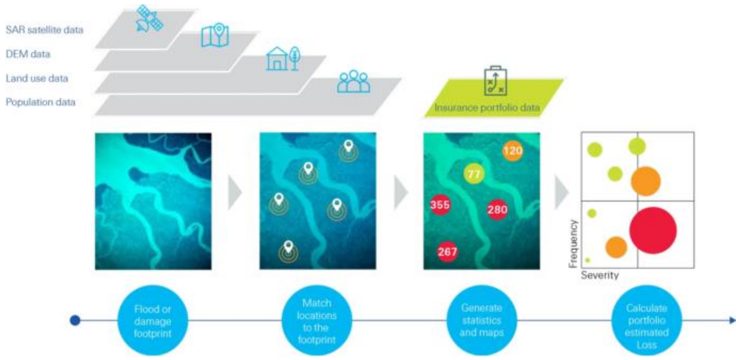
Nonetheless, studies comparing DL architectures and thresholding-based approaches have demonstrated promising results, with **UNet** emerging as a widely adopted architecture due to its effectiveness in feature reconstruction.

Chapter 2

Literature Review

2.1 Flood modeling using earth observation data and SAR

The paper titled "**Flood modeling and prediction using earth observation data [1]**" reviewed the utility of satellite remote sensing, popularly referred to as Earth Observation (EO), to map and monitor floods and its integration with flood modeling approaches.



Many of the existing and future satellite missions and airborne platforms provide rich data with great potential for enhanced monitoring, measuring, and mapping of floods, improving hydraulic models through new data assimilation techniques and parameter scaling behavior, and ultimately for an exploration of the ways in which new data sources may reduce uncertainty in flood predictions.

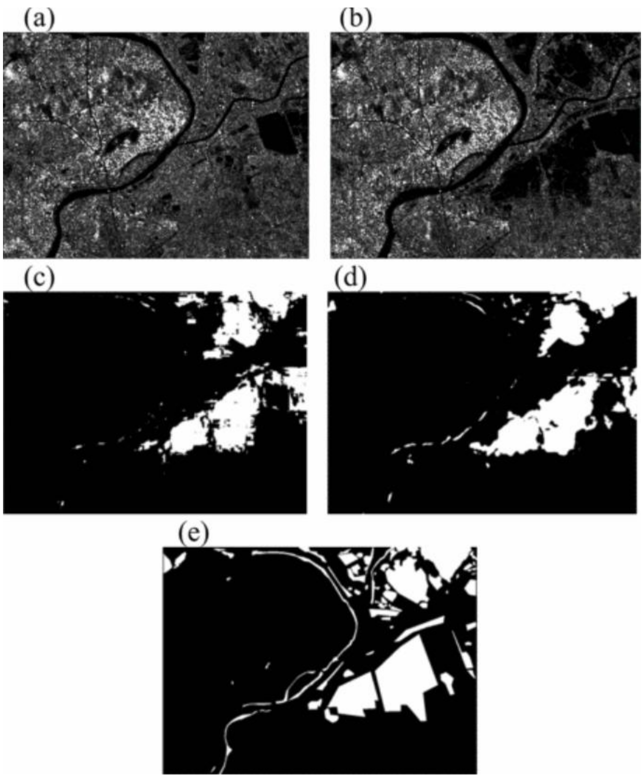
This has led not only to a better understanding of flood processes at various spatial and temporal scales and better flood forecasts, but also to global initiatives and applications that utilize and promote remote sensing for improved decision-making activities. With the recent advances in the use of machine learning models and interoperability between models and data, the global user and research communities are entering an era of ever-increasing opportunities but also many new challenges to solve along the way.

The paper titled "**Flood Detection with SAR: A Review of Techniques and Datasets [2]"** delves into various *SAR data processing techniques* such as speckle filtering and terrain correction, emphasizing their significance in enhancing the quality of SAR imagery and accurately identifying flooded regions. Furthermore, the discussion extends to *diverse flood mapping algorithms*, including traditional *threshold-based methods* and advanced machine learning and deep learning approaches.

