Flood Impact Detection on Areas Using U-Net

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Project Idea

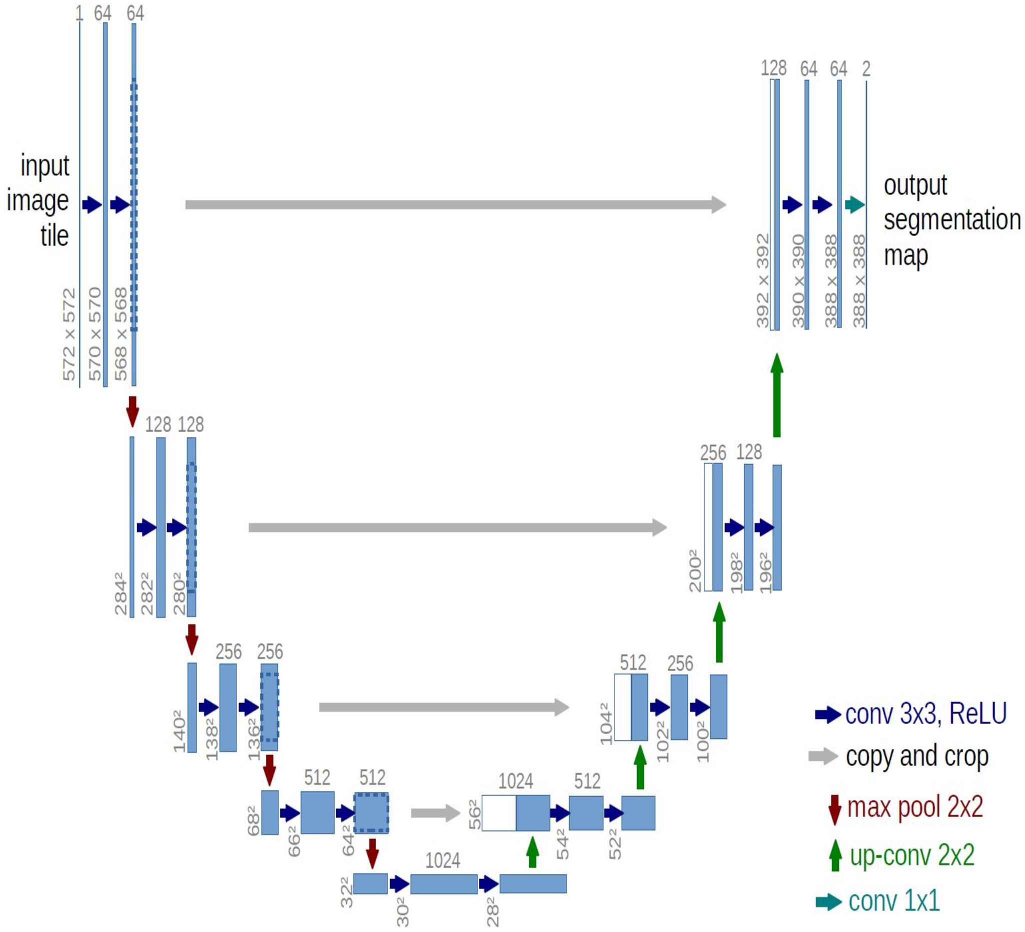
Design a U-net model for the classification and segmentation of parts of road images in Bangladesh affected by flood. This would be useful for evaluating the effects of floods on road construction as a way of determining the extent of damage in areas that experience flood ravages during certain seasons of the year. Segment out flooded region of roads in Bangladesh using satellite images or from any aerial view.

