AMRITA VISHWA VIDYAPEETHAM
DEEMED TO BE UNIVERSITY

Extraction Of Water Bodies From SAR Images

Team Number: A1_S1

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Project Code: R & D

Guide: Dr .Don S

Instructions

Identify to which category your project belong to: Give the code in slide 1

1. **Research Project (R) :** To contribute to academic knowledge by identifying gaps in existing research and proposing novel methodologies or theories.
2. **Product-Based Project Development(D):** To solve real-world problems or create practical, innovative solutions with potential industrial applications.
3. **Research and Development Project(R&D)** : Combines the pursuit of knowledge (research) and practical solutions (products).

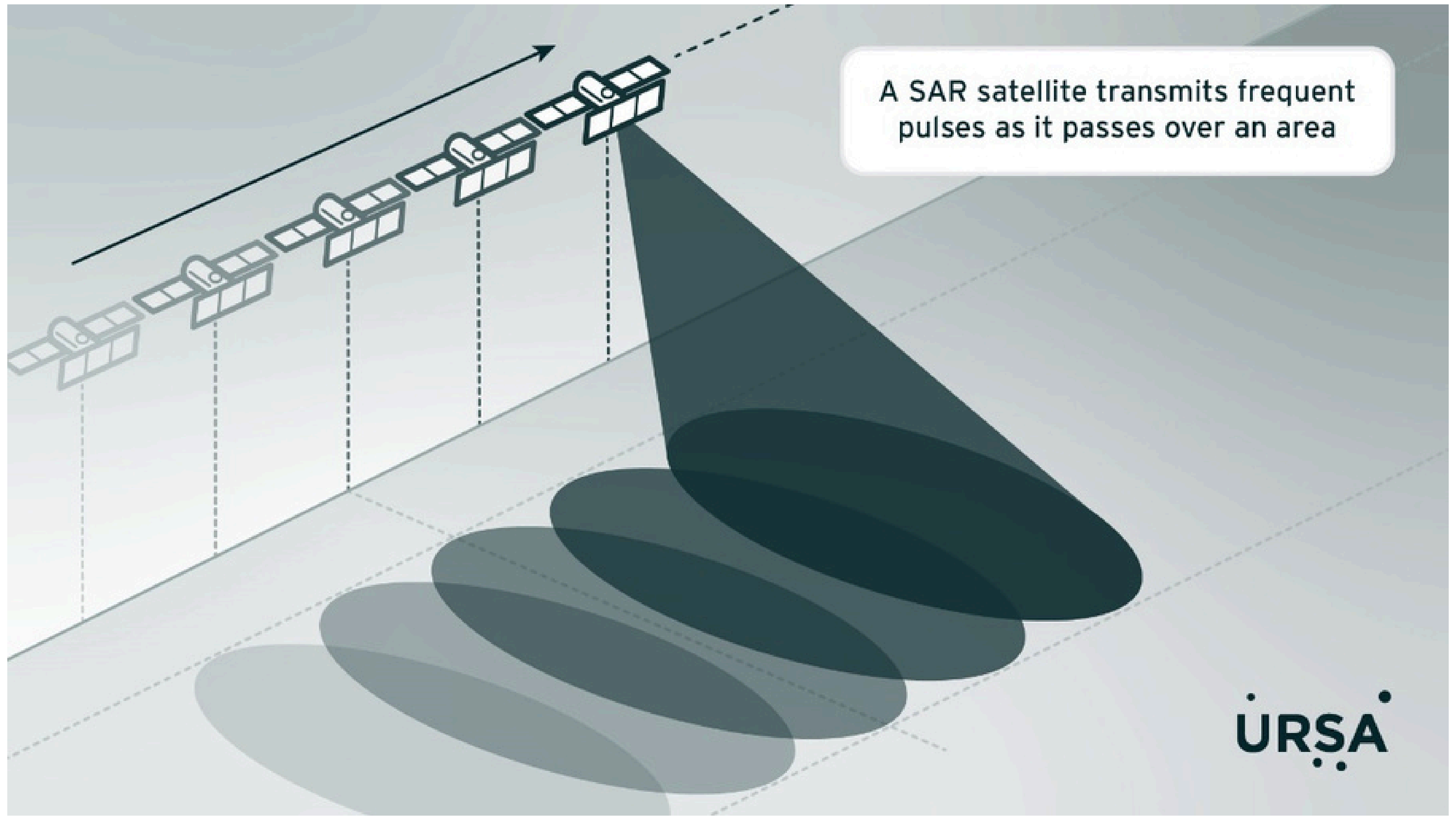
- The presentation should have a smooth flow of information with sufficient background, problem addressed, Existing Solutions, Your proposed novel approach, Results and Performance evaluation.
- Have a neat comprehensive block diagram which depicts the entire flow of the project. Avoid lengthy paragraphs—use **concise bullet points t**o highlight key ideas. Ensure each bullet is self-explanatory but leaves room for elaboration during your talk. Have good visuals for better explanation of concepts. Avoid slides that are either too sparse or too cluttered. Provide strong result and performance evaluation slides with graphs/tables, and comparison with existing work.

- **Clearly emphasize what is unique about your approach in comparison to existing solutions**

Background of the work

SAR (Synthetic Aperture Radar) is a technology that uses radar signals to capture detailed images of the Earth's surface. SAR works in all weather conditions, day or night, and can see through clouds. This makes it extremely reliable for monitoring areas where traditional optical satellites fail, such as during floods or bad weather.

SAR Images in Water Body Segmentation:
SAR images highlight differences in surface properties like water, vegetation, or land. Water surfaces reflect radar signals differently than land, making them easier to identify. This helps in detecting water bodies even in challenging environments, such as urban areas with shadows or regions with dense vegetation. By using deep learning models like U-Net, SAR images can be processed to automatically segment water bodies. These models analyze the unique patterns in SAR images, separating water from non-water regions with high accuracy.



Problem addressed and Motivation

Problem Description:

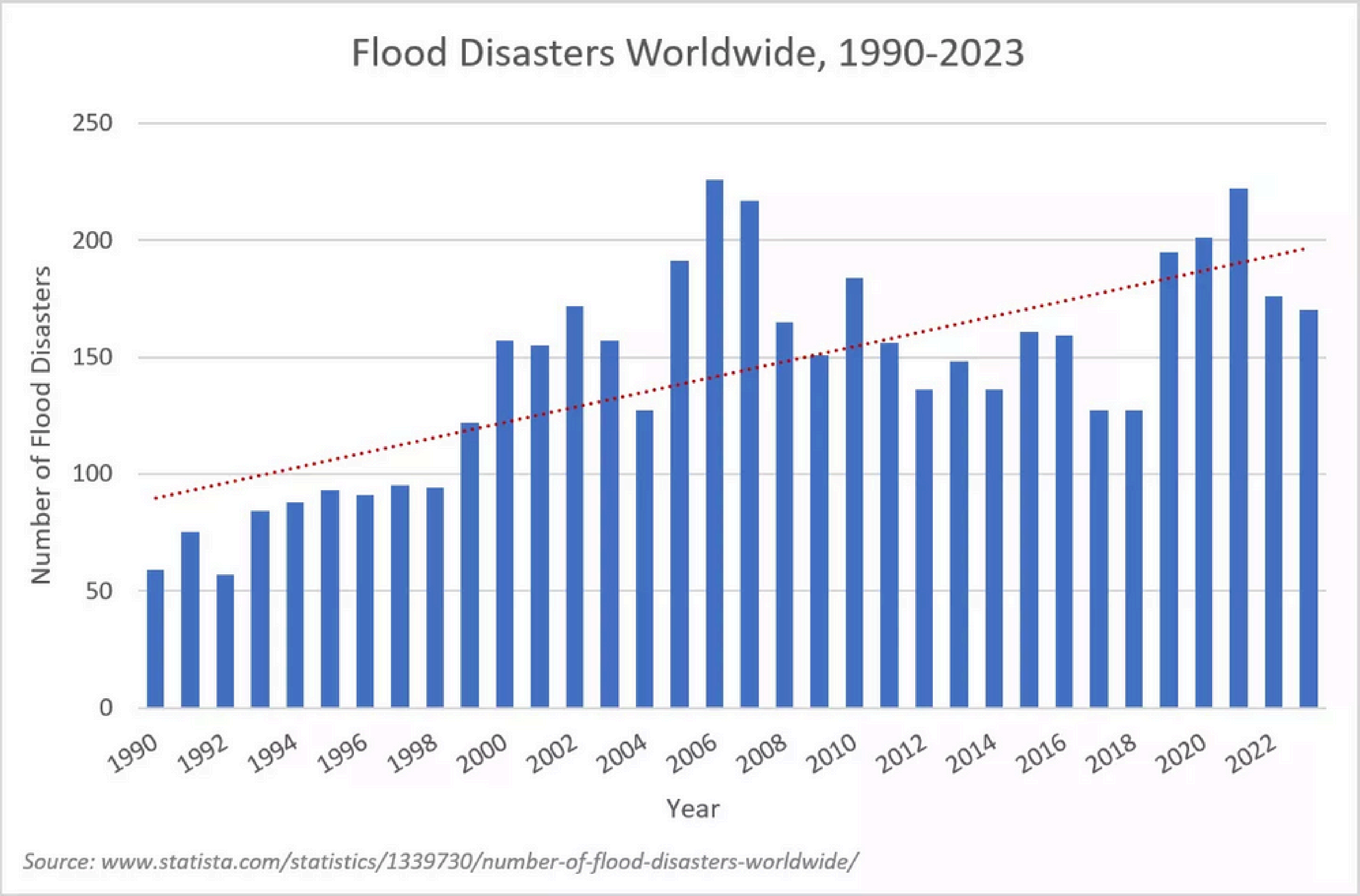
Traditional methods for finding and monitoring water bodies often use optical satellite images, but these have many limitations. They do not work well in bad weather, under clouds, or at night, which leads to incomplete or inaccurate data. This is a big problem in situations like flood monitoring or drought assessment, where quick and accurate information is very important.

