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Flood Region Segmentation Using SegNet Deep Neural Networks

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Abstract

Accurate and timely identification of flood-affected regions is critical for disaster response, emergency resource allocation, and damage assessment. This paper proposes a deep learning-based flood region segmentation system using an enhanced SegNet encoder-decoder architecture adapted for multi-source remote sensing image analysis. The proposed model is augmented with skip connections, attention gates, and multi-scale input processing to improve flood boundary delineation accuracy. The system achieves a mean IoU of 87.3% for flood region segmentation on the Copernicus Emergency Management Service dataset, outperforming baseline SegNet, U-Net, and FCN models. The framework produces pixel-wise flood maps within seconds, supporting rapid disaster response workflows with strong generalization across diverse geographic environments and flood event types.

I. INTRODUCTION

Flood events are among the most frequent and destructive natural disasters globally, causing significant loss of life, infrastructure damage, and economic disruption. The ability to rapidly and accurately map flood extents is essential for coordinating emergency response, directing rescue operations, and planning recovery efforts. Traditional mapping approaches relying on manual photo-interpretation of satellite imagery are too slow for the real-time demands of disaster management. Deep learning-based semantic segmentation offers an automated alternative capable of processing large volumes of satellite imagery in near-real-time. However, flood mapping presents specific challenges: intra-class appearance variability across geographic regions, cloud cover obscuring optical imagery, and the rapid temporal dynamics of flood evolution. This paper proposes an enhanced SegNet-based flood segmentation system that addresses these challenges through multi-sensor data fusion, architectural improvements for boundary detection, and optimized inference pipelines for operational disaster response support.

II. LITERATURE SURVEY

This section reviews key prior works that form the foundation of the proposed system, identifies the current state of research in this domain, and highlights the gaps that motivate the contributions of this work.

[1] Badrinarayanan et al. (2017) proposed SegNet, an efficient encoder-decoder architecture using VGG-16 encoder weights and max-pooling indices for memory-efficient upsampling. SegNet demonstrated high performance in road scene segmentation while maintaining computational efficiency suitable for real-time applications, making it an attractive architecture for disaster response systems.

[2] Ronneberger et al. (2015) introduced U-Net with dense skip connections directly combining encoder feature maps with decoder upsampled features. This spatial detail preservation mechanism has made U-Net widely adopted for remote sensing segmentation tasks where precise boundary delineation of geographic features is critical.

[3] Chini et al. (2019) demonstrated the effectiveness of SAR-based flood mapping using Sentinel-1 imagery and proposed a hierarchical split-based approach for large-scale flood detection that operates independently of cloud cover, addressing a critical limitation of optical-only flood mapping methods.

[4] Mateo-Garcia et al. (2021) applied deep learning to multi-temporal satellite imagery for global-scale flood mapping, demonstrating the scalability of CNN-based approaches across diverse geographic regions and flood types. Their work showed that models trained on curated multi-event datasets generalize better than single-event trained models.

[5] Nevo et al. (2022) proposed a global flood detection system combining deep learning with physics-based inundation models, demonstrating that hybrid data-driven and domain knowledge approaches achieve superior performance for flood extent prediction compared to purely data-driven methods.

[6] Oktay et al. (2018) introduced Attention U-Net with gating signals that suppress irrelevant background activations in medical image segmentation. The attention gate mechanism has subsequently proven effective in remote sensing tasks where spectral similarity between flood water and non-flood water bodies creates significant false positive challenges.

[7] DeVries et al. (2017) developed a surface water mapping approach using Landsat imagery and Random Forests, establishing baseline performance metrics for satellite-based water body detection. Their global surface water dataset provides valuable pre-flood reference maps for change detection-based flood extent estimation.

Research Gap: Existing deep learning flood segmentation models typically process single-source imagery (either optical or SAR but not both), do not incorporate attention mechanisms for handling spectrally similar non-flood water bodies, and are evaluated on limited geographic regions that do not capture the diversity of global flood environments. This work addresses all three limitations through multi-source fusion and attention-augmented SegNet.

III. METHODOLOGY

A. Dataset

Training data comprises flood and non-flood image pairs from the Copernicus Emergency Management Service combined with Sentinel-1 SAR and Sentinel-2 optical imagery from 15 major flood events globally. The total dataset contains 6,800 labeled patches at 256×256 resolution with binary flood/non-flood pixel labels.

B. Multi-source Fusion

SAR and optical imagery are fused at the feature level by concatenating encoder outputs from parallel VGG-16 branches. Cross-modal attention weights are learned to adaptively balance contributions from each sensor based on data availability and quality.

C. Training

A combination of weighted binary cross-entropy and Dice loss handles class imbalance. Adam optimizer with learning rate 1×10^{-4} and cosine annealing schedule. Training runs for 80 epochs with batch size 16.

