Extraction of Water Bodies from SAR Images

A PROJECT REPORT

Submitted in partial fulfillment for the Degree of

Bachelor of Technology under the

School of Computing

Submitted by

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BONAFIDE CERTIFICATE

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Abstract

Flood detection and water body mapping are essential for disaster management, environmental conservation, and sustainable water resource planning. However, optical satellite images often struggle in bad weather or cloudy conditions, especially during floods. Synthetic Aperture Radar (SAR) satellites overcome these challenges by capturing images regardless of weather or lighting, making them ideal for real-time flood monitoring and damage analysis. SAR's capability to operate under challenging conditions ensures consistent monitoring of disaster-prone regions, providing a reliable alternative to optical imaging.

This project utilizes U-Net, a state-of-the-art deep learning model, to extract and segment water bodies from SAR images with high accuracy. The U-Net architecture, known for its strong performance in image segmentation, is enhanced with multi-scale feature integration and post-processing techniques to refine outputs further. Post-processing steps include removing cloud interference and reducing noise, leading to clearer and more accurate results. These enhancements address challenges such as mixed land-water boundaries, dense vegetation, and urban interference, improving the model's adaptability across diverse environments.

The practical applications of this work are extensive. During floods, timely and precise water detection helps authorities make informed decisions, allocate resources effectively, and protect lives. Beyond disaster response, the technology contributes to long-term water resource planning and environmental conservation. By addressing the limitations of existing methods and incorporating innovative solutions, this project advances the use of SAR technology for climate resilience, disaster mitigation, and sustainable development.

Chapter 1

Introduction

1.1 Background

The extraction and monitoring of water bodies are essential for numerous environmental and infrastructural applications, including flood management, water resource planning, and environmental conservation. Traditional methods for identifying and segmenting water bodies often rely on optical imagery, which is significantly limited by weather conditions, cloud cover, and lighting. These constraints can result in incomplete or inaccurate data, especially in critical situations such as flood monitoring or drought assessment.

Synthetic Aperture Radar (SAR) technology addresses these limitations by providing detailed imagery under all weather and lighting conditions. SAR's capability to penetrate clouds and capture data during the night ensures uninterrupted and consistent monitoring. However, analyzing SAR images manually is time-intensive and prone to human error, particularly when distinguishing water bodies from surrounding terrain in complex environments.

Modern advancements in deep learning have introduced robust solutions for automating the segmentation of water bodies from SAR images. These techniques leverage Convolutional Neural Networks (CNNs) and novel architectures to process large datasets efficiently, achieving precise segmentation even in challenging conditions such as vegetation cover, urban shadows, or mixed land-water boundaries. By integrating these advanced methods, this project aims to bridge the gap between remote sensing technology and practical applications, providing a scalable and efficient solution for water body extraction.

1.2 Problem Addressed

The existing approaches for segmenting water bodies from SAR images, while working well under several situations, do encounter significant issues while making proper identification under conditions involving complexities such as heavy vegetation cover, mixed boundaries between land and water, shadow under an urban area, or clouds interference. All the above-mentioned methods necessitate more manual interference, thereby requiring much more time to develop and often include potential for errors. Further, for very large-scale applications that include disaster management and water resource planning, the lack of standardized and automated solutions leads to poor scalability and inefficiency.

Therefore, this project addresses challenges by developing an automatic system with U-Net-the architecture that is particularly strong for image segmentation deep learning. The novel technique is here presented as improved from the rest to enhance the capabilities of the U-Net model to produce better image segmentation performance within different kinds of geospatial environments. Post-processing operations can remove interference by clouds, allowing for clear and more reliable output for SAR images. It gives a faster identification accuracy concerning regions of water, an enhanced sense of playing a vital role for immense decision-making processes such as environmental monitoring, disaster response, and sustainable water management.

1.3 Motivation

The increasing frequency of extreme weather events and the ongoing challenges in managing water resources highlight the critical need for efficient and reliable methods to identify and monitor water bodies. Synthetic Aperture Radar (SAR) imaging provides a unique opportunity to address these challenges due to its ability to operate under all-weather and lighting conditions. This project focuses on leveraging SAR images for accurate water body extraction, providing a significant step forward in environmental conservation, disaster management, and sustainable water resource planning.

Main Objectives:

- Design an Advanced Water Body Detection Framework: Develop a robust system to identify water bodies with precision from SAR images and to overcome issues such as noise and variability in data.
- Segmentation on SAR Imagery and Optical Images from Various Sources: Apply segmentation techniques to both SAR and optical imagery from diverse sources to enhance water body detection precision by leveraging complementary information.
- Improve Flood Monitoring and Response: Real-time water mapping should be enhanced to facilitate effective disaster response during floods.

Specific Objectives:

- Data Preparation: Process and augment the dataset containing SAR images and NDWI-based masks to have quality inputs into the model.
- Model Building and Training:
  - Design the architecture of a UNET specific to SAR images.
  - Train the model using preprocessed data and optimize to achieve segmentation.