What is the Unet

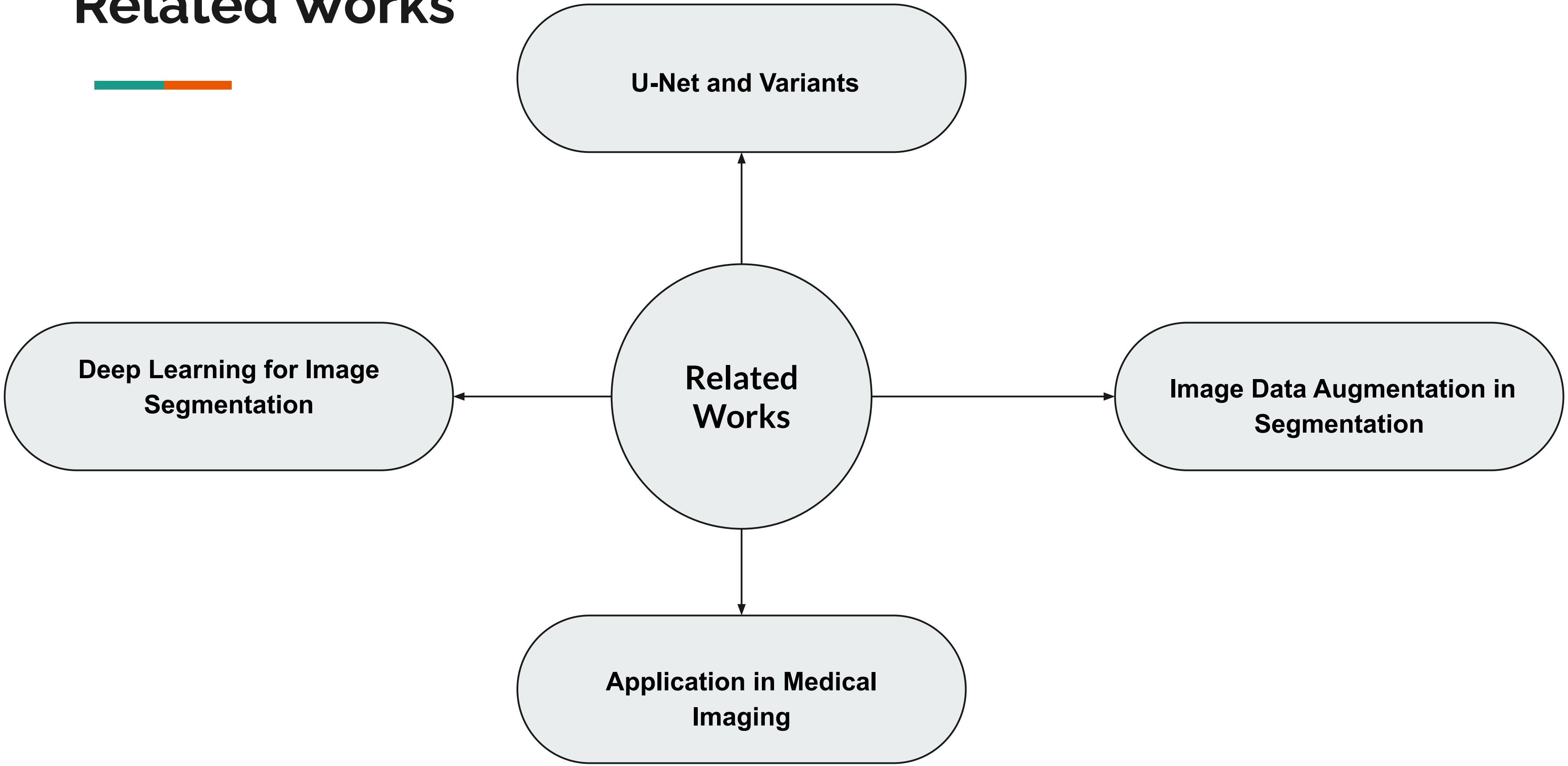
U-net is an encoder-decoder-based convolutional self-design network for image segmentation developed for biomedical image analysis in recent years. Its distinctive U-shape is formed by two main parts: A road within which the magnitude grows, the said encoder is the road that is the compressing dimension, and the extended road is a decoder. The contracting layers decrease the context of this load inversely, the expansive part increases this context by reconstructing the features which concatenated with features that can be obtained from the encoder part through the Skip connection. The connection links make it possible to reproduce geo-spatial correlation if the image affords correct spatial relations; geometric and photo-realistic attributes of the environment, the chained levels of spatial hierarchy, and the segmentation feature of complicated images with high accuracy even though only a few samples are taken. This is well exemplified by the U-Net architecture because it is fulfilling the segmentation function and is very helpful to medical image analysis because the task normally gets down to pixel level.