2.2 Flood Area Detection using Unet based models

The paper titled "**Flood area detection from a pair of sentinel-1 synthetic aperture radar images using Res-Unet Based Method [3]"** provides a detailed exploration of flood mapping techniques utilizing Synthetic Aperture Radar (SAR) data to manage flood damage, satellite images are instrumental in identifying affected areas due to their wide-area observation capability.

Deep learning, known for its efficacy in image segmentation and recognition, offers a solution. This paper employs Res-Unet, a deep learning architecture based on U-net, to detect flood areas from SAR image pairs. Prior to training and prediction with Res-Unet, the SAR images undergo preprocessing and normalization. Comparative analysis with U-net reveals that both models effectively detect flood areas, with Res-Unet yielding superior visual results.



(a) Nakonsawan SAR image from 2021/9/10
(b) Nakonsawan SAR image from 2021/10/4
(c) U-Net result (d) Res-Unet result (e) Ground truth

	Naknonsawan		Sukagawa	
	U-net	Res-Unet	U-net	Res-Unet
ACC	0.916	0.919	0.958	0.958
IOU	0.516	0.535	0.554	0.553
TP	8.96	9.347	5.194	5.134
TN	82.624	82.526	90.624	90.709
FP	2.413	2.511	1.613	1.528
FN	6.003	5.616	2.57	2.63

2.3 Semantic segmentation

The article “**Loss functions for semantic segmentation**” by G. Chlebus offers a concise yet comprehensive review of various loss functions for semantic segmentation. Categorical cross entropy CCE and Dice index DICE are popular loss functions for training of neural networks for semantic segmentation.

Through clear delineation of their principles, strengths, and limitations, it provides valuable guidance for selecting optimal loss functions in semantic segmentation tasks.

The practical examples and comparisons presented aid in understanding their efficacy, enriching the discourse on semantic segmentation methodologies. The loss function in my implementation has been derived from this discussion

Chapter 3

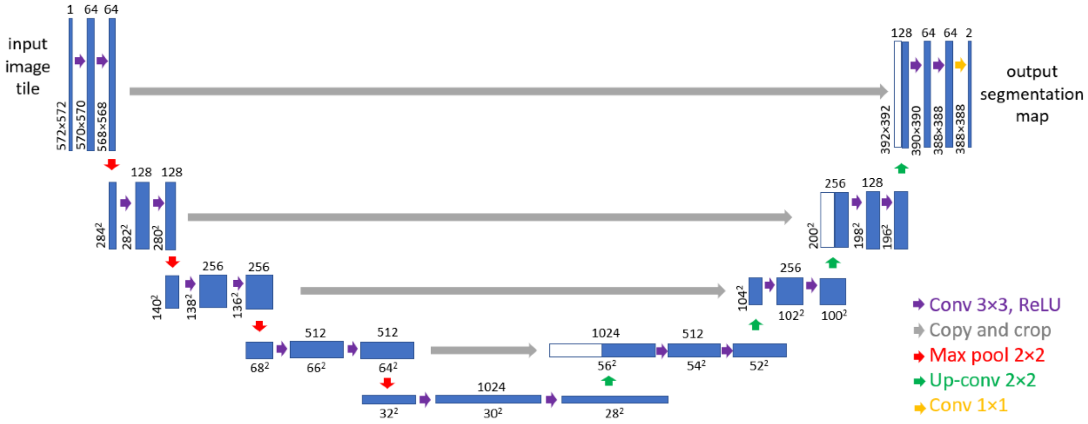
Progress of Work

3.1 Model Architecture

I have used the U-Net architecture is renowned for its efficacy in semantic segmentation tasks, and its design is tailored to extract detailed spatial information while maintaining computational efficiency.

U-Net Architecture

U-shaped encoder-decoder network architecture, which consists of four encoder blocks and four decoder blocks that are connected via a bridge.
The encoder network (contracting path) half the spatial dimensions and double the number of filters (feature channels) at each encoder block. Likewise, the decoder network doubles the spatial dimensions and half the number of feature channels.