- Evaluation and Validation:
  - Evaluate the model performance on NDWI masks to assess accuracy.
  - Optimize the model to reduce false positives and enhance boundary detection.
- Real-world Relevance: Demonstrate the utility of the model in practice, for example, flood detection and urban planning.

  This project aims to set a benchmark for SAR-based water body detection by addressing current limitations and integrating state-of-the-art technologies to achieve precise and scalable results.

1.4 Scope of the Study/Project

The scope of this project encompasses the development of a robust framework for water body detection using Synthetic Aperture Radar (SAR) images. It focuses on leveraging SAR's unique capabilities to provide accurate and reliable water body mapping under various environmental conditions.

Included:

- Processing a dataset of SAR images and NDWI-based masks to ensure high-quality inputs for model training.
- Developing a CNN-based(UNET) architecture specifically designed for analyzing SAR images.
- Integrating multisource data, such as optical satellite imagery or environmental metadata, to enhance detection accuracy.
- Evaluating the model's performance using established benchmarks, including NDWI masks, to assess accuracy and reliability.

Excluded:

- Analysis of non-SAR imaging techniques alone without integration with SAR data.
- Addressing challenges outside the context of water body detection, such as vegetation or urban structure mapping.
- Developing hardware or sensor-based solutions for data acquisition.

Target Domain and Dataset

In this project, we propose a deep learning-based water segmentation approach using KOrean Multi-Purpose SATellite (KOMPSAT-5) images. To efficiently develop the deep learning-based model, we have curated a SAR water dataset comprising over 1800+ sheets based on KOMPSAT-5. Water segmentation is performed using a representative deep learning-based model such as U-Net.

This structured approach ensures that the boundaries of the project are clearly defined, with a logical and coherent flow throughout the report.

Chapter 2

Literature Review/ Existing System

2.1 Existing System Study

2.1.1 For Research/Product-Based Projects

Literature Survey: Below are the five selected research papers that align closely with the objectives of this project. Each paper is summarized with its contributions, limitations, and open problems for future work.

1. **Water Body Automated Extraction in Polarization SAR Images With Dense-Coordinate-Feature-Concatenate Network.** *Journal:* Journal of Selected Topics in Applied Earth Observations and Remote Sensing *Contributions:* Introduced a Dense-Coordinate-Feature-Concatenate (DCFC) network for automatic water body extraction in polarization SAR images, significantly enhancing spatial feature integration. *Limitations:* High computational cost due to the complexity of the deep learning network and potential overfitting with small datasets. *Open Problems/Future Work:*
   - Develop computationally efficient architectures for practical deployment.
   - Address overfitting issues by leveraging data augmentation or transfer learning. [1]
2. **Water Extraction in SAR Images Using Feature Analysis and Dual-Threshold Graph Cut Model.** *Journal:* Key Laboratory of Technology in Geo-Spatial Information Processing and Application System, Chinese Academy of Sciences *Contributions:* Proposed a dual-threshold graph cut model for automatically extracting water bodies from polarization SAR images, improving accuracy through dense coordinate features. *Limitations:* High computational demand and susceptibility to overfitting with small datasets. *Open Problems/Future Work:*
   - Explore lightweight graph cut models for enhanced scalability.
   - Investigate adaptive thresholds to handle diverse SAR image characteristics. [2]

3. **Water-Body Segmentation for SAR Images.** *Journal:* Journal of Selected Topics in Applied Earth Observations and Remote Sensing *Contributions:* Provided a comprehensive review of water body extraction methods, from traditional machine learning to advanced deep learning approaches like U-Net and DeepLab. *Limitations:* Focused solely on SAR image water-body segmentation, limiting applicability to other remote sensing domains. *Open Problems/Future Work:*

   - Expand research to multimodal image segmentation techniques.
   - Develop algorithms for cross-domain adaptability [3]

4. **DeepAqua: Semantic Segmentation of Wetland Water Surfaces with SAR Imagery Using Deep Neural Networks.** *Journal:* IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing *Contributions:* Targeted wetland water segmentation using advanced neural networks, demonstrating improved detection in complex environments. *Limitations:* Limited by SAR data availability and generalization challenges for non-wetland environments. *Open Problems/Future Work:*

   - Enhance generalization capabilities through transfer learning.
   - Address SAR data accessibility by exploring synthetic or augmented datasets. [4]

5. **Extracting Urban Water Bodies from High-Resolution Radar Images.** *Journal:* International Journal of Applied Earth Observation and Geoinformation *Contributions:* Developed a framework for extracting urban water bodies using morphological features, achieving high prediction accuracy. *Limitations:* Framework tailored for urban environments, limiting generalizability to non-urban areas. *Open Problems/Future Work:*

   - Adapt the framework to rural and natural water body environments.
   - Investigate the use of global datasets for broader applicability. [5]

The reviewed studies reveal key challenges in water body segmentation from SAR images,such as handling noise, distinguishing complex boundaries, and ensuring model generalization across diverse conditions. Issues like computational efficiency and the need for high-quality datasets further complicate the task.

2.1.2 Research Gap/Scope for Improvement and Innovation

The review of existing literature and solutions for water body segmentation using SAR imagery reveals several critical gaps and opportunities for innovation