Hurricane Florence Water Segmentation Utilizing UAVSAR and Deep Learning

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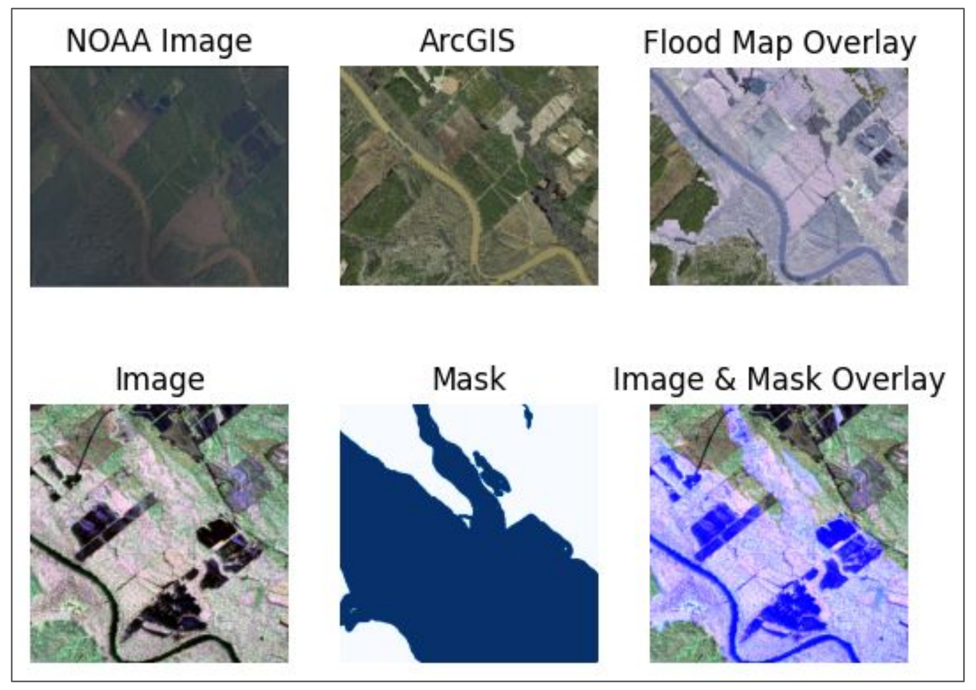
Abstract

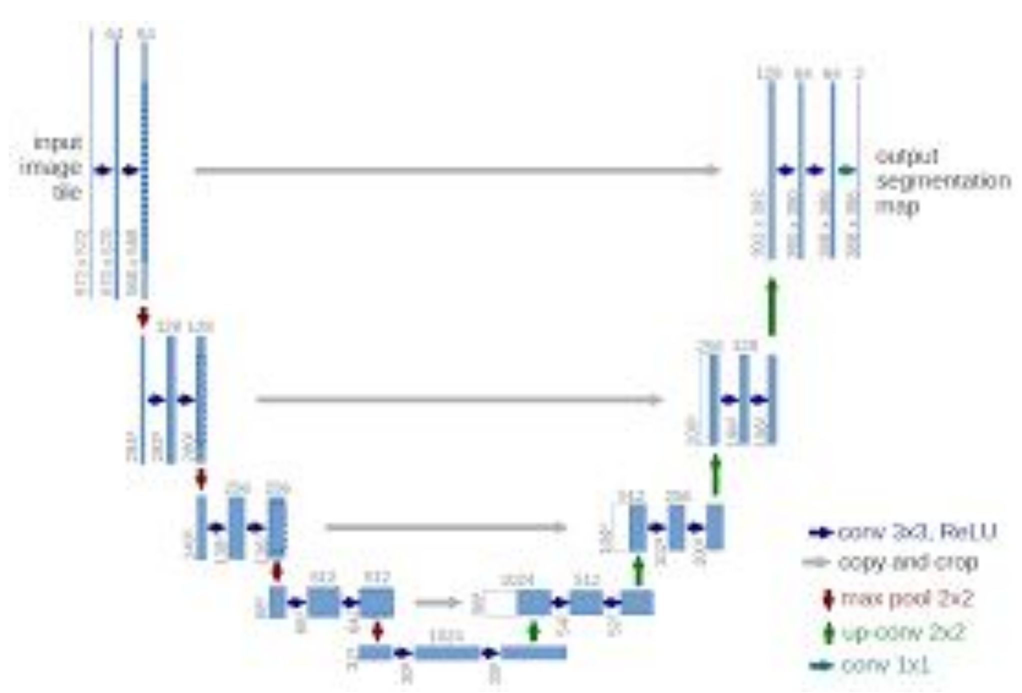
In 2018, Hurricane Florence in North Carolina caused $16.7 billion in damages and forty-two casualties. As the quantity and severity of floods is expected to increase, response efforts to reduce the risk associated with massive inundation is needed. The development of systems in radar technology to segment flooded areas is a modern approach that allows for efficient response and recovery efforts; synthetic aperture radar, a type of radar that produces high-resolution images independent of the time of day and weather conditions, has been used to segment a variety of disasters. While classical machine learning techniques can segment bodies of water, they are often sensitive to noise and outliers. Deep learning, the use of artificial neural networks with many hidden layers, has led to the successful development of models capable of segmenting synthetic aperture radar,. To develop a deep learning model employing a U-Net Architecture, two flight paths from NASA's Uninhabited Aerial Vehicle Synthetic Aperture Radar were used to construct a dataset. 1008 images were hand labeled utilizing NOAA digital imagery and a flood map as guides. A model was trained using VV, VH, and HH polarization. This model achieved a 89.4% pixel accuracy, a global DICE coefficient of .792, a precision of 0.769, and a recall of .817.