Manually analyzing SAR images takes a lot of time and can lead to mistakes, especially in areas with mixed land and water, thick vegetation, or urban shadows. Current automated methods are not always accurate or able to handle large-scale challenges.
This project solves these problems by using SAR images and advanced deep learning techniques. It aims to create a strong system for identifying water bodies in any environmental condition.

Problem addressed and Motivation

Motivation:

The increasing occurrence of extreme weather events and the ongoing struggles with managing water resources emphasize the urgent need for effective and reliable methods to detect and monitor water bodies. With climate change, the importance of such methods has grown significantly. Synthetic Aperture Radar (SAR) imaging stands out as a valuable tool for addressing these challenges because it can work in all weather conditions and at any time of day or night, unlike optical imagery which can be affected by weather and sunlight. This project aims to utilize SAR images to accurately detect and extract water bodies. It also supports decision-making by providing real-time data that can be used in various sectors, including agriculture, urban planning, and emergency response.



Literature Review/Existing System

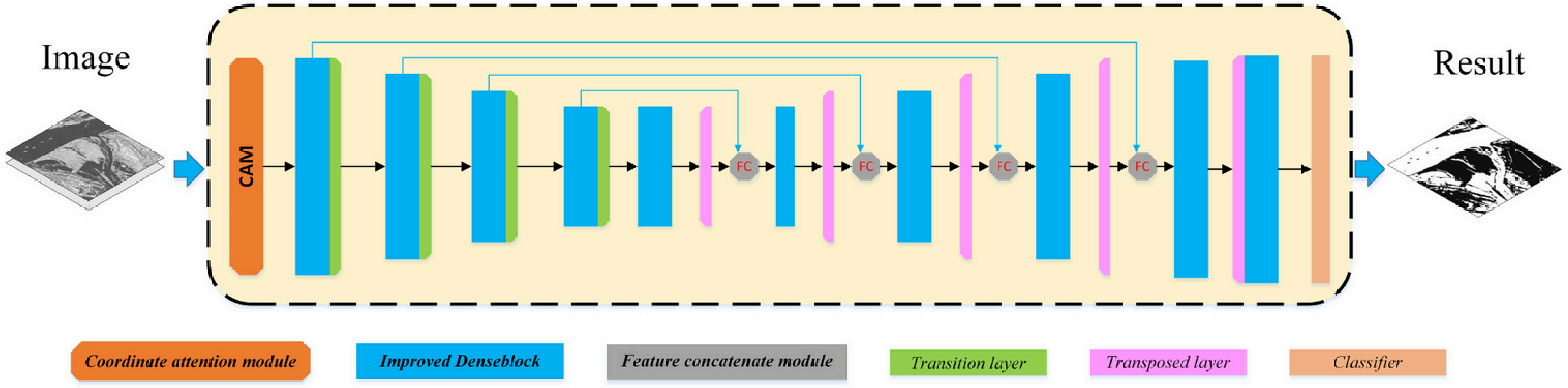
Water Body Automated Extraction in Polarization SAR Images With Dense-Coordinate-Feature-Concatenate Network

Dense-Coordinate-Feature-Concatenate Network

Coordinate Attention Module (CAM)

Dense Block Module

Feature Concatenate Module



These modules work together to improve both the accuracy of the water body extraction and the generalization across different environments and SAR sensors. This makes DCFNet a powerful model for tasks like flood monitoring, coastline change detection, and resource management using SAR imagery

Limitations: High computational costs, requiring significant processing power. Additionally, small datasets may lead to overfitting, reducing the model's ability to generalize effectively.

Semantic segmentation of wetland water surfaces with SAR imagery using deep neural networks

U-Net architecture is specifically designed for image segmentation, where the goal is to classify each pixel of the input image into a certain class (e.g., water, land).

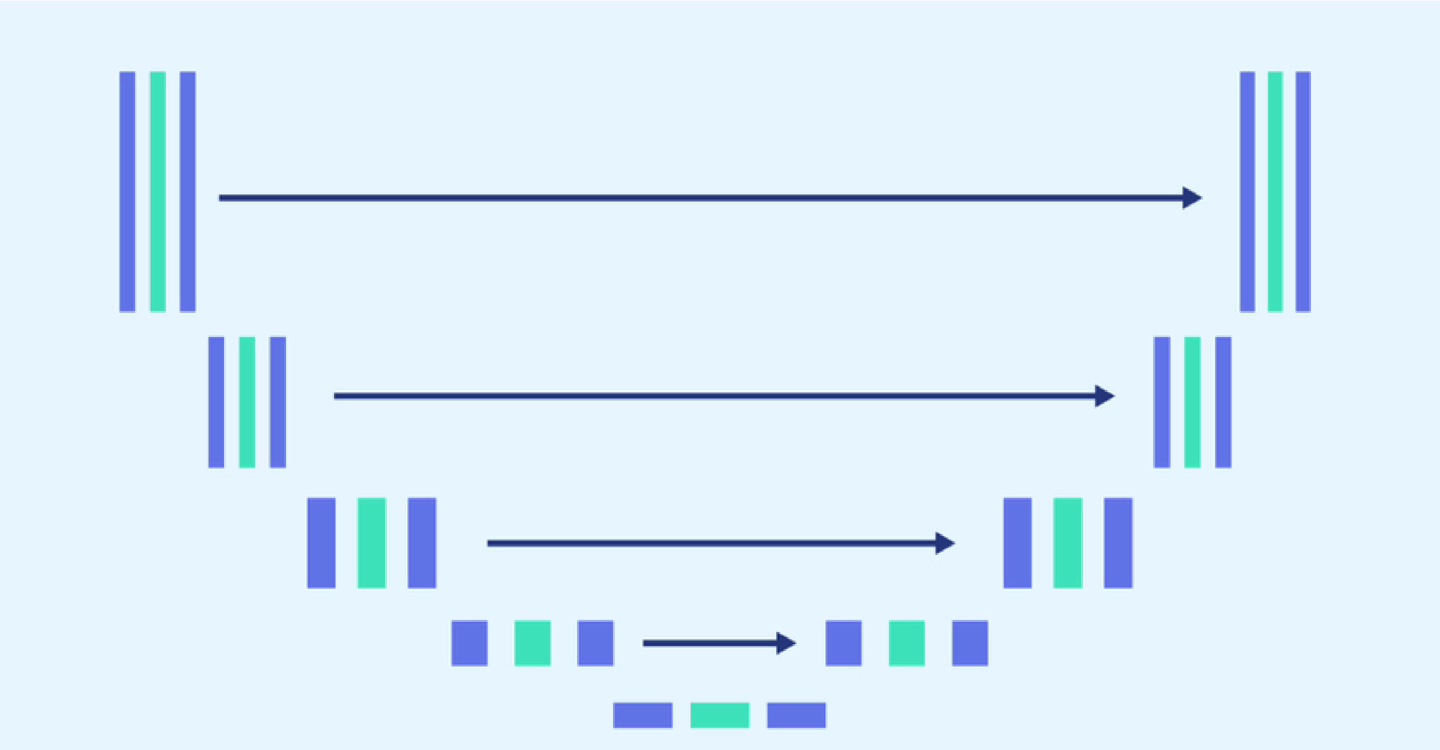
Components:

Encoder:
extracts features and reduces image size.

