EAI Endorsed Transactions
on Internet of Things

Research Article EAI.EU

Flood Mapping employing U-Net: A Case Study of Teesta Dam

Akanksha Singh[1, *], Syed Wajahat Abbas Rizvi[1], Prabhat K. Srivastava[2]

[1]Amity School of Engineering and Technology, Amity University, Lucknow, 226028, Uttar Pradesh, India

[2]Department of Computer Science and Engineering, IMS Engineering College, Street, Ghaziabad, 201015, Uttar Pradesh, India

Abstract

River Teesta is prone to weather fluctuations that leads to cloud burst or heavy rainfall resulting in overflowing of Teesta dam (27.0018057°N, 88.4404352°E) situated across the Teesta Basin region. Dam overflow is one of the major causes of sudden and uncontrolled release of water, which often leads to flooding in nearby downstream areas. Accurate flood mapping is important to reduce the damage caused by floods in low-lying areas. This study uses a U-Net deep learning model to identify flooded regions near Kalimpong in the Teesta River area using satellite images. The proposed method identifies flood-affected areas accurately and provides useful support for early warning and water management systems. The model was compared with existing methods such as Otsu thresholding, Random Forest, SegNet, and PSPNet using IoU, F1-score, precision, and recall values. The proposed U-Net model achieved 98% IoU, 98% F1-score, 99% precision, and 97% recall, showing better results than the other methods. The IoU value was 26% higher than Otsu thresholding, 18% higher than Random Forest, 10% higher than SegNet, and 8% higher than PSPNet. The training and validation graphs show stable learning with very little overfitting and steady performance during all 100 epochs. In addition, NDVI time-series analysis for Lachung city and the Lachung–Teesta meeting point showed important changes in vegetation that are useful for water resource management. These results show that the proposed U-Net model can identify flood areas effectively and can help improve early warning systems and safe dam management. However, the study is limited to Sentinel-2 image-based flood segmentation for the Teesta basin and does not include real-time hydrological inputs.

Keywords: Flood mapping, Teesta dam, NCC natural colour composite, U-Net, Sentinel 2-A

Received on 01 January 2026, accepted on 20 June 2026, published on 21 July 2026

doi: 10.4108/eetiot.11486

1. Introduction

Floods has a major effect on human well-being, endangering social development goals such as poverty alleviation, enough food, water, sanitation, and environmental protection. [1] Flood prognosis henceforth plays an essential role in handling disasters because it allows rapid evacuation, avoids the destruction of life and possessions, and supports in efficient utilization of resources. It enables officials and population to take preventive actions to reduce the socioeconomic repercussions of floods. [2]

The Teesta River is a prominent river in the eastern Himalayas that flows from Sikkim's Tso Lhamo Lake. It runs from Sikkim and West Bengal before merging with the Brahmaputra in Bangladesh. Teesta has a basin of around 12,159 square kilometres, and serves as a supply of water for the farming, hydropower production and water for consumption. [3,4] The Teesta Barrage and related dams are part of a massive hydropower and irrigation initiative with the goal of maximizing the river's capacity. While these facilities give several benefits, they have also increased flood dangers, particularly during monsoon seasons. [5] Figure 1 shows flood inundation monitoring for regions such as Gajoldoba Tea Garden using Synthetic

[*] Corresponding author. Email:ankakaanjphd@gmail.com

Aperture Radar (SAR) imagery. SAR imagery is useful for flood observation because it can capture ground conditions regardless of cloud cover or sunlight availability. Gajoldoba is located near the Teesta Barrage, which is part of a major irrigation and hydropower project for managing water resources from the Teesta River. During monsoon periods and heavy rainfall events, surplus water released from the barrage may increase downstream water levels and contribute to flooding in low-lying areas such as Gajoldoba Tea Garden. The SAR-based visualization was used for preliminary flood observation, while the proposed U-Net framework was trained and evaluated using Sentinel-2 optical satellite imagery.

U-Net is a convolutional neural network (CNN) algorithm initially used for image segmentation tasks, with the purpose of classifying each pixel in an image into a specified category. U-Net was originally created for biological picture segmentation, but it has shown to be extremely effective in a variety of applications, including flood mapping, where spatial precision is crucial. [6,7]

Objectives of our study is to

- Develop a U-Net-based flood inundation mapping framework for the Teesta Dam region using Sentinel-2 imagery.
- Evaluate segmentation performance using IoU, F1-score, Precision, and Recall metrics.
- Validate flood inundation patterns using NDVI and MNDWI analysis.

Figure 1. Flood Inundation map of Gojaldoba Tea Garden

This study uses a U-Net deep learning model to improve flood mapping near the Teesta Dam area. The U-Net model uses an encoder–decoder design with skip connections to clearly identify water areas from satellite images by capturing both detailed and surrounding information. By creating detailed flood maps, this method helps dam authorities and disaster management teams understand flood conditions better and take timely decisions in the Teesta River Basin.