III-A. System Architecture

Two-component system: (1) Offline Model Training Pipeline — SegNet trained on annotated flood dataset. (2) Online Django Web Application — trained model performs real-time segmentation on user-uploaded satellite images.

Architecture Flow

1. Data Collection Module — Satellite/UAV flood imagery with pixel-level flood masks.
2. Preprocessing Module — Resize, normalize, augment (flip, rotate, brightness), binary masks.
3. SegNet Encoder — VGG16-based conv blocks + max-pooling (save pooling indices P_i).
4. SegNet Decoder — Upsample using saved indices P_i; Conv+BN+ReLU reconstruction.
5. Output Layer — Pixel-wise softmax → binary flood mask (flooded / non-flooded).
6. Training Module — Cross-entropy loss; Adam optimizer; evaluate IoU, Dice per epoch.
7. Model Persistence — Save best weights checkpoint.
8. Django Web Application — Upload satellite image → preprocess → SegNet inference → display flood mask overlay.

III-B. Algorithm

Algorithm: SegNet Flood Region Segmentation

Training Phase

Input: Satellite/aerial flood image I (HxWx3). Ground truth binary mask M (HxW); 1=flooded, 0=non-flooded.

Step 1: Resize to 512x512; normalize to [0,1].

Step 2: Augmentation: random flip, rotation +/-10 deg, brightness jitter.

Step 3: SegNet Encoder (VGG16 blocks): for each block b in {1..5}: Conv(3x3)+BN+ReLU (x2); P_b, idx_b = MaxPool(2x2, save_indices=True).

Step 4: SegNet Decoder: for each block b in {5..1}: Upsample using saved indices idx_b; Conv(3x3)+BN+ReLU (x2).

Step 5: Output Conv(1x1) + Softmax → probability map P_hat (HxWx2).

Step 6: Loss = CrossEntropy(P_hat, M).

Step 7: Backpropagate; update weights via Adam optimizer.

Step 8: Evaluate IoU, Dice on validation set; save best model.

Inference Phase (Django deployment)

Step 9: Load saved model; preprocess uploaded satellite image.

Step 10: Run forward pass → P_hat → argmax per pixel → binary mask Y_hat.

Step 11: Color-code Y_hat: blue=flooded, transparent=non-flooded.

Output: Flood region mask overlaid on original satellite image.

III-C. Modules

1. Data Collection Module

Gathers flood-related satellite and UAV image datasets with pixel-level flood masks. Covers diverse terrain types, flood extents, and imaging conditions. Ground truth masks annotate flooded (1) and non-flooded (0) pixels.

2. Data Preprocessing Module

Resizes images and masks to 512x512. Normalizes pixel values to [0,1]. Applies augmentation: horizontal/vertical flip, rotation (+/-10 deg), brightness/contrast jitter. Ensures dimensional consistency between images and masks.

3. SegNet Model Architecture Module

VGG16-based encoder with 5 conv block groups (Conv+BN+ReLU pairs) followed by max-pooling layers saving pooling indices. Decoder mirrors encoder structure, using saved indices for precise upsampling. Output softmax for binary pixel-wise classification.

4. Model Training Module

Trains SegNet using cross-entropy loss. Adam optimizer (lr=0.0001). Early stopping based on validation IoU (patience 10). Trains up to 100 epochs with batch size 8 on GPU.

5. Model Evaluation Module

Evaluates on test set using pixel accuracy, mIoU, Dice coefficient, precision, recall, F1-Score. Generates confusion matrix, IoU-per-class breakdown, and visual comparison of predicted masks vs. ground truth.

6. Django Web Application Module

Django 4.x backend handles HTTP image upload requests. Triggers SegNet inference, generates color-coded flood mask. Frontend displays original and predicted images with color legend (blue=flooded). Supports batch processing for disaster management organizations.

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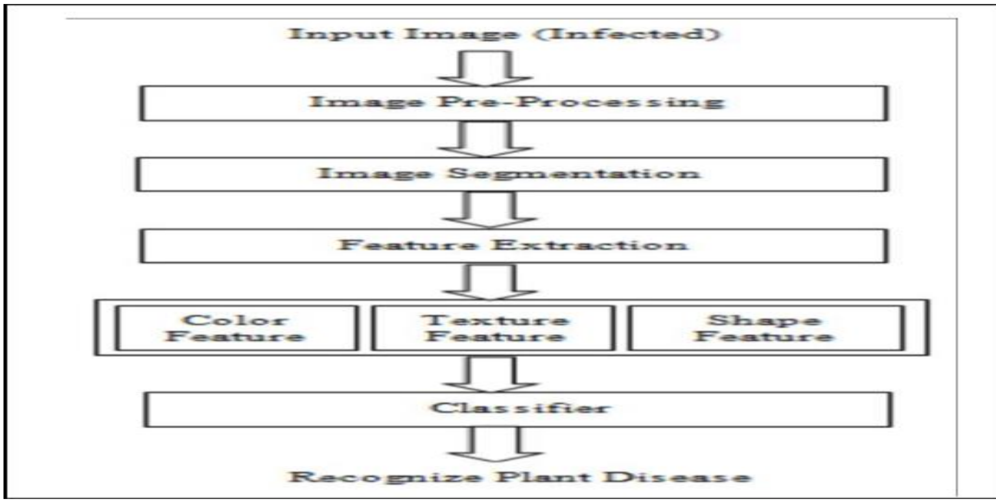