UNet architecture

White boxes represent copied feature maps.
Number of channels indicated on top of the box.
Blue boxes correspond to a multi-channel feature map
The x- and y-size of each feature map is provided at the lower left edge of the box.

Encoder Network: Comprising four encoder blocks, this section serves as the feature extractor. Each block doubles the number of filters while halving the spatial dimensions through convolutions followed by ReLU activation. Max-pooling further reduces spatial dimensions, minimizing computational overhead.

Skip Connections: These connections bridge the gap between encoder and decoder blocks, preserving finer details. By enabling the direct flow of gradients during backpropagation, they facilitate better learning and feature representation, particularly crucial for preserving spatial information in semantic segmentation tasks.

Bridge: Connecting encoder and decoder networks, the bridge section ensures seamless information flow. It consists of convolutions followed by ReLU activation, facilitating feature mapping and abstraction.

Decoder Network: The decoder reverses the process of the encoder, expanding spatial dimensions and refining feature representations. It begins with transpose convolutions to upsample the feature maps, followed by concatenation with skip connection features. This integration of high-level semantic information with finer details aids in generating precise segmentation masks.

Output Layer: A 1x1 convolution with sigmoid activation generates the final segmentation mask, representing pixel-wise classification probabilities. The U-Net architecture's strengths lie in its ability to capture intricate spatial features through the contracting and expansive paths while incorporating skip connections for preserving details.

This design not only facilitates effective learning of hierarchical representations but also ensures the retention of spatial context crucial for accurate semantic segmentation.

Moreover, its relatively lightweight structure enables efficient computation, making it well-suited for various image analysis tasks, particularly for SAR images where intricate patterns and textures require detailed feature extraction.

3.2 Dataset

3.2.1 Data: Features and Labels

The primary data consist of satellite imagery captured between 2016 and 2020 from different regions around the world. The data consists of Sentinel-1 radar images stored as GeoTIFFs and a set of metadata for the training set that contains country and date information for each chip. Each GeoTIFF contains a set of metadata including bounding coordinates, an affine transform, and its coordinate reference system (CRS) projection.

Training Dataset

The training set consists of 542 chips (1084 images) from 13 flood events.
The images are named {image_id}.tif which is equivalent to {chip_id}_{polarization}.tif.
A chip_id consists of a three-letter flood_id and a two-digit chip_number.
Each chip has a _vv and _vh polarization band. For example, awc05_vv.tif represents the vv band for chip number 05 from event awc.

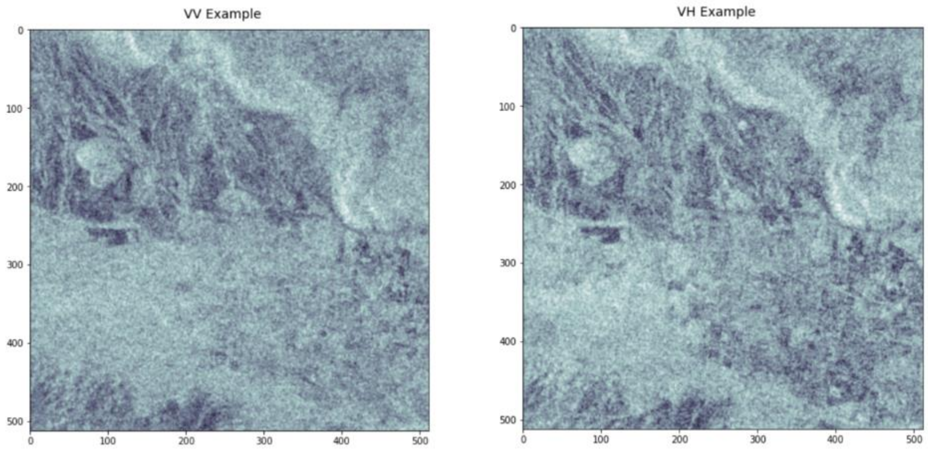
Features

The features in this dataset are *the radar images themselves*. While radar can be difficult to interpret visually, it is especially useful for detecting features through vegetation, cloud coverage, and low lighting.