2. Related Work

Flood mapping has been widely studied because it plays an important role in disaster management and flood control. Flood mapping have been made using a variety of methodology, including classic hydrological simulations and statistical techniques as well as modern deep learning-based systems.

2.1. Review of Conventional Flood Mapping Techniques

1. Hydrological simulations, such as HEC-RAS is one of the conventional flood mapping that mimics the flow, distribution, and control of water in both natural and manmade systems. Strength of this model is accurate simulation of water flow when appropriate data is provided. This model has certain limitation which include data gathering and preparation, which is computationally costly and less adaptive to dynamic and real-time circumstances. [8,9]

2. Statistical techniques have been utilized to identify correlations among prior data and flood events. Time-series modelling, statistical regression, and autoregressive integrated moving average (ARIMA) are among various methods used. Strengths: Easier to implement; takes less processing resources. Limitations: They are ineffective for complicated or unusual flood occurrences since they do not capture nonlinear linkages or geographical patterns. [10,11]

2.2. Review of Modern Flood Mapping Techniques

1. CNNs for Spatial Data Analysis: Convolutional Neural Networks (CNNs) excel in interpreting spatial information such as satellite imagery, and extracting flood extent characteristics. CNNs can recognize flood-affected bodies of water, towns, and foliage. These algorithms can learn correlations in pixel-level information making them useful for flood mapping. [12,13]

2. Deep learning models are widely used for flood mapping and satellite image analysis. Encoder–decoder models with skip connections help in identifying flood-affected regions and preserving flood boundaries in satellite images. These models are useful for flood extent mapping and post-flood damage analysis. [14,15].

Despite progress, significant obstacles remain in the field of flood mapping:

Despite major progress in flood inundation mapping, some problems still exist in identifying flood-affected areas correctly in Himalayan river regions like the Teesta basin. Many earlier studies mainly focused on general flood mapping methods or SAR-based flood studies without giving proper attention to the geographical and environmental conditions of the Teesta region. In addition, several traditional flood mapping methods are not able to clearly preserve flood boundaries and small spatial details in satellite images.

Deep learning models such as U-Net have shown good results in image segmentation tasks. However, only a few studies have used U-Net for flood inundation mapping in the Teesta Dam region using Sentinel-2 satellite imagery along with NDVI and MNDWI validation. Also, comparison of U-Net with both traditional and deep learning flood mapping methods under the same preprocessing and evaluation conditions is still limited for Himalayan flood-prone regions. Therefore, this study develops a U-Net-based flood inundation mapping framework for the Teesta basin using Sentinel-2 imagery and evaluates its performance using environmental index validation and comparative analysis. Table 1 briefly elaborates the various techniques along with advantages and limitation of each.

Table 1. Comparative analysis of recent techniques

Model / Technique	Advantages	Limitations	Reference (Year)
Otsu Thresholding	Simple, fast, unsupervised	Sensitive to noise, poor performance on complex scenes	[16] (1979)
Random Forest Pixel Classifier	Handles high-dimensional data, interpretable feature importance	Ignores spatial dependencies, requires manual feature extraction	[17] (2001)
SegNet	Learns hierarchical features, better spatial consistency	Computationally intensive, moderate accuracy	[18] (2017)
PSPNet	Captures multi-scale context, good global information aggregation	Complex architecture, large memory footprint	[19] (2017)
Proposed U-Net	Precise pixel-level mapping, good boundary preservation, efficient	May require large labelled datasets for training	This study (2026)

3. Methodology

3.1. Study Area and Data Sources

The study area for this work is located near the Teesta Dam region in Kalimpong, northeast India. Sentinel-2 Level-2A satellite imagery obtained from the Copernicus Open Access Hub was used for flood inundation analysis. [21] The geographical coordinates of the study area are approximately 27.0018057°N and 88.4404352°E. Figure 2 presents the Natural Color Composite (NCC) image of the study area. Figure 3 shows its geographical location with reference to the map of India.