Decoder:
restores the original size, producing a segmented output.

Bottleneck:
holds compressed but rich feature information.

Skip connections:
ensure that the detailed features from the encoder are preserved in the decoder



Strengths: The DeepAqua method is good at detecting wetland water surfaces using SAR images, which work well in different weather and lighting conditions. The use of deep learning helps make the segmentation more accurate.

Limitations: The method depends on the availability and high cost of SAR data, and it may have trouble working in non-wetland areas without retraining.

Semantic segmentation of wetland water surfaces with SAR imagery using deep neural networks

Knowledge Distillation (Teacher-Student Model)

The core idea of knowledge distillation here is that the teacher model (NDWI) generates water masks from optical images. These masks act as "pseudo-labels" for training the student U-Net model on SAR images, eliminating the need for human-labeled data.

Cross-Modal Learning

The key challenge is that SAR images are harder to interpret than optical images, especially when it comes to distinguishing water surfaces hidden under vegetation. However, by learning from the teacher model the student model gradually learns to segment water surfaces from SAR imagery. [where knowledge is transferred from one type of data (optical) to another (SAR).]

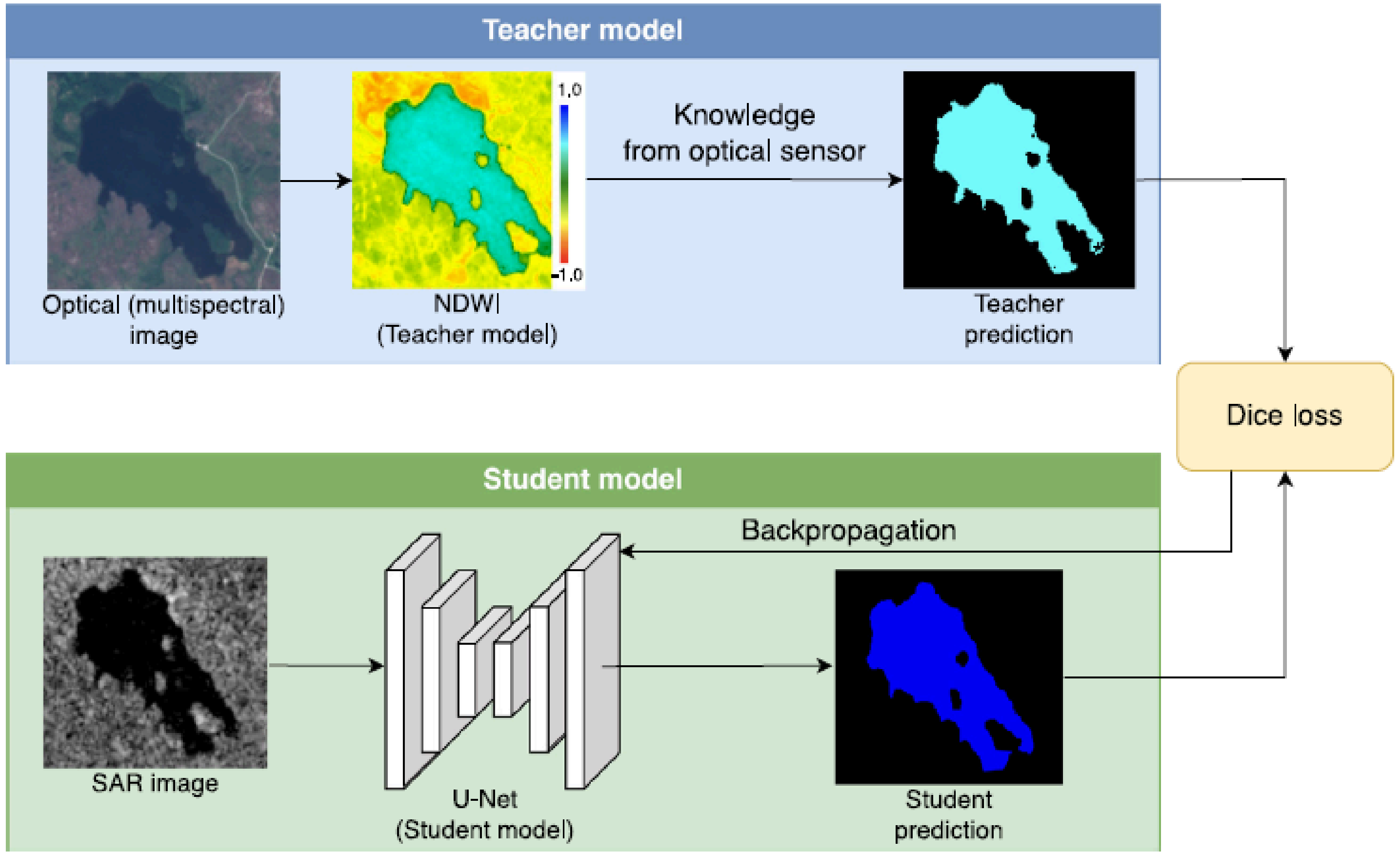


Fig. 3. The process of training a CNN model to recognize water boundaries from SAR imagery by learning from a NDWI model.

Segmentation of Water Bodies in Remote Sensing Satellite Images Using Nested Dense Residual U-Net

Nested Dense Residual U-Net [NDR U-Net]

U-Net Backbone

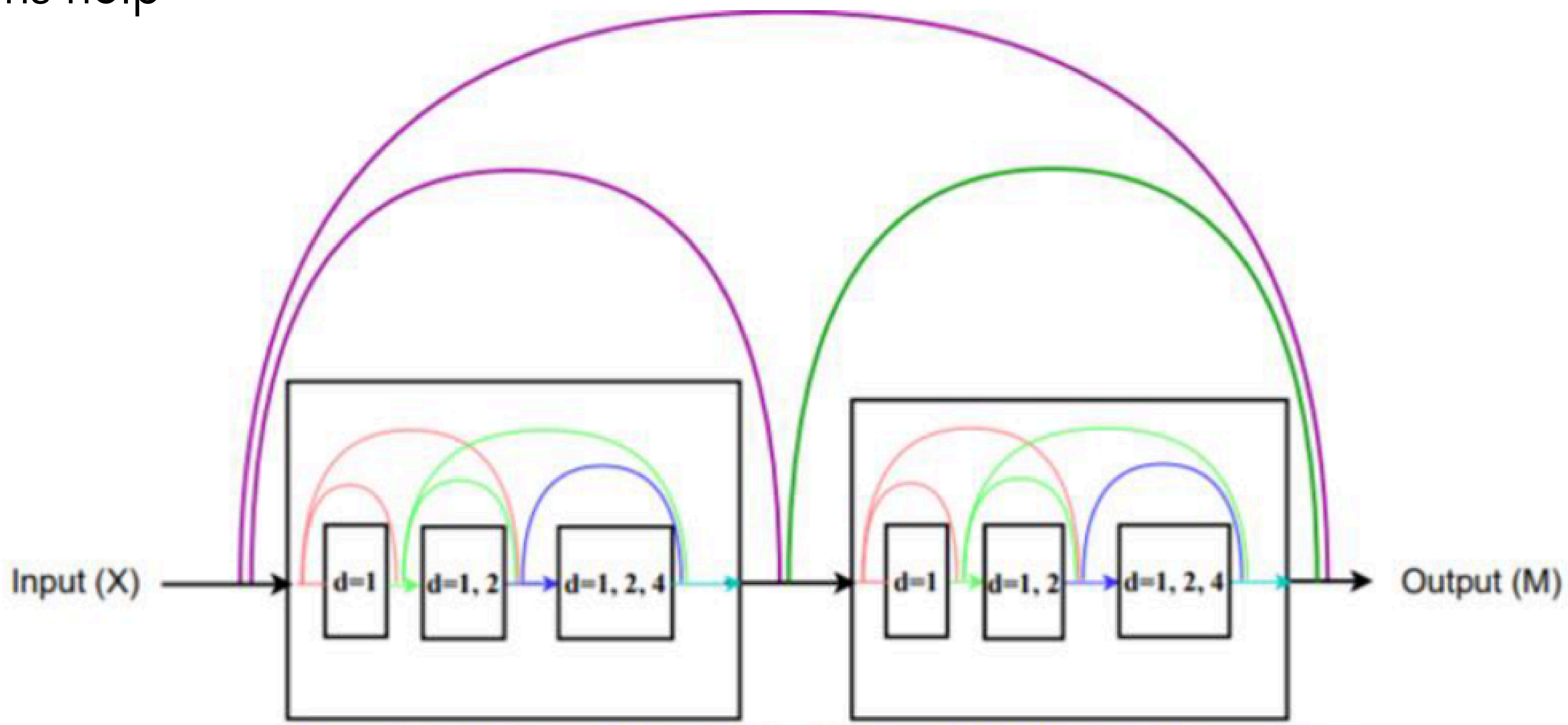
Dense Residual Connections

Skip Connections

Dense Residual Connections (D3Net) are used in the NDR U-Net model to improve the flow of information between layers, making the model more efficient and accurate. These connections help the network reuse information from earlier layers, which strengthens the learning process.

