Flood Segmentation Using UNet with Batch Normalization

Purple

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1 Objective

The primary goal of this project was to develop a model capable of accurately segmenting flood-affected areas from surrounding landscapes in satellite imagery. Due to limited availability of labeled data, we focused on creating a robust model to achieve high segmentation performance.

2 Approach

2.1 Model Architecture: UNet with Batch Normalization

We employed the UNet model, a well-known architecture for image segmentation tasks. UNet's encoder-decoder structure, combined with skip connections, allows it to capture both low-level and high-level image features, which is crucial for pixel-level accuracy in segmentation.

Enhancement: Unlike the original UNet paper, we introduced **Batch Normalization** layers. This adjustment helped stabilize and accelerate the training process, particularly given the small dataset size. Batch Normalization mitigates internal covariate shifts and enables faster convergence, contributing to improved generalization.

2.2 Loss Function

We used Binary Cross-Entropy (BCE) loss due to the binary nature of our segmentation task. BCE is effective in pixel-wise classification, separating flooded areas from non-flooded ones.

2.3 Metrics

We utilized two metrics to assess segmentation performance:

- **Intersection over Union (IoU)**: Measures the overlap between predicted and ground-truth masks, providing insight into how well the model identifies flood regions.

- **Dice Coefficient**: Measures similarity between predicted and actual masks, giving weight to both flooded and non-flooded regions. Dice is sensitive to class imbalance, making it a key metric for this problem.

2.4 Data Challenges & Solutions

The dataset comprised only 290 images, posing a significant challenge for training a deep learning model. We tackled this issue with comprehensive **data augmentation**, including flipping, rotation, scaling, and contrast adjustments. These augmentations helped the model learn invariant features, improving robustness to various conditions.

Hand-Labeled Masks Issue: During data analysis, we discovered that the training masks were hand-labeled using black markers, leading to inaccuracies in pixel-wise annotations. This label noise likely limited the model's ability to achieve its full potential.

2.5 Training and Validation Split

We applied an 80:20 train-validation split, maximizing the data available for training while ensuring proper validation to evaluate performance.

3 Results

After 85 epochs, the model achieved:

- **Validation IoU**: 0.7851
- **Validation Dice Coefficient**: 0.8729

These results demonstrate that the model performed well despite the small dataset and noisy labels.

4 Conclusion

The addition of **Batch Normalization** significantly improved training stability and performance. Despite challenges from the dataset's limited size and label inaccuracies, the UNet model exhibited strong flood segmentation capabilities. In future work, improving label accuracy and exploring techniques such as transfer learning or semi-supervised learning could further enhance performance.

5 Project Resources

- **Github:** https://github.com/divyansh44/Cosmolligance2k24

This project highlights the importance of architectural enhancements and data augmentation techniques in overcoming data limitations for image segmentation tasks.