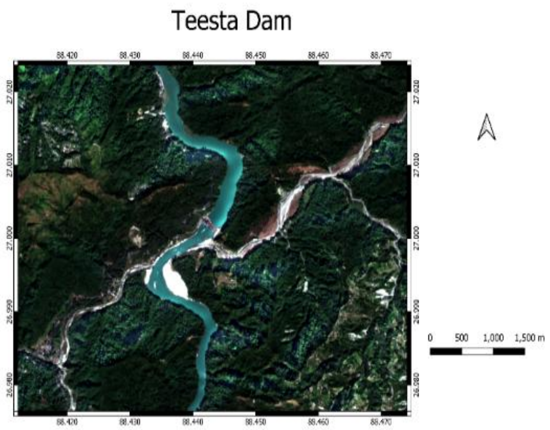

Figure 2. Natural colour composite image of Teesta Dam

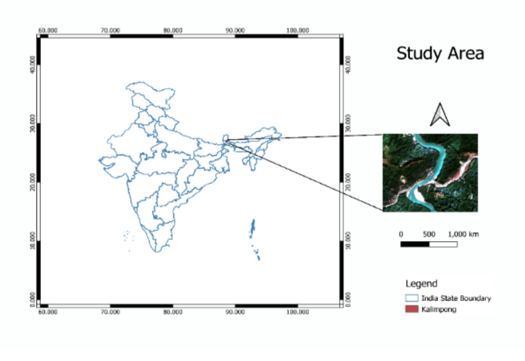

Figure 3. Location with reference to map of India

Figure 4. DEM Image of Study Area

Figure 4 represents Digital Elevation Model (DEM) of the study area near Teesta dam. DEM is a three-dimensional depiction of a terrain's surface, which is frequently employed for flood mapping and topographical study. This DEM elevation model is created using satellite data from SNAP tool to provide comprehensive elevation information. Figure 5 presents integration of NCC image with DEM visualization. A Natural Colour Composite (NCC) Image is a satellite picture made by blending red, green, and blue (RGB) bands to simulate how humans see colours in nature. Usually Combining spectral and elevation information helps in understanding both land-cover characteristics and terrain variations within the study area.

Figure 5. Natural Colour Composite Image with Elevation of Teesta Dam

3.2. Data processing

The original image and its mask image or a classified image are shown in Figure 7. Classifying an image is a procedure of identifying the features in natural composite picture. Identification and extraction of feature is a way to highlights one structure's pixel while depreciating other one. The SNAP tool is used here to prepare classified image for the actual sentinel-2A pictures in this work. [22] Sentinel toolbox (SNAP) version 9.0.0 is used to extract features and create classified images along with atmospheric correction, band processing, cloud removal, water index calculation, DEM generation, and dataset preparation for flood segmentation. The preprocessing workflow followed in this study is shown in Figure 6.

Atmospheric Correction

Atmospheric correction was carried out using the Sen2Cor processor available in SNAP. This process converted Level-1C images into Level-2A images and helped reduce the effects of haze, aerosols, and atmospheric noise. The corrected images provided clearer surface information for flood analysis.

Band Selection

The important spectral bands were selected from Sentinel-2 imagery for water-body extraction. The Green and Near-Infrared (NIR) bands were used to calculate NDWI, while the Green and Short-Wave Infrared (SWIR) bands were used to calculate MNDWI.

Cloud Masking

Pixels of Cloud coverage were eliminated using Sen2Co in SNAP. Eliminating this enhanced the visibility of land and water regions and strengthened the accuracy of flood segmentation.

Resampling

Resampling of selected bands were done to a common spatial resolution of 10 m × 10 m. This process balanced uniformity in all satellite bands throughout feature extraction and model training.

Coordinate Reference System (CRS)

The satellite images were projected in the WGS 84 / UTM coordinate system so that all images of the study area followed the same geographic reference.

NDWI and MNDWI Calculation

The NDWI and MNDWI indices were calculated to identify water bodies more clearly and to distinguish water regions from non-water areas [20]. These indices enhanced flood and reservoir regions in the satellite images.

NDWI formula:

$$\mathrm{NDWI} = (\mathrm{Green} - \mathrm{NIR})/(\mathrm{Green} + \mathrm{NIR})$$

MNDWI formula:

$$MNDWI = (\mathrm{Green} - \mathrm{SWIR})/(\mathrm{Green} + \mathrm{SWIR})$$

After calculating MNDWI, threshold-based classification was applied to separate water and non-water regions. Pixels with MNDWI values greater than 0 were identified as water pixels, while values below 0 were classified as non-water regions. The threshold value was selected through visual inspection and comparison with flood-affected areas to improve water extraction accuracy under different environmental conditions.

DEM Generation

A Digital Elevation Model (DEM) of the study area was also generated using SNAP 9.0.0 to observe terrain elevation and topographical features around the Teesta Dam region. The DEM helped in understanding low-lying areas, drainage flow, and flood-prone regions. Although the proposed U-Net model mainly used Sentinel-2 spectral imagery for segmentation, the DEM supported terrain visualization and geographical analysis during preprocessing.

Patch Extraction and Dataset Generation

After water-body enhancement, the processed satellite images and classified flood masks were divided into smaller image patches for deep learning model training. The image patches were normalized to improve training stability and model performance.