Unet Architecture

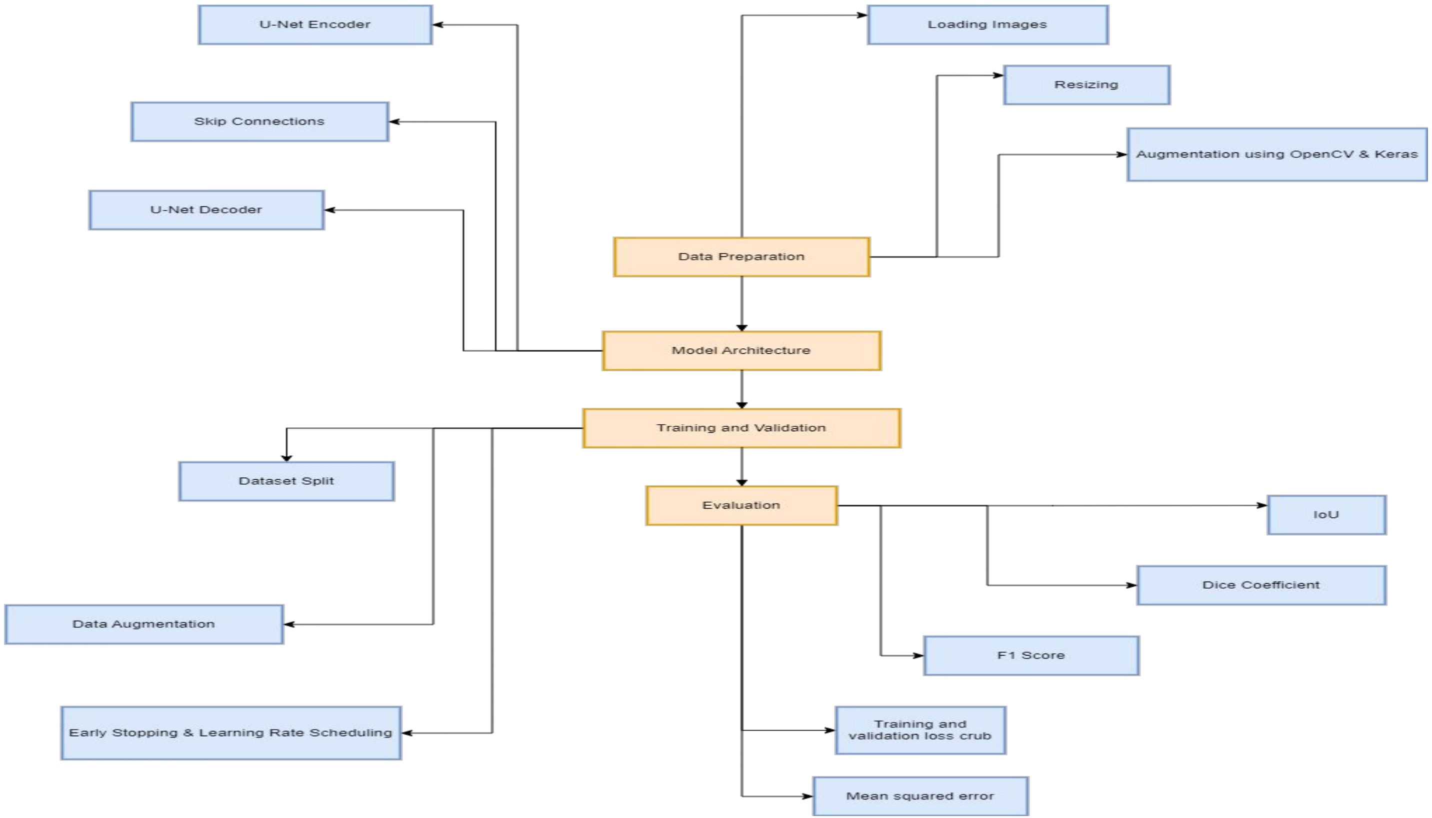
U-net was originally invented and first used for image segmentation. Its architecture can be broadly thought of as an encoder network followed by a decoder network.