There is *one image per band* and *two bands per chip*. Each image is 512 x 512 pixels and is stored as a GeoTIFF. Each pixel in a radar image represents the energy that was reflected back to the satellite measured in decibels (dB). Pixel values can range from negative to positive values. A pixel value of 0.0 indicates missing data.

Sentinel-1 is a phase-preserving dual polarization SAR system, meaning that it can transmit and receive a signal in both horizontal and vertical polarizations. Different polarizations can be used to bring out different physical properties in a scene. The data for this challenge includes two microwave frequency readings: VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive).

VV and VH band for a single chip, visualized with arbitrary colors:



Supplementary data

Information about a geography's natural topography and permanent water sources may also help your model to better detect floodwater. Elevation data from the NASA Digital Elevation Model (NASADEM) global surface water data from the European Commission's Joint Research Centre (JRC), including map layers for seasonality, occurrence, change, recurrence, transitions, and extent During training, these datasets can be accessed through the Planetary Computer by searching for images that overlap an area during a specific time.

Testing dataset

Test set images are not georeferenced.

Labels

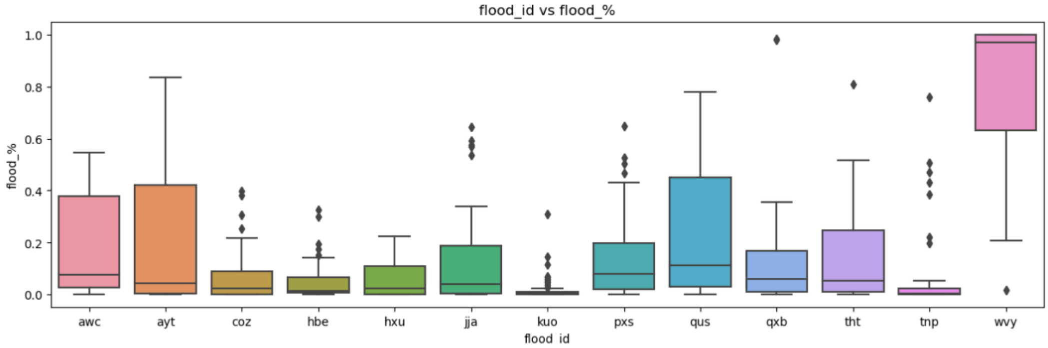
Each chip corresponds with a single label, stored as a GeoTIFF.
A label is a 512 x 512-pixel mask indicating which pixels in a scene contain water, where:
  1 indicates the presence of water
  0 indicates the absence of water
  255 indicates missing data
Labels are named {chip_id}.tif.
Each set of two polarization bands (VV and VH) corresponds with a single label.

3.2.2 Data preparation and loading

Explorative Data Analysis (EDA)

I initially examined an arbitrary image as a part of the explorative data analysis and found that the dataset has 542 unique chip id and that every id has two images _vh and _vv. I enhanced the visualization of sentinel-1 radar images and water labels by

- Scaling the images to adjust image values
- Created masks – numpy and gdal to exclude irrelevant or missing data
- Generated false color composites by combining radar bands for improved visualization of features
- Visualized chips with labels
- Check if the data is well distributed among flood events



Analysis of the training data to see if there was imbalance between the flood ids. For example, the flood wvy has a lot more flood pixel than the flood kuo.