The flood segmentation dataset was prepared using Sentinel-2 satellite imagery collected for the Teesta Dam region during flood-related events. The satellite images were pre-processed using SNAP 9.0.0, and corresponding flood masks were generated using MNDWI-based water extraction together with visual verification. After pre-processing, the images and flood masks were divided into smaller patches of size 256 × 256 pixels for U-Net training. The prepared dataset contained approximately 2,000 image patches representing flooded and non-flooded regions. The dataset was divided into training, validation, and testing sets using a ratio of 70:15:15 to maintain consistency during model evaluation. The final dataset contained paired satellite image patches and flood masks for flood segmentation using the proposed U-Net model.

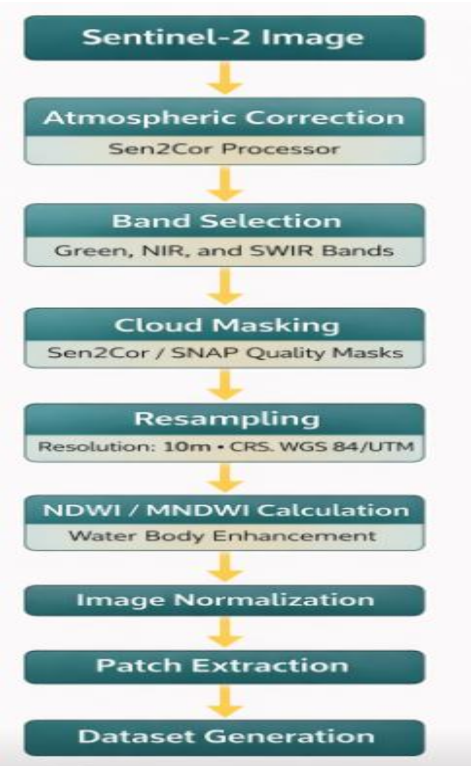

Figure 6. SNAP Workflow for Flood Dataset Generation

The function Mask manager in SNAP is used to generate new classified images for actual natural composite pictures.

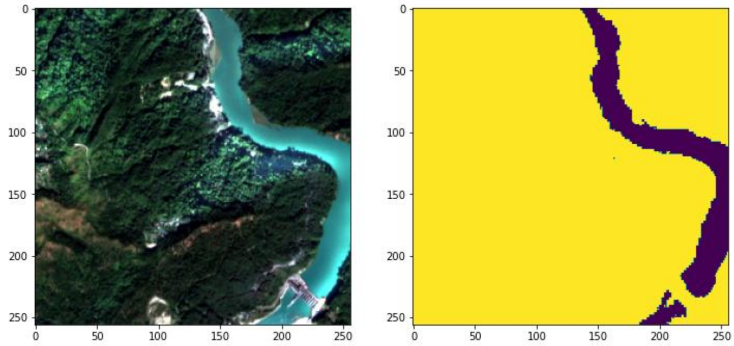

Figure 7. Classified Teesta Dam using MNDWI

Figure 8 explains the overall methodology followed in this study. First, the Natural Colour Composite (NCC) image was obtained from the Copernicus platform and pre-processed using the SNAP toolbox. The classified flood masks generated through MNDWI-based water extraction were then used together with the NCC images as inputs for the U-Net model.

The proposed U-Net architecture consists of two main stages: the encoder stage and the decoder stage. In the encoder stage, the spatial dimensions of the feature maps are reduced while the number of channels increases for extraction of high-level flood-related features. In the decoder stage, the feature maps are up-sampled to restore the original spatial dimensions and generate pixel-level flood segmentation outputs.

The proposed U-Net model contains more than 200,000 trainable parameters and produces detailed flood inundation maps from Sentinel-2 satellite imagery