Related Works



Methodology



Data Preparation

- Dataset: Images and Corresponding Masks
- Libraries: Python (OS, glob), OpenCV (cv2)
- Preprocessing: Image resizing, normalization, augmentation
- Image Augmentation: Rotation, flipping, and zooming (via Keras' ImageDataGenerator) to boost generalization and prevent overfitting

Model Architecture

- Contracting Path (Encoder)
- Expanding Path (Decoder)
- Skip Connections
- Tools: TensorFlow, Keras
- Optimizer: Adam
- Loss Function: Binary Cross-Entropy or Dice Loss for segmentation accuracy

Training & Validation

- Data Split: Training and validation sets
- Augmentation: Applied to the training set for better generalization
- Techniques: Early stopping, learning rate scheduling, and model checkpoints to avoid overfitting and optimize training

Evaluation

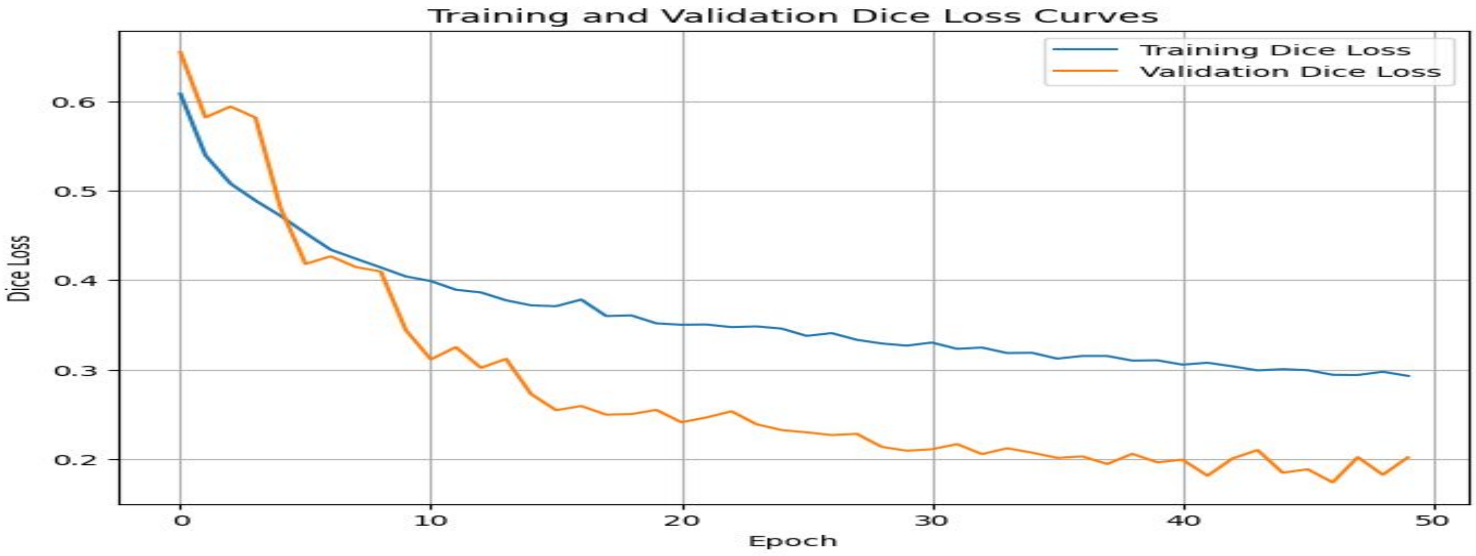
- IoU (Intersection over Union): Measures overlap between predicted and true masks
- Dice Coefficient: Evaluates the accuracy of the segmentation
- F1 score: The F1 score is the harmonic mean of precision and recall, balancing both.
- MSE: Mean Squared Error measures the average squared difference between predicted and actual values.
- Training and Validation loss curve: Training and validation loss curves show model performance over epochs.
- Visualisation: Side-by-side comparison of predicted masks and ground truth for insight into performance