Multi-Dilated Convolutions (MDC):
MDC layers apply convolution operations with different dilation factors. i.e. Small dilation factors focuses on fine details

To address challenges such as limited area coverage we use NDR U-Net method. Even for tiny and hazy satellite Images, this model performs well. Additionally, NDRUNet's architecture produces best results for water bodies that are close to a land boundary.

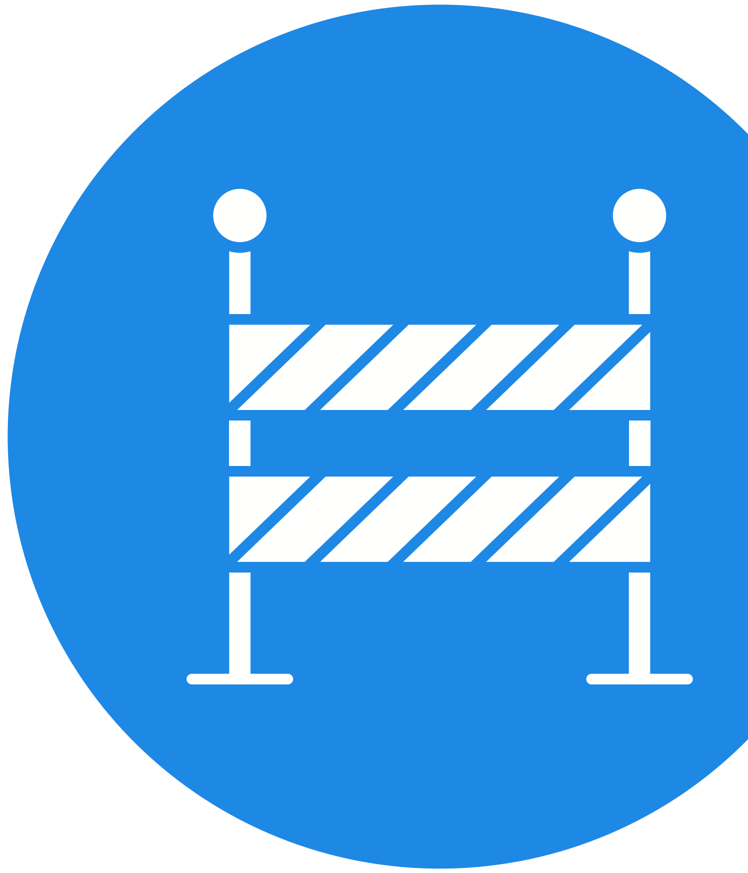


Nested Dense Residual Network Combination of Multi-Dilated Convolutions

Research Gap/Scope for Improvement

Limitations

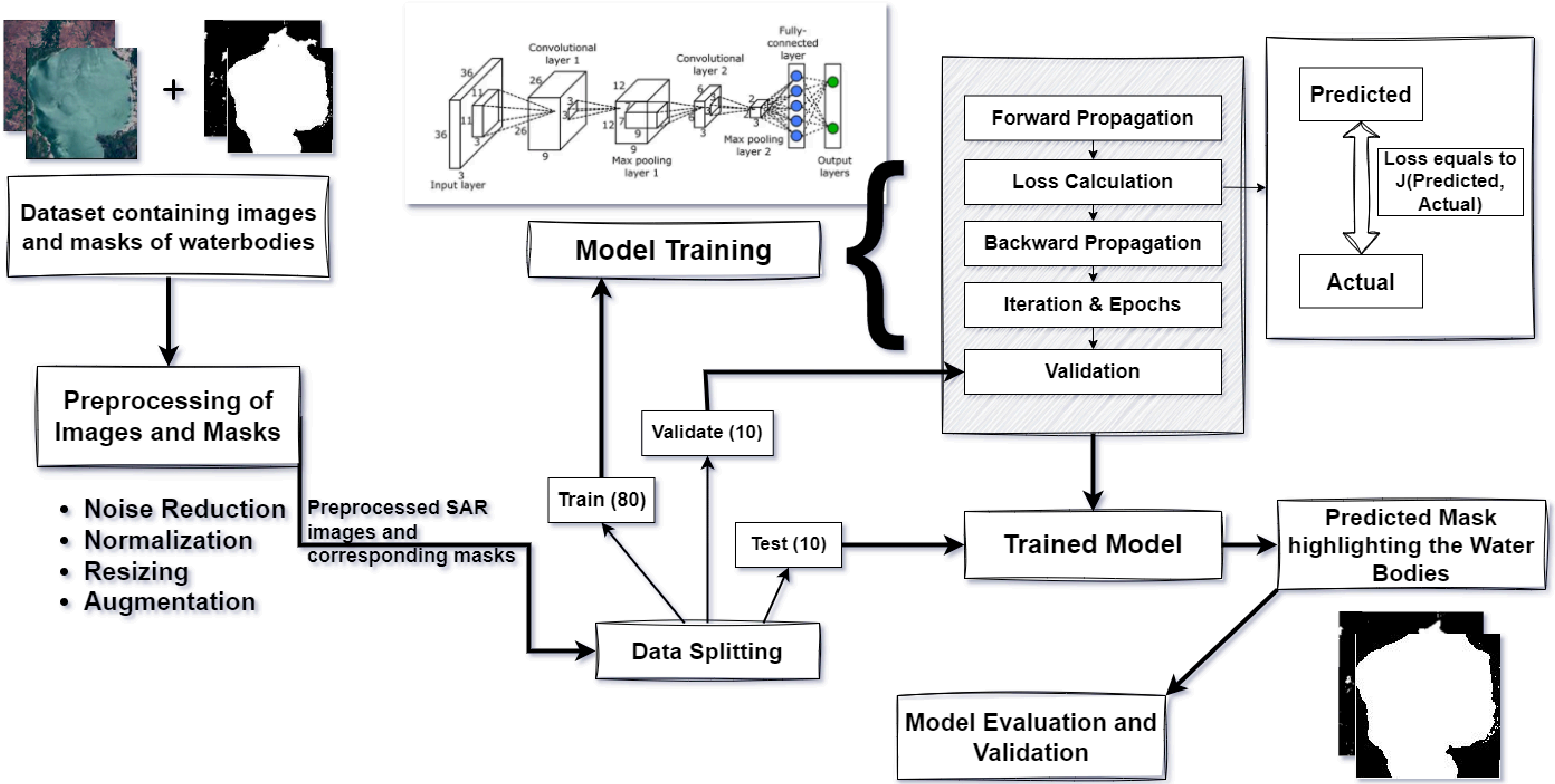
- Existing methods struggle with noise and inconsistencies in SAR images, especially in varying environments.
- Deep learning-based methods require high computational resources, limiting scalability.
- Frameworks tailored to specific environments often fail to generalize to other contexts.
- Boundary detection remains difficult, particularly in regions with complex water-land transitions.
- Many solutions depend on high-quality labeled datasets, which are often scarce.



These gaps hinder the accurate, scalable, and adaptable use of SAR-based methods for water body detection. Issues like noise, overfitting, and boundary detection challenges limit real-world applications in diverse environments. Additionally, the reliance on high-quality data and high computational costs restricts the widespread deployment and generalization of these methods.