Data

- Used flights from the Cape Fear and Lumberton areas of North Carolina after Hurricane Florence
- Labeled 1008 images using NOAA aerial imagery and a flood map reporting a 92% accuracy
- The edges of the flight path created a padding effect on many images
  - Images that are less than a quarter padding are kept, and padding was replaced with random pixel values
  - After reducing the dataset size, **679** images remained
- Data Augmentation : Random cropping and random flipping

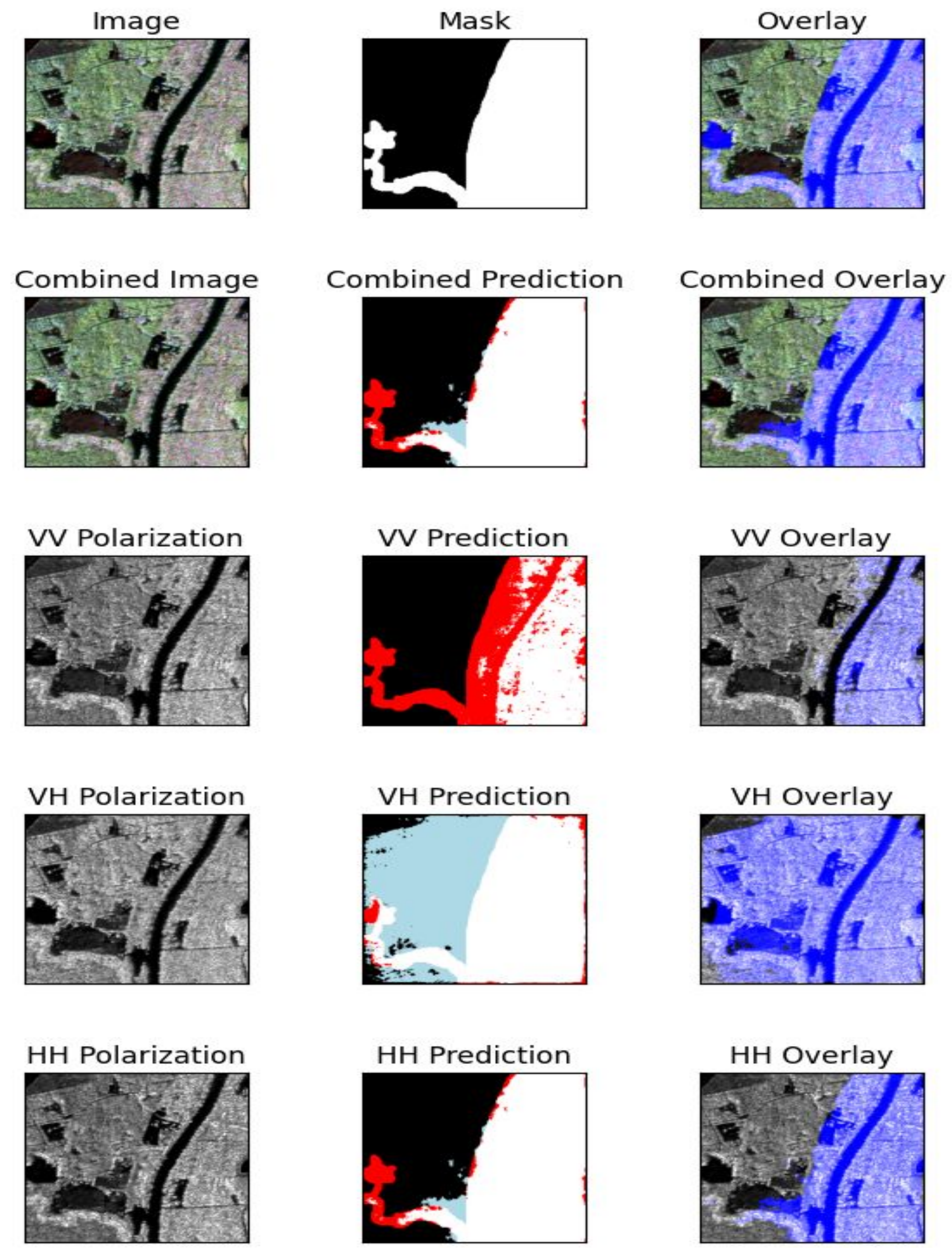


Model



- The U-Netused a dropout of 0.5
- Used 5 folds to train the data, each using ten epochs (50 epochs total)
- Used binary cross entropy as the loss function, the Adam Optimizer, and a learning rate of .0005

Results



Model Comparison

Model	Pixel Accuracy	DICE	Precision	Recall
Three Channel	89.4%	0.792	0.769	0.817
VV	83.54%	0.550	0.853	0.406
HH	83.38%	0.568	0.798	0.441
HV	56.47%	0.481	0.341	0.815

Conclusion

- Utilizing a U-Net architecture, image manipulation augmentation techniques, a five-fold crossover, and other techniques, four models were developed.
  - Three models used individual polarizations, the fourth used all three polarizations
- The model that acquired information from all three polarizations performed the best and was able to reach an 89.4% pixel accuracy, a global DICE coefficient of .792, a precision of 0.769, and a recall of .817.
  - Demonstrates the ability of deep learning to accurately segment water in flood events using UAVSAR
- Out of the individual polarizations, the two cross polarizations (VV and HH) performed nearly identical
  - VV slightly underpredicts, HH slightly overpredicts
  - Confirmed results from classical methods in SAR
- The cross polarization, HV, performed the worst by a substantial margin, overprediction a large amount of the data
- Promising future avenues expanding on this work include adding new and diverse flood events, new architectures and techniques to fill in the padding, and implementing advanced augmentation techniques such as GANs to acquire synthetic data.

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