Result Analysis

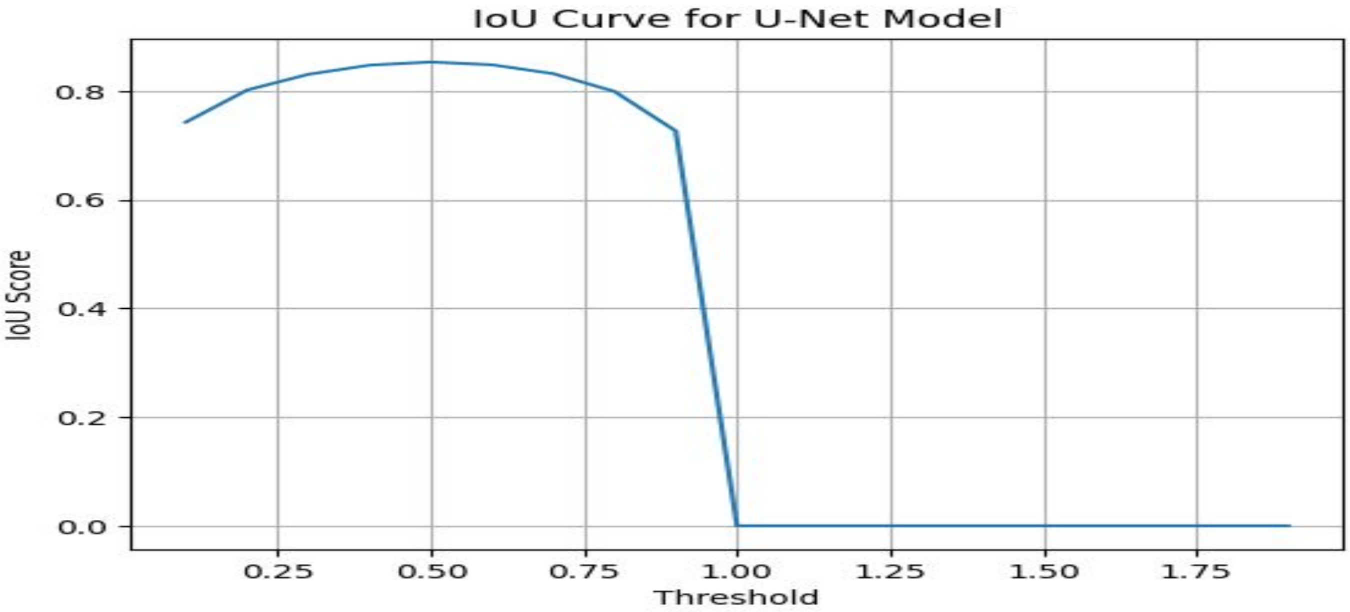
Model Setup

- Loading the dataset
- Validation of Dataset
- Random Display of Image-Mask Pairs
- Evaluation Metrics