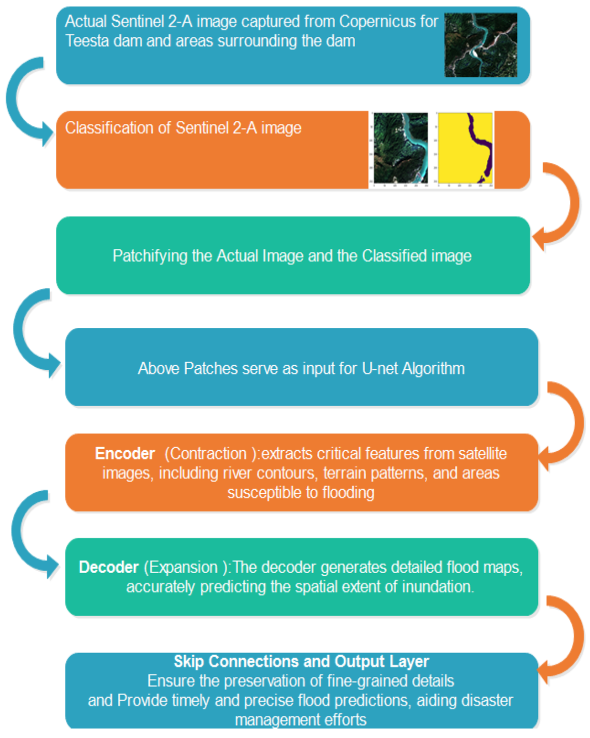

Figure 8. Overall Methodology of the Proposed Flood Segmentation Framework

3.3. U-NET Architecture

U-Net is a well-known model of deep learning in the field of image segmentation, but its utilization for mapping flood in the region of Teesta Basin using Sentinel-2 imagery gives crucial, practical and region-specific insights. The contribution of this article lies in building a reproducible framework of flood segmentation by unifying pre-processing of satellite imagery, validation of environmental index (NDVI and MNDWI), and comparable analysis of our approach with pre-existing segmentation methodology for assessment of dam-induced flood.

The U-Net model described in Figure 9 was trained for 100 epochs to improve flood segmentation performance and achieve stable results. The model uses a symmetric encoder–decoder architecture for pixel-level flood detection from Sentinel-2 satellite images.

In the encoder part, each block contains two 3×3 convolution layers followed by ReLU activation functions. A 2×2 max-pooling layer is used after each block to reduce the image size and extract important flood-related features. The number of filters increases gradually from 64 to 128, 256, and 512 to learn more complex patterns from the satellite images. The bottleneck layer connects the encoder and decoder sections and stores the important deep features learned from the input imageIn the decoder part, 2×2 transposed convolution layers are applied for up-sampling to recover the original image size. Skip connections link the encoder and decoder layers to retain important spatial features and improve the identification of flood boundaries. Each decoder block also contains two 3×3 convolution layers with ReLU activation to improve feature learning.

Finally, a 1×1 convolution layer with sigmoid activation is used to generate binary flood masks representing flooded and non-flooded regions. The model was trained using the Adam optimizer and Dice Loss function to handle class imbalance during flood segmentation. The loss was reduced iteratively using backpropagation and gradient descent, which improved the prediction accuracy over the training epochs.

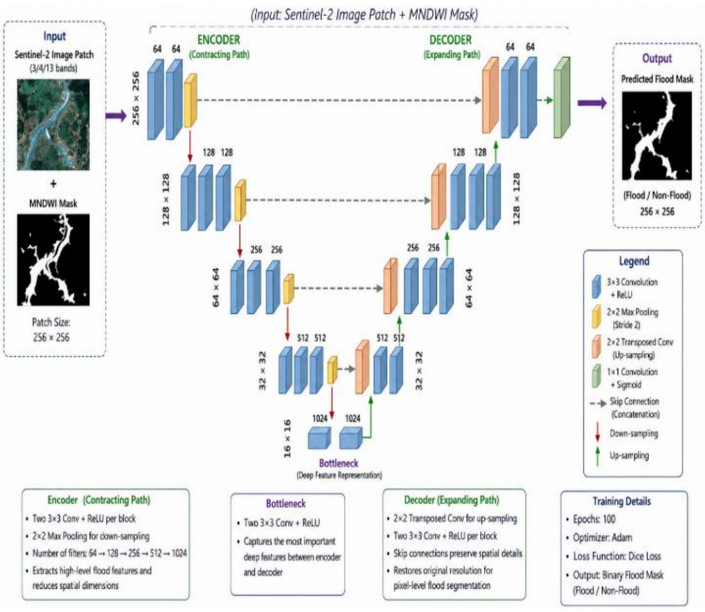

Figure 9. U-Net-Based Flood Segmentation Architecture

4. Result

U-net in our case was made to run for 100 epochs to get better results. Throughout each epoch, the U-Net model was analysing training pictures so that it can pick up spatial and semantic characteristics for classification purposes. The encoder phase collected high-level information, which was further refined by decoder to pixel-level prediction. With every epoch, the algorithm iteratively improves the predictions by lowering the amount of loss through gradual descent.
Figure 10 represent intersection graph over Union (IoU) and Figure 11 represents loss graphs which is used here to assess and show U-Net model's effectiveness during training and validation. These graphs aided in flood prediction using the Teesta Dam dataset by monitoring model advances and detecting flaws such as overfitting or underfitting.

The segmentation performance of the proposed U-Net model was evaluated using the Intersection over Union (IoU) metric, which measures the overlap between the predicted flood region and the ground truth flood mask.
The IoU is computed as:

$$IoU = TP/(TP + FP + FN)$$

where:
TP (True Positive): correctly identified flooded pixels
FP (False Positive): non-flooded pixels incorrectly classified as flooded
FN (False Negative): flooded pixels incorrectly classified as non-flooded
A higher IoU value indicates better segmentation accuracy and stronger overlap between predicted and actual flood regions.
For evaluation, the IoU value was calculated separately for each test image, and the final reported IoU score is the average value obtained from all test images in the dataset.
The IoU metric was used to measure the overlap between the predicted flood map and the actual flood map. It is calculated by dividing the overlap area by the total combined area of both maps.
In the IoU graph:

1. The x-axis shows the number of epochs.
2. The y-axis shows the IoU value from 0 to 1.

The IoU curve shows how accurately the model predicts flood areas compared to the real data. A higher IoU value means better model performance. A plateau indicates that the model has reached its learning capability on the dataset.