Gaps addressed in Phase1

- **Noise and Inconsistencies: Used diverse data, including land, vegetation, and cloud coverage.**
- **Incorporated different types of data sources, such as SAR and optical imagery.**
- **Utilized various architectures, including U-Net and Link-Net to enhance performance across multiple conditions.**



High Level Design of proposed system

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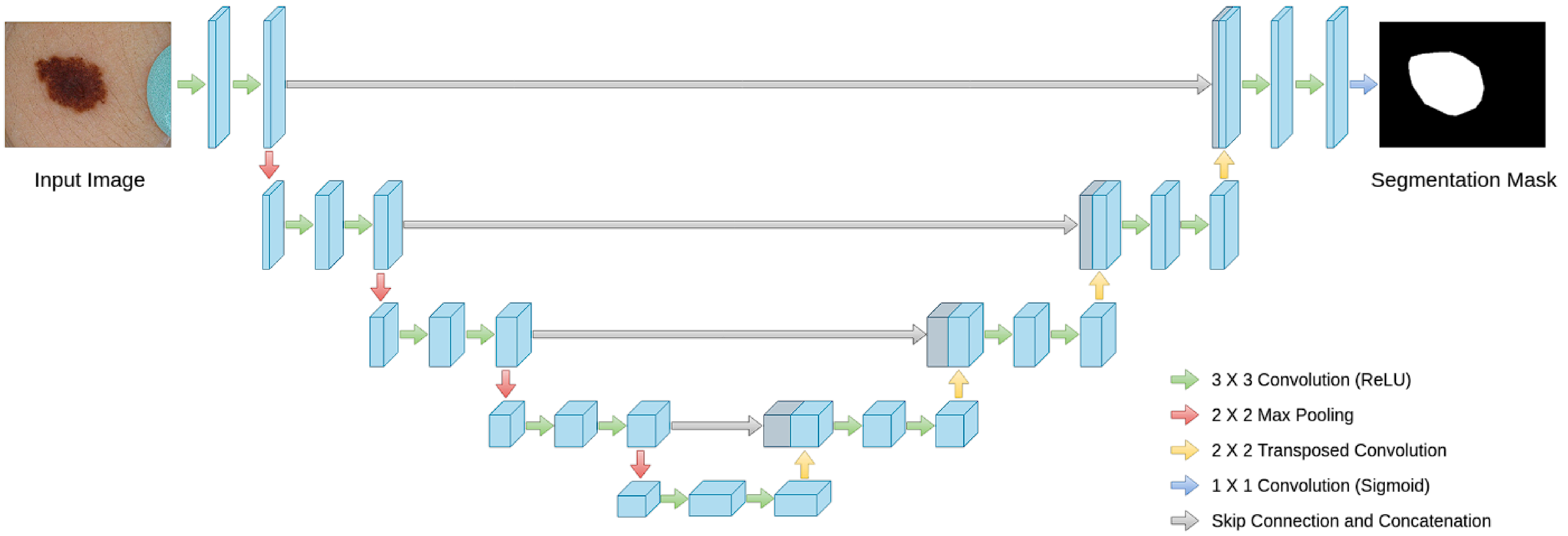
Algorithms/Methodology

UNet for SAR Images:

- Dataset Review and Preparation: Looked at the dataset to check the quality of SAR images, masks, and environmental conditions; applied noise reduction, resizing, and normalization.
- Model Training and Testing: Trained the model, checked its performance, and used metrics like Accuracy, Precision, Recall, and IoU to evaluate it.
- Postprocessing and Analysis: Removed cloud effects from the images, analyzed how well the model worked in different environments, and found areas to improve for real use.



Algorithms/Methodology

- Input Processing: The model takes SAR images of size (256, 256, 1) as input, representing grayscale data for water body detection.
- Feature Extraction: Convolutional layers with increasing filters (64, 128, 256) capture spatial patterns and detailed features. Max pooling progressively reduces spatial dimensions to focus on significant features.
- High-Level Encoding: The bridge layer uses 1024 filters to encode complex and high-level representations of the input image.
- Upsampling and Decoding: Transposed convolution layers and skip connections from earlier stages reconstruct the spatial dimensions and refine the feature maps.

Table 3.2: Enhanced U-Net Architecture for SAR Images

Layer Type	**Output Shape**	**Description**
Input Layer	(256, 256, 1)	Accepts SAR images
Conv2D (64 filters)	(256, 256, 64)	Extracts spatial features
MaxPooling2D	(128, 128, 64)	Reduces spatial dimensions
Conv2D (128 filters)	(128, 128, 128)	Captures detailed features
MaxPooling2D	(64, 64, 128)	Reduces dimensions further
Conv2D (256 filters)	(64, 64, 256)	Encodes complex spatial patterns
Bridge (Conv2D)	(32, 32, 1024)	Encodes high-level representations
Conv2DTranspose	(64, 64, 512)	Up-samples feature maps
Decoder Layers	(256, 256, 64)	Reconstructs the segmentation mask
Output Layer (Sigmoid)	(256, 256, 1)	Produces the binary mask

- Output Generation: A sigmoid-activated output layer produces a binary segmentation mask of size (256, 256, 1), identifying water bodies in the SAR image.

Algorithms/Methodology

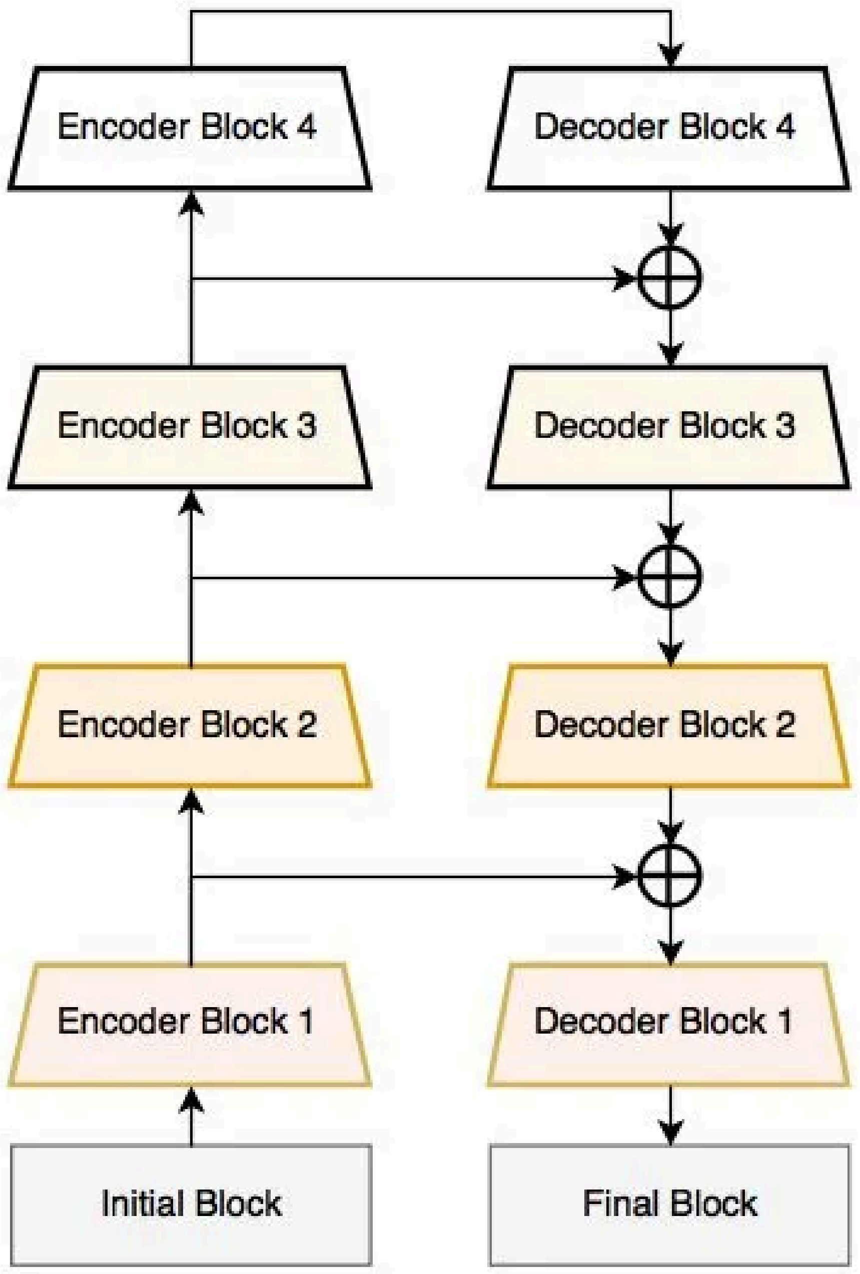
LinkNet for Optical Images:

Encoder-Decoder Design

Residual Connections

LinkNet is a lightweight and efficient deep learning architecture designed for image segmentation tasks. It balances performance and computational efficiency by using an encoder-decoder structure with residual connections, enabling precise feature extraction and reconstruction.