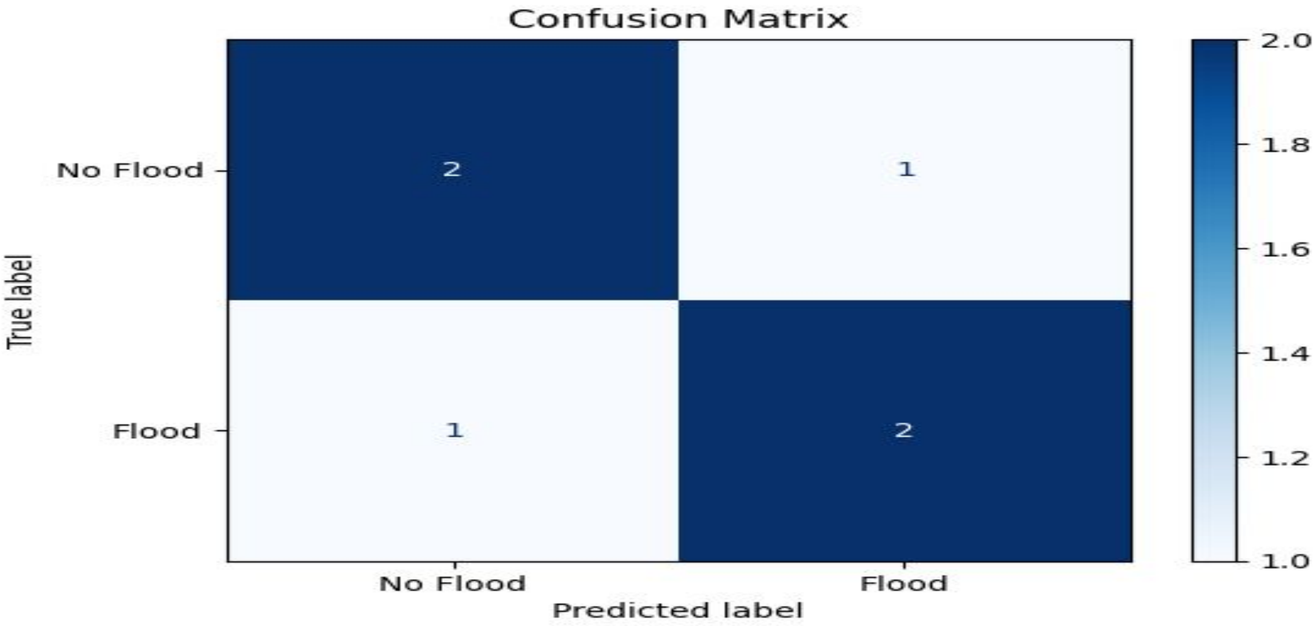
Dice Loss Curve



IoU Curve


IoU Curve for U-Net Model
IoU Score
0.0
0.2
0.4
0.6
0.8
0.25
0.50
0.75
1.00
1.25
1.50
1.75
Threshold