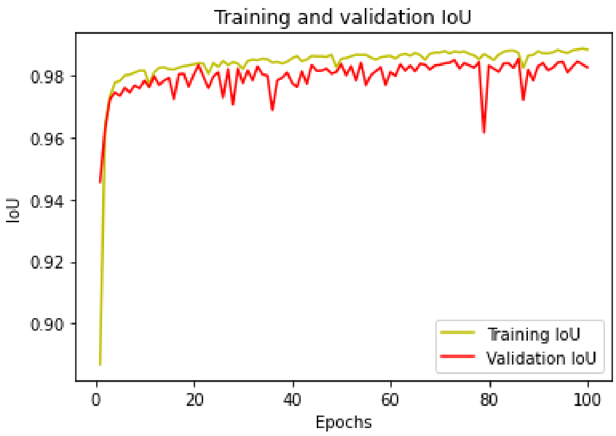

Figure 10. Curves for IOU

Whereas the loss curve represents the error between the predicted and actual outputs during training and validation. The loss function Dice Loss is minimized here during training.

Characteristics:
1. Here X-Axis represents Number of epochs.
2. And Y-Axis represents Loss value.

Loss curve tracks the model's convergence and generalization. Training Loss here is decreasing as the model learns from the data. Validation Loss is also decreasing and stabilize it did not increase in our study as the model did not overfits.

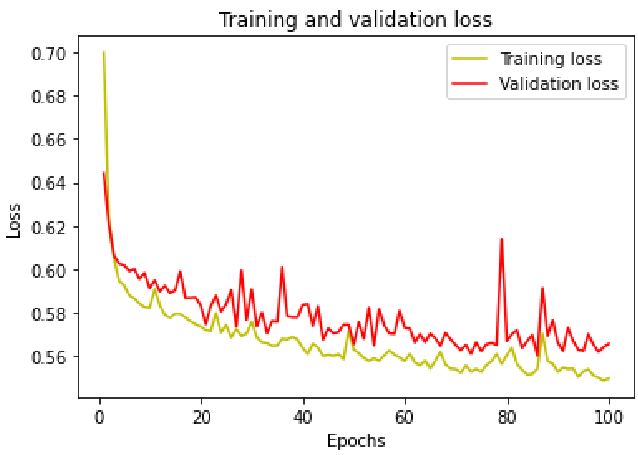

Figure 11: Curves for Loss

Hyperparameter Tuning and Dice Loss

The proposed U-Net model was trained using the Adam optimizer and Dice Loss function for flood segmentation. Dice Loss was selected because flood regions usually cover a smaller area compared to the background. This creates class imbalance during training. Dice Loss helps the model learn the flood boundaries more accurately and improves segmentation performance.
The model was trained using a learning rate of 0.001 and a batch size of 8 for 100 epochs. The ReLU activation function was used in the hidden layers, and the Sigmoid activation function was used in the output layer for binary flood segmentation. Different training settings were tested to achieve stable learning and improve segmentation accuracy. The training and validation losses were continuously monitored during the optimization process to reduce overfitting and improve model convergence.
The selected hyperparameters provided stable training performance and helped the model generate accurate flood segmentation masks from Sentinel-2 satellite imagery.

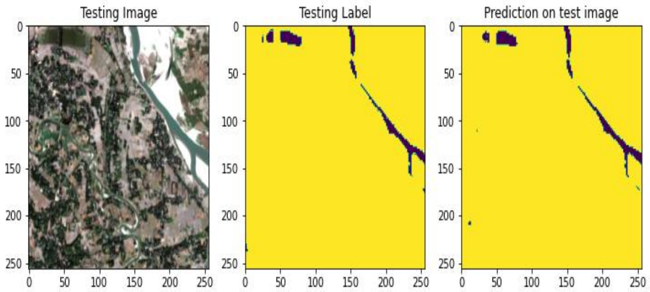

Figure 12. Predicted classified image

Figure 12 briefs the final segregation outcomes and results. The figure shows the real picture (Testing picture), the ground truth (Testing Label), and the expected mask (Prediction on test image) using U-Net. As can be seen, the segmentation results for dam photos are adequate, despite the loss value that have been seen in our case.

5. Validation and Comparative Analysis

Heavy rainfall caused the South Lhonak lake to rupture in October 2023, causing major flooding in Sikkim1. Significant water level rises were caused by this disastrous event in a number of locations, notably Lachen City (Point 1) and the Lachung River's merging with the Teesta River (Point 2).

All comparative models including Random Forest, SegNet, PSPNet, and the proposed U-Net were trained and evaluated using the same Sentinel-2 flood dataset and identical preprocessing workflow. The dataset was divided into training, validation, and testing sets using the same data split ratio for all models to ensure fairness in comparison.

The same evaluation metrics including Intersection over Union (IoU), F1-score, Precision, and Recall were used for performance assessment across all models. The experiments were conducted under similar training conditions to maintain consistency during evaluation.

Random Forest was implemented as a pixel-based classifier using spectral features extracted from Sentinel-2 imagery. SegNet and PSPNet were trained using the same flood masks and satellite image patches used for the proposed U-Net model.

The proposed U-Net achieved better flood-boundary preservation and segmentation accuracy shown in table 2 due to the presence of skip connections and symmetric encoder-decoder architecture.

Table 2. Performance Comparison of the Proposed U-Net Model with Existing Flood Segmentation Methods

Model / Technique	IoU (%)	F1-score (%)	Precision (%)	Recall (%)	Reference
Otsu Thresholding	72	78	80	75	[16]
Random Forest Pixel Classifier	80	85	88	82	[17]
SegNet	88	90	91	89	[18]
PSPNet	90	92	93	91	[19]
Proposed U-Net	98	98	99	97	This study

Analysis of NDVI and NDWI

Two indices, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI), were used to study changes in vegetation and water in the flood-affected area. NDVI helped in identifying vegetation conditions, while NDWI was used to observe changes in surface water and flood spread. These indices together provided a clear understanding of how flooding affected the land cover in the study area.
During the flood period, the NDWI values increased in the affected locations, showing an increase in surface water and flooded areas. At the same time, NDVI values decreased, indicating damage or reduction in vegetation cover due to floodwater. In several regions, vegetation was

submerged under water, which further reduced the NDVI values.
The results obtained from NDVI and NDWI closely matched the flood inundation patterns predicted by the U-Net model. Areas identified as flooded by the model showed higher NDWI values and lower NDVI values. This similarity confirms the reliability of the flood mapping results and shows that flooding had a strong impact on both water spread and vegetation condition.
Therefore, NDVI and NDWI are useful indices for monitoring flood damage, identifying inundated regions, and understanding landscape changes after flooding.
The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) are useful for studying vegetation condition and water presence. During the flood period, both indices showed noticeable increases, indicating a higher amount of water in the affected areas.

Validation of the U-Net Model

The flood-affected areas were identified and mapped using the U-Net model, which is a type of convolutional neural network. The model results were supported by high NDVI and NDWI values observed in October 2023 (Figures 13–14). The increase in these values confirmed the presence of water in the selected locations.
Lachen City (Point 1) showed a clear increase in water level during the flood according to the NDVI and NDWI values. The Lachung River and Teesta River meeting point (Point 2) also showed high NDVI and NDWI values, indicating heavy water presence in that area.
These results support the flood maps generated by the U-Net model and show that the model can successfully identify flood-affected regions.