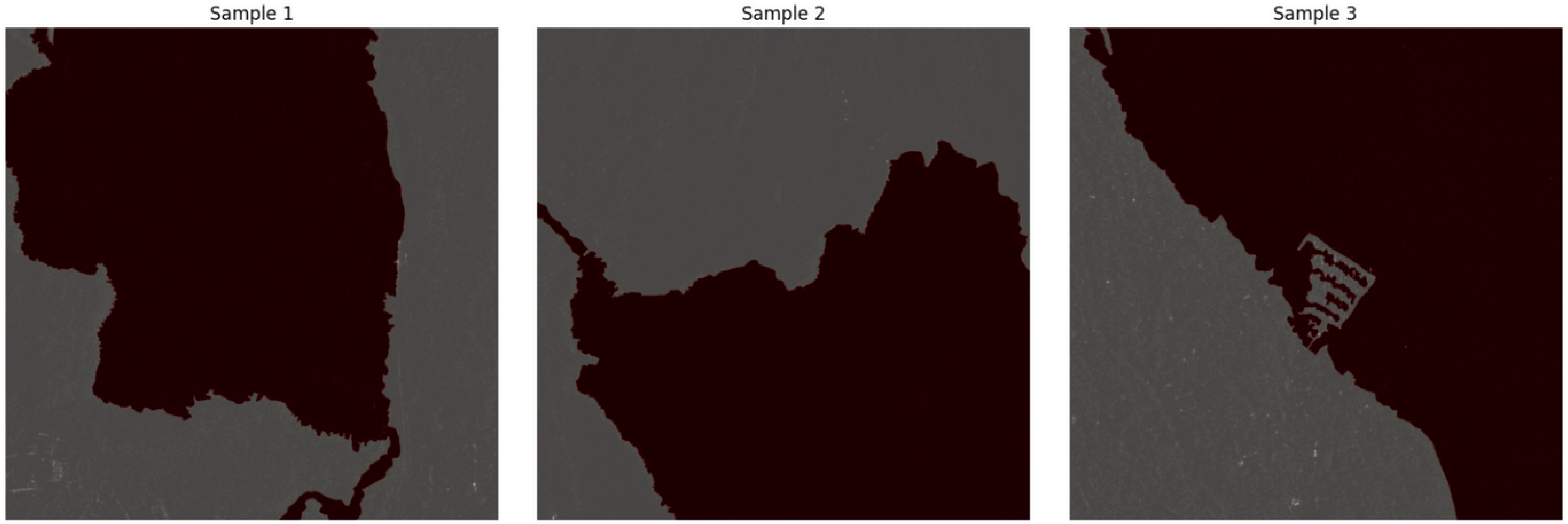
LinkNet is great for segmentation tasks because it keeps important details, helping to capture fine boundaries like those of water bodies. Its simple design makes training and testing faster, so it works well for real-time use. The model performs well in different environments and ensures clear edges, which is important for complex tasks. It also handles noisy data better, making it perfect for detecting water bodies quickly and accurately.



Experimental Setup

SAR Images Dataset:

Real-world SAR imagery from KOMPSAT-5, covering urban, wetland, agricultural, and complex water-land transitions. It includes 3,000+ images with validated water body masks, averaging 31.20% mask pixels. The dataset's geographic diversity improves generalization across terrains.



Experimental Setup

Types of Experiments Done:

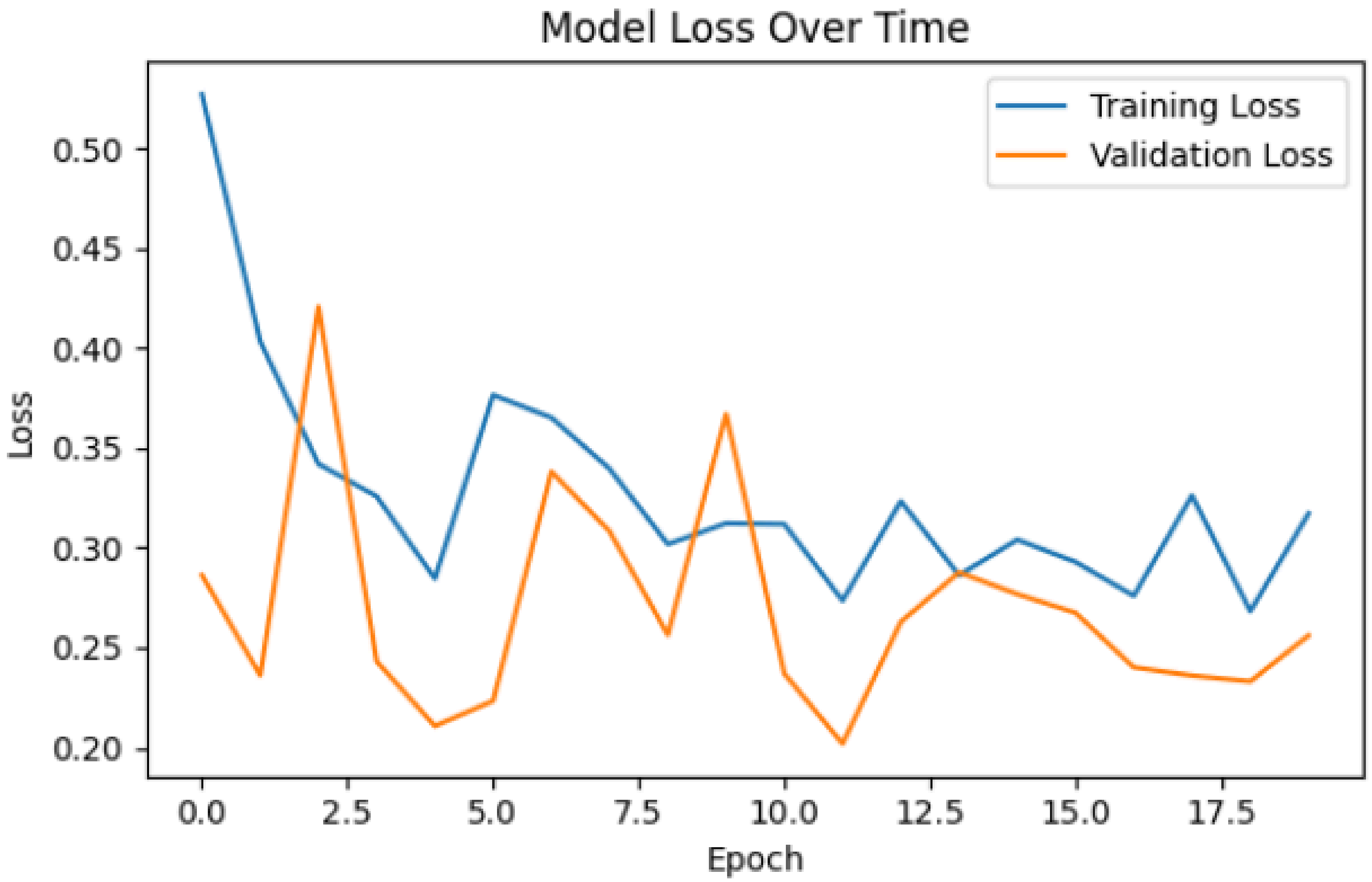
- Dataset Size Variations: Used subsets of the dataset to simulate limited data scenarios and test model adaptability.
- Data Split Variations: Analyzed how different training and testing splits impact model consistency and performance.
- Batch Size Variations: Tested different batch sizes to study their effect on training efficiency and accuracy.
- Model Complexity Variations: Adjusted the number of layers in the U-Net to evaluate the trade-off between complexity and segmentation performance.