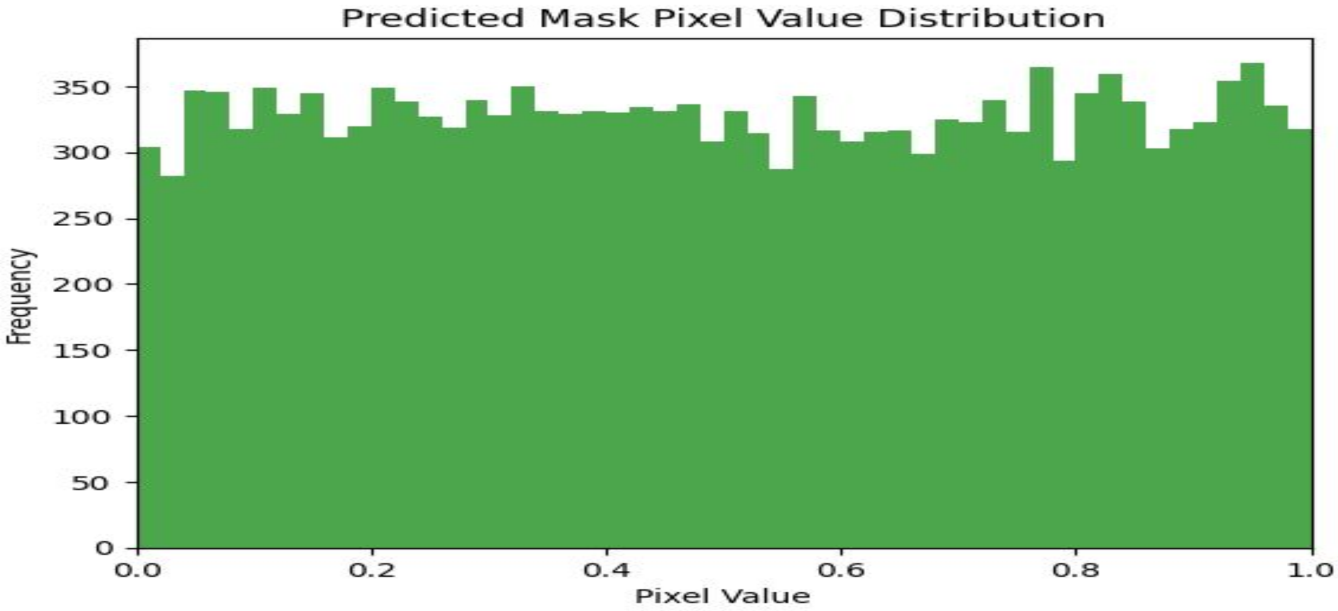
Confusion Matrix



Classification Report

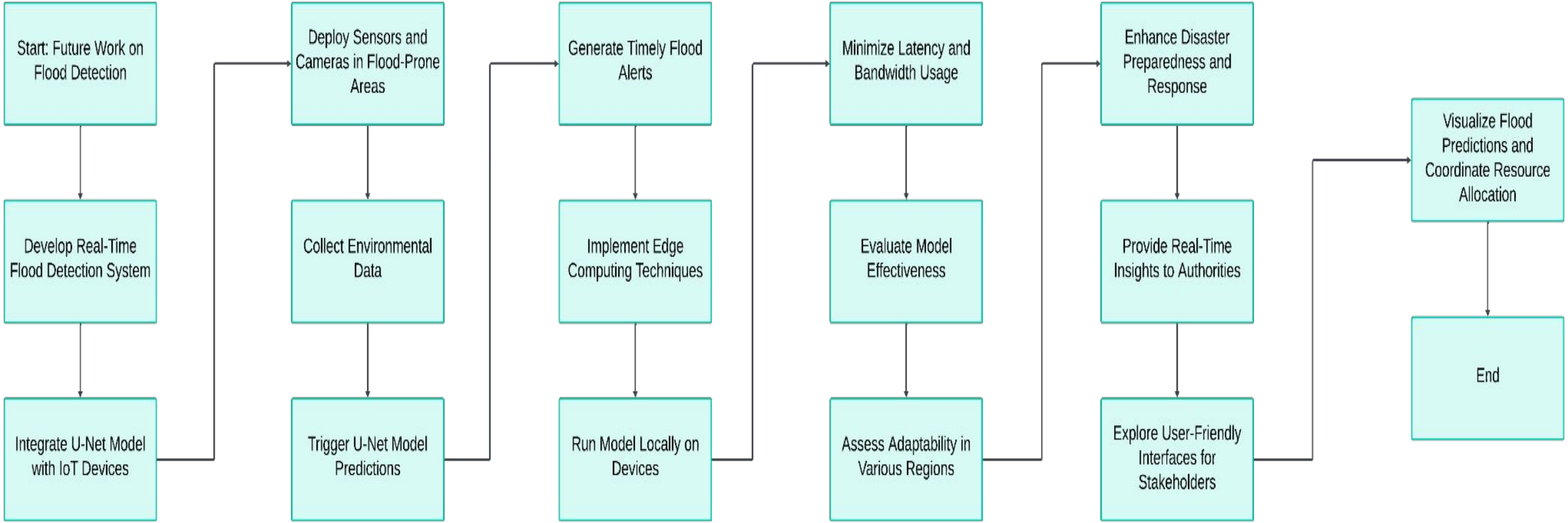
	precision	recall	f1-score	support
No Flood	0.67	0.67	0.67	3
Flood	0.67	0.67	0.67	3
accuracy			0.67	6
macro avg	0.67	0.67	0.67	6
weighted avg	0.67	0.67	0.67	6

Pixel Value



Predicted Mask Pixel Value Distribution
Frequency
0
50
100
150
200
250
300
350
0.0
0.2
0.4
0.6
0.8
1.0
Pixel Value

Future Works



Conclusion

In recent years, computer vision techniques have been widely applied to flood detection and monitoring systems. This paper compares three image segmentation methods: thresholding, region growing, and hybrid techniques, concluding that the hybrid approach achieved the best performance with over 76% segmentation accuracy. While these methods were effective, switching algorithms for different images remains a challenge. Semantic segmentation and deep learning approaches, particularly a U-Net based CNN model, were explored for satellite imagery with promising results. Future work aims to improve segmentation precision by incorporating geometric hints and uncertainty-weighted multi-task loss.

Project Dataset

Flood Area Segmentation

Link : https://www.kaggle.com/datasets/faizalkarim/flood-area-segmentation

Reference

1. U-Net: Convolutional Networks for Biomedical Image Segmentation. link - https://doi.org/10.48550/arXiv.1505.04597
2. Image Segmentation Methods for Flood Monitoring System. link - https://doi.org/10.3390/w12061825
3. Road Extraction by Deep Residual U-Net. link- https://arxiv.org/pdf/1711.10684
4. Satellite Image Segmentation for Building Detection using U-net. link - https://cs229.stanford.edu/proj2017/final-reports/5243715.pdf