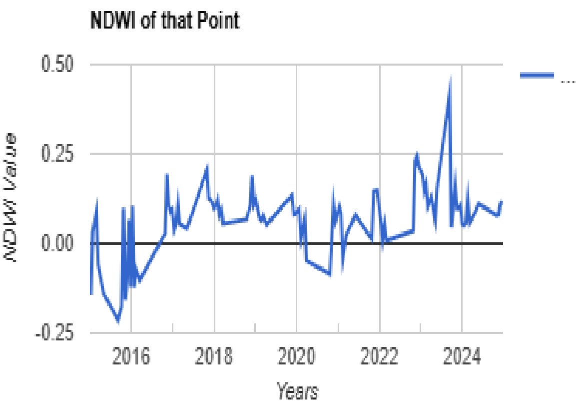

Figure 13. Lachung point near Lachen city

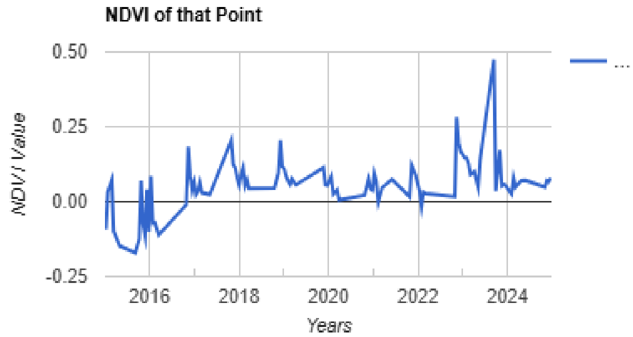

Figure 14. Lachung river merger with Teesta point

6. Conclusion

This study presented a U-Net-based flood mapping framework for the Teesta Dam region using Sentinel-2 satellite images. The model successfully identified flood-affected areas and generated detailed flood maps with clear boundary detection.
The proposed U-Net model achieved 98% IoU, 98% F1-score, 99% precision, and 97% recall, showing better performance than Otsu Thresholding, Random Forest, SegNet, and PSPNet. The flood results produced by the model were also supported by NDVI and NDWI analysis.
The study shows that deep learning-based flood mapping can help in flood monitoring and disaster management in Himalayan river basin areas such as the Teesta region. However, the current work only uses satellite images and does not include real-time hydrological, weather, or IoT sensor data.
In future work, real-time environmental and hydrological data will be added to develop better flood prediction and early warning systems.

References

[1] Levy JK, Gopalakrishnan C, Lin Z. Advances in decision support systems for flood disaster management: Challenges and opportunities. *Water Resources and Decision-Making Systems*. 2016; 81–100.
[2] Munawar HS, Hammad AW, Waller ST. Remote sensing methods for flood prediction: A review. *Sensors*. 2022; 22(3): 960.
[3] Islam MF, Islam MF. The Teesta River and its basin area. *Water Use and Poverty Reduction*. 2016; 13–43.
[4] Hossen MA, Connor J, Ahammed F. Valuation of the Teesta River water by hydro economic model. *Water Conservation Science and Engineering*. 2024; 9(1): 17.

[5] Goyal MK, Goswami UP. Teesta River and its ecosystem. *The Indian Rivers: Scientific and Socio-Economic Aspects*. 2018; 537–551.
[6] Siddique N, Paheding S, Elkin CP, Devabhaktuni V. U-Net and its variants for medical image segmentation: A review of theory and applications. *IEEE Access*. 2021; 9: 82031–82057.
[7] Li W, Wu J, Chen H, Wang Y, Jia Y, Gui G. U-Net combined with attention mechanism method for extracting flood submerged range. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 2022; 15: 6588–6597.
[8] Tamiru H, Dinka MO. Application of ANN and HEC-RAS model for flood inundation mapping in lower Baro Akobo River Basin, Ethiopia. *Journal of Hydrology: Regional Studies*. 2021; 36: 100855.
[9] Costabile P, Costanzo C, Ferraro D, Barca P. Is HEC-RAS 2D accurate enough for storm-event hazard assessment? Lessons learnt from a benchmarking study based on rain-on-grid modelling. *Journal of Hydrology*. 2021; 603: 126962.
[10] Al-Hussein AA, Khan S, Ncibi K, Hamdi N, Hamed Y. Flood analysis using HEC-RAS and HEC-HMS: A case study of Khazir River (Middle East–Northern Iraq). *Water*. 2022; 14(22): 3779.
[11] Samantaray S, Sahoo A, Agnihotri A. Assessment of flood frequency using statistical and hybrid neural network method: Mahanadi River Basin, India. *Journal of the Geological Society of India*. 2021; 97: 867–880.
[12] Karim F, Armin MA, Ahmedt-Aristizabal D, Tychsen-Smith L, Petersson L. A review of hydrodynamic and machine learning approaches for flood inundation modeling. *Water*. 2023; 15(3): 566.
[13] Baloch F, Kalhoro AN, Memon F. Flood disaster estimation using images and machine learning. *Journal of Computing & Biomedical Informatics*. 2023; 5(1): 403–414.
[14] Jenifer AE, Aparna A, Sudha N, Kumar A. AgriFloodNet: A dual patch CNN architecture for mapping flooded agricultural lands via bi-temporal multi-sensor images. *Geocarto International*. 2022; 37(26): 13618–13637.
[15] Li Z, Demir I. U-Net-based semantic classification for flood extent extraction using SAR imagery and GEE platform: A case study for 2019 central US flooding. *Science of the Total Environment*. 2023; 869: 161757.
[16] Otsu N. A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*. 1979; 9(1): 62–66.
[17] Breiman L. Random forests. *Machine Learning*. 2001; 45(1): 5–32.
[18] Badrinarayanan V, Kendall A, Cipolla R. SegNet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 2017; 39(12): 2481–2495.
[19] Zhao H, Shi J, Qi X, Wang X, Jia J. Pyramid scene parsing network. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2017; 2881–2890.
[20] Xu H. Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*. 2006; 27(14): 3025–3033.
[21] Drusch M, Del Bello U, Carlier S, Colin O, Fernandez V, Gascon F, Hoersch B, Isola C, Laberinti P, Martimort P, Meygret A, Spoto F, Sy O, Marchese F, Bargellini P. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment*. 2012; 120: 25–36.
[22] European Space Agency. Sentinel Application Platform (SNAP). 2024. Available at: https://step.esa.int/main/toolboxes/snap/