Evaluation Metrices Used:

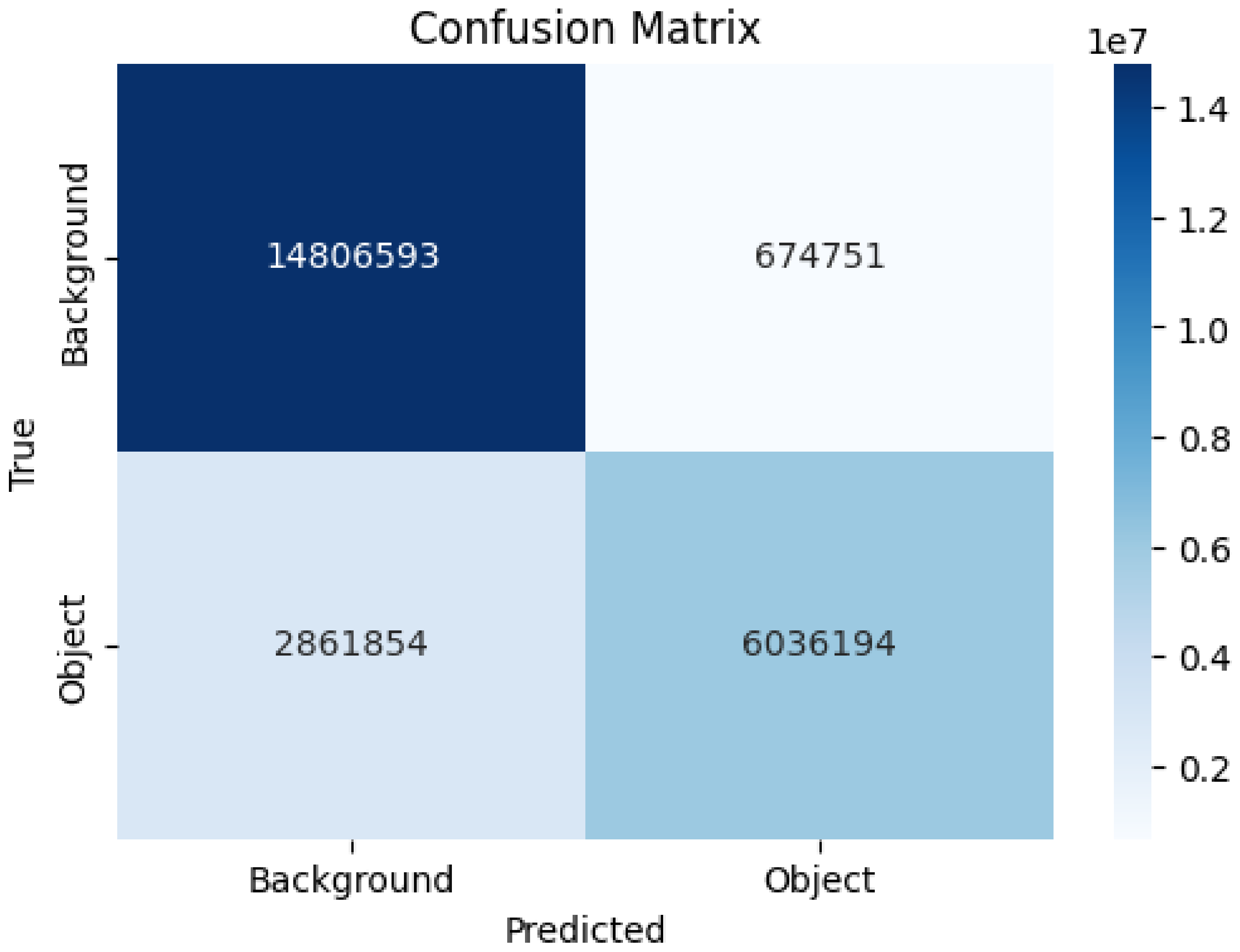
The model's performance was assessed using Test Set Accuracy for overall pixel classification, Precision and Recall for water body detection accuracy, IoU for segmentation overlap, Dice/F1 Score for balanced precision and recall evaluation, and the Confusion Matrix for detailed analysis of true and false positives and negatives.