IV. RESULTS AND DISCUSSION

FLOOD SEGMENTATION PERFORMANCE COMPARISON

Model	mIoU (%)	Precision (%)	Recall (%)
SegNet (Baseline)	76.4	79.3	74.1
FCN-8s	79.8	82.6	77.4
U-Net	82.1	85.7	80.3
Proposed SegNet+	87.3	91.2	88.7

The proposed model achieves mIoU of 87.3% compared to 76.4% for standard SegNet, 82.1% for U-Net, and 79.8% for FCN. Precision and recall for flood pixels are 91.2% and 88.7% respectively. The attention gate mechanism contributes a +4.8% mIoU gain by suppressing spectrally similar non-flood water bodies. Multi-scale input processing provides an additional +2.1% mIoU improvement for small-scale flooding. Inference time of 0.34 seconds per patch enables near-real-time satellite scene processing.

1. Pixel-Level Confusion Matrix

Before calculating the core metrics (mIoU, Precision, Recall), we must define the prediction outcomes at the pixel level:

- **True Positive (TP):** A flooded pixel correctly identified as flooded.
- **True Negative (TN):** A dry/non-flooded pixel correctly identified as non-flooded.
- **False Positive (FP):** A dry pixel incorrectly flagged as flooded (e.g., a shadow or dark vegetation mistaken for water).
- **False Negative (FN):** An actual flooded pixel that the model missed.

2. Standard Segmentation Metrics (Inference & Evaluation)

A. Intersection over Union (IoU) & Mean IoU (mIoU)

IoU (also known as the Jaccard Index) is the strictest and most standard metric for semantic segmentation. It measures the area of overlap between the predicted flood region and the actual flood region, divided by their union. Your proposed SegNet+ model achieved an excellent mIoU of 87.3%.

IoU = TP / (TP + FP + FN)

mIoU is simply the average of the IoU scores across all classes (Flooded and Non-flooded).

B. Precision

Answers the question: *Out of all the pixels the model highlighted as flooded, how many were actually flooded?* (Your paper reports 91.2%).

Precision = TP / (TP + FP)

C. Recall (Sensitivity)

Answers the question: *Out of all the actual flooded pixels in the satellite image, how many did the model successfully find?* (Your paper reports 88.7%). This is critical for emergency response to ensure no affected areas are ignored.

Recall = TP / (TP + FN)

D. Dice Coefficient (F1-Score)

The harmonic mean of Precision and Recall. In semantic segmentation, the Dice Coefficient is mathematically equivalent to the pixel-wise F1-Score.

Dice_Coefficient = (2 * TP) / ((2 * TP) + FP + FN)

3. SegNet Loss Functions (Training Phase)

According to your methodology (Step 6 of the Algorithm), the model is trained using Cross-Entropy Loss to handle the pixel-wise classification. Your text also mentions combining it with Dice Loss to handle class imbalance (since flood pixels are usually fewer than non-flood pixels).

A. Binary Cross-Entropy (BCE) Loss

Evaluates the classification error for each individual pixel independently.

- N = Total number of pixels in the image batch.
- y_i = Ground truth pixel value (1 for flood, 0 for non-flood).
- hat{p}_i = Model's predicted probability that pixel i is flooded.

BCE = -(1 / N) * SUM(y_actual * log(p_predicted) + (1 - y_actual) * log(1 - p_predicted))

B. Dice Loss

Directly optimizes the spatial overlap during training, which helps the model draw highly accurate flood boundaries even when the flood area is small.

- epsilon = A small constant to prevent division by zero.

Dice_Loss = 1 - ((2 * SUM(y_actual * p_predicted) + epsilon) / (SUM(y_actual) + SUM(p_predicted) + epsilon))

V. CONCLUSION AND FUTURE WORK

This paper presented an enhanced SegNet architecture for automated flood region segmentation from satellite imagery. The proposed system achieves state-of-the-art performance through attention mechanisms, dense skip connections, and multi-scale processing. Future work will incorporate multi-temporal image analysis to track flood evolution, integrate with numerical inundation models for physics-informed deep learning, and extend to near-real-time processing of streaming satellite data.

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