Loading, Train-Test Split

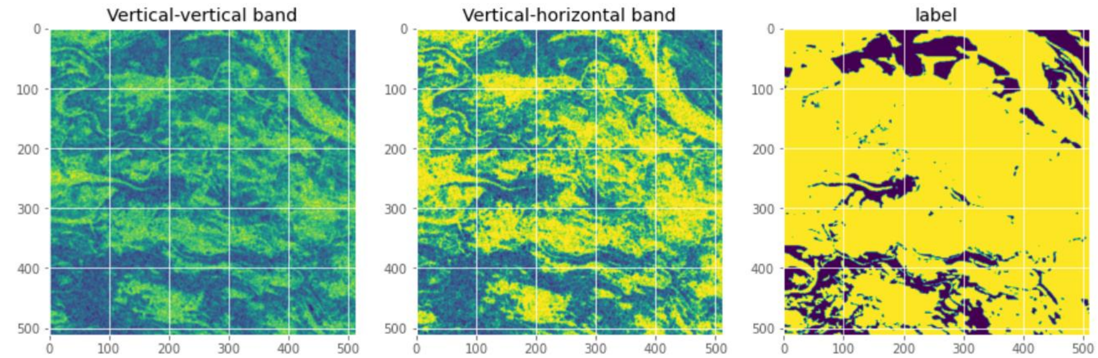
- Loading VV and VH files' IDs.
- Splitting the IDs into training and test sets.
- Choosing from 3 different splits for building 3 models for prediction.
- Loading VV, VH, label, and additional data from the Planetary Computer.

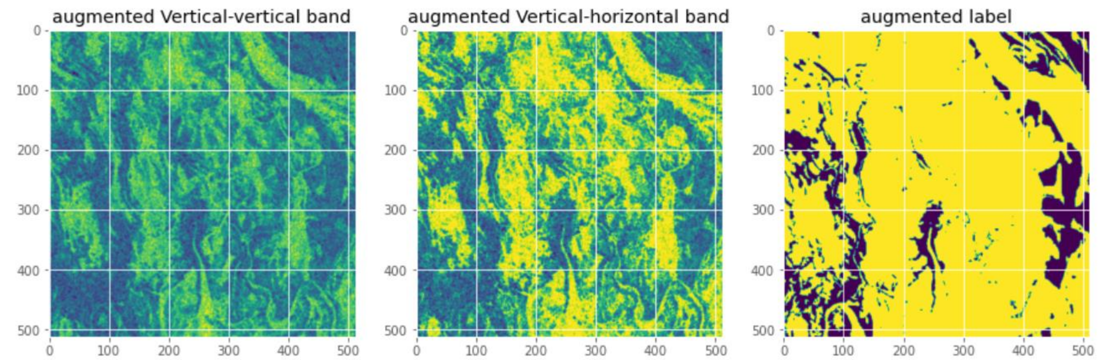
Preprocessing

- Preprocessing VV and VH images:
    - Clipping values outside of the range -30 to 0.
    - Mapping these values to 0-255.
    - Converting to uint8.
- Preprocessing NASADEM data: Clipping values outside the range 0-255.
    - Converting to uint8.
    - No transformation applied to the rest of the data.

3.2.3 Data Augmentation

- Albumentations library to generate new images from the original ones.
- Applying random transformations: RandomRotate90, HorizontalFlip, and VerticalFlip.
- Appending these new images to the original data.





3.3 Implementation

3.3.1 Loss functions for semantic segmentation

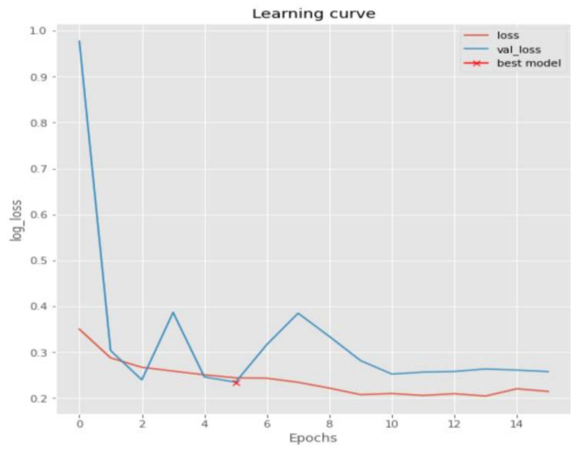
The Dice loss function, denoted as DICE, is a widely used metric in semantic segmentation tasks. It quantifies the similarity between predicted and ground truth segmentation masks by measuring the overlap of their respective pixel values. The formulation involves computing the intersection over union of the predicted and ground truth masks, with a smoothing term ε to prevent division by zero. Additionally, an alternative formulation, DICE_SQUARE, incorporates squared terms in the denominator, proposed by Milletari1, which further penalizes false positives. Mathematical Representation:

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|}$$

Here, A is the set of true pixels and B is the set of predicted pixels

3.3.2 Trained and Validated the Unet Models

- Training a UNET model on the data.
- Using dice loss square for the loss function as it gives better results.
- Set threshold = 0.5 to consider a flood pixel while outputting the tif file.
- Training and validation loss over epochs:



3.4 Performance Metrics

To measure the model's performance a metric called **Jaccard index** is used, also known as Generalized Intersection over Union (IoU).

Jaccard index is a *similarity measure between two label sets*. In this case, it is defined as the size of the intersection divided by the size of the union of non-missing pixels. The Jaccard index can be calculated as follows:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}.$$

where A is the set of true pixels and B is the set of predicted pixels.

This computation excludes predictions on missing data.
Because it is an accuracy metric, a higher value is better.

3.5 Results and Analysis

The prediction of my three best models and taking the average of their output. Combining my three best models took the IOU from 0.89 to 0.908.

Train duration	30 mins
Inference duration	9 min 20 sec
Independent Unet IOU	0.89
Three Unets averaged IOU	0.908

Chapter 4

Conclusion

4.1 Learnings

In this project, I gained knowledge and hands-on experience of flood detection techniques using deep learning, focusing on the analysis of Synthetic Aperture Radar (SAR) imagery. I have a deeper understanding of SAR data, including its unique characteristics such as speckle noise and complex textures.

By selecting the U-Net architecture, I aimed to leverage its effectiveness in semantic segmentation tasks, crucial for interpreting SAR imagery accurately. The preprocessing of SAR data involved various techniques like clipping values and data augmentation to enhance model performance.

Training and evaluating deep learning models on SAR datasets provided valuable insights into model optimization and performance assessment using metrics like Intersection over Union (IoU). Experimenting with ensemble learning techniques, particularly model averaging, led to significant performance improvements.

Navigating through this project posed several significant challenges. Understanding the intricacies of SAR imagery proved to be a complex task due to its unique characteristics, such as speckle noise and varying illumination conditions.

Mapping this data accurately was particularly challenging, requiring specialized knowledge and techniques. Furthermore, determining the optimal test-train split was crucial for model training and evaluation. Balancing the size of the training data while ensuring model generalization was a delicate task, complicated by the limited availability of labeled SAR datasets and the risk of overfitting.

Fine-tuning model weights and hyperparameters was another obstacle to overcome. This process demanded extensive experimentation and iteration to strike the right balance between model complexity and generalization, considering the nuances of SAR imagery analysis.

Moreover, I focused on optimizing training and inference processes to ensure computational efficiency while maintaining high accuracy.

Overall, this project not only deepened my understanding of flood detection and SAR imagery analysis but also highlighted the importance of accurate flood prediction for disaster management and environmental monitoring. It equipped me with valuable skills and insights for future projects in this domain.

4.2 Future Scope

Using different baseline models

In the literature review, it has been observed that there is minimal disparity in performance between the U-Net and ResUNet architectures. However, ResUNet has shown slightly superior visual results. Exploring modifications to the encoder-decoder ensembles may lead to the discovery of improved models.

Additionally, hybrid models combining deep CNNs with ResUNet architecture have shown promise, as indicated by existing literature.

Work on flood prediction

In this project, I’ve read and implemented models for flood detection and would be inclined to shift my focus towards tackling more intricate and rewarding aspects of flood prediction. This endeavor involves delving into deeper and more complex challenges within the domain, aiming to develop advanced models that can provide enhanced accuracy and insights in predicting flood.

Chapter 5

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