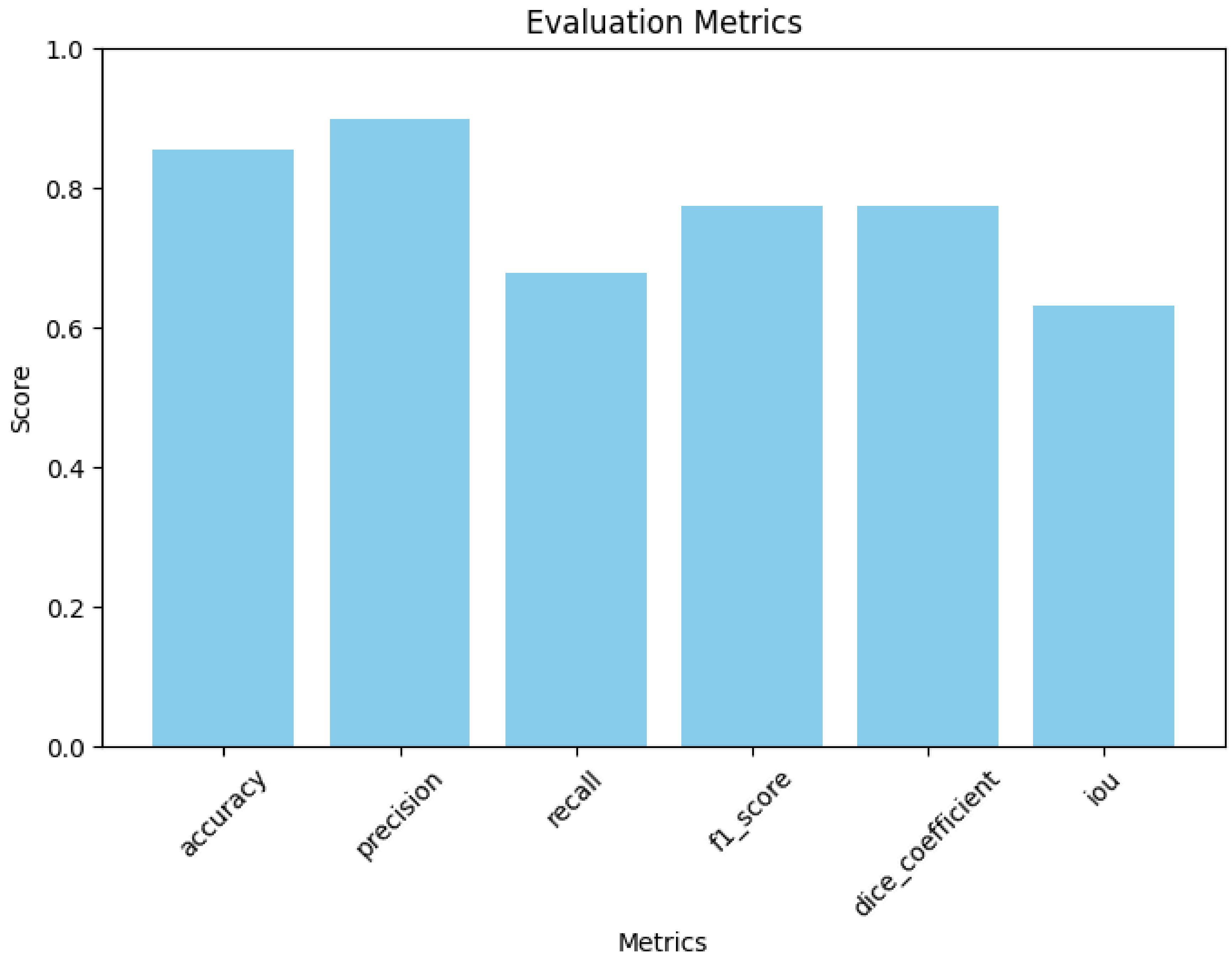
Experiments and Results

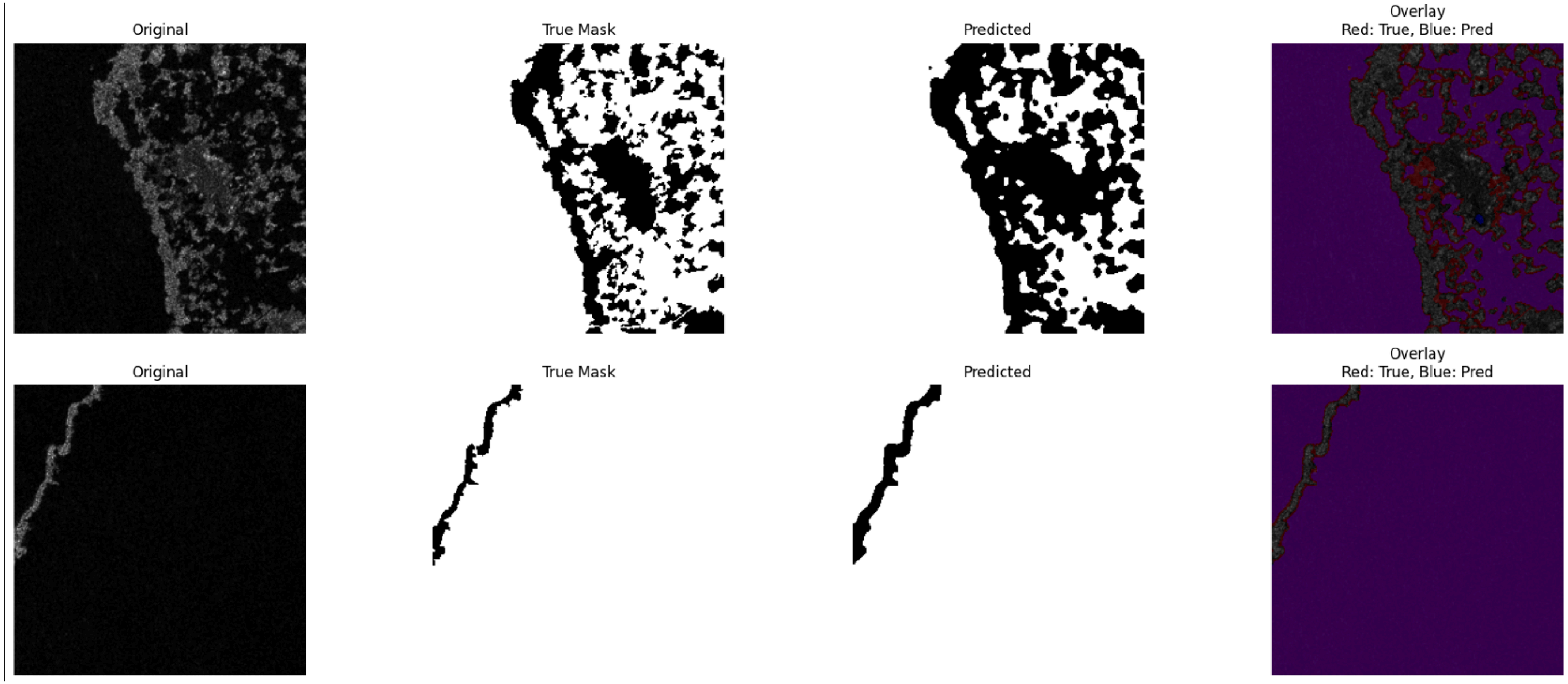
Training and Validation Performance Over Epochs



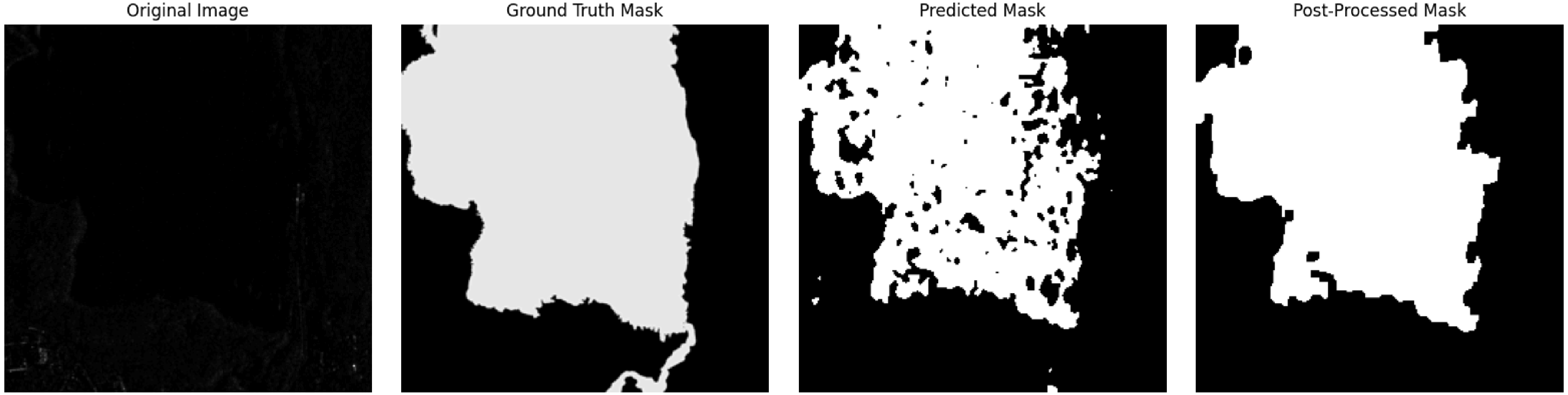
Experiments and Results







Model Predictions



After Post Processing

Findings

Training and Validation Performance Over Epochs

- No Overfitting Observed: Validation metrics outperform training metrics, indicating no apparent overfitting.
- Convergence: The learning process stabilizes and largely converges after approximately 12-15 epochs.
- Unusual Accuracy Gap: A slight gap exists between training and validation accuracy, with validation accuracy being higher, which is atypical and merits further investigation.
- Performance Achievement: The model achieves upto 90% validation accuracy, showcasing its effective learning capabilities.

Findings

Confusion Matrix and Evaluation Metrices

- Accuracy: The model achieves an overall accuracy of 85.49%, reflecting good performance in classifying pixels correctly.
- Precision: With a precision of 89.95%, the model effectively avoids false positives, accurately identifying water bodies.
- Recall: A recall of 67.84% indicates that the model misses some actual water bodies, leading to false negatives.
- F1 Score: The F1 score is 77.34%, showing a balance between precision and recall but leaving room for improvement.
- IoU (Intersection over Union): The IoU score is 63.05%, indicating decent spatial overlap between predicted and ground truth masks.
- Observation from Confusion Matrix: The confusion matrix shows the model's strength in minimizing false positives, ensuring accurate water body detection, but also highlights issues with false negatives, impacting its ability to detect all water regions.

Findings

Model Prediction and Post-Processing Results

- Large Water Bodies: The model performs well in segmenting large water bodies, producing accurate predictions.
- Thin Water Segments: It struggles with detecting thin water segments, leading to incomplete segmentation in such cases.
- Cloudy Regions: Before post-processing, cloudy regions negatively impact segmentation accuracy by introducing noise and errors.
- Post-Processing Effectiveness: Post-processing significantly improves segmentation quality, particularly in cloudy regions, by reducing noise and refining boundaries.
- Overall Improvement: The combined effect of the model and post-processing delivers better delineation of water bodies, enhancing reliability.

Conclusion

This project develops a framework using an enhanced **U-Net** architecture for **water body segmentation** from **SAR images**, tackling challenges like **noise**, **inconsistent boundaries**, and **environmental variability**. By integrating **SAR** and **optical imagery**, it improves detection accuracy, especially in complex conditions. The model is useful for **disaster management**, **flood monitoring**, and **water resource planning**, performing well even in **cloudy** or **vegetative** environments. However, it faces limitations, such as difficulty detecting **thin water bodies**, **false negatives**, and the need for **high computational power** and **labeled datasets**, which hinder deployment in **resource-constrained environments**.

Plan for Phase II project

- Expand the dataset by adding data from different regions and sources, which will make the model stronger and better at working in various environments.

- Improve the model's accuracy by adjusting the current U-Net architecture and testing new models that use attention or a combination of different approaches to improve segmentation.

- Work on fixing issues with detecting boundaries, especially in areas where water meets land, to get more accurate segmentation of water bodies.

- Focus on making the model work well in different environments, like urban, rural, and wetland areas, by adding more data to the training set and improving how the model adapts to new conditions.

- Phase II will improve on the work done in Phase I by refining the segmentation process with different datasets, fixing issues with noise and boundary inconsistencies, and making the model more adaptable. It will use the success of Phase I in flood monitoring and disaster management to create stronger and real-time solutions, improving accuracy and performance in different environments.

References

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[4] F. J. Pe˜na, C. H¨ ubinger, A. H. Payberah, and F. Jaramillo, “Deepaqua: Semantic seg mentation of wetland water surfaces with sar imagery using deep neural networks without manually annotated data,” International Journal of Applied Earth Observation and Geoin formation, vol. 126, p. 103624, 2024.

[5] H.-Y. Liao and T.-H. Wen, “Extracting urban water bodies from high-resolution radar images: Measuring the urban surface morphology to control for radar’s double-bounce effect,” International journal of applied Earth observation and geoinformation, vol. 85, p. 102003, 2020.

Link to the Project Demo

The code should be uploaded in GitHub.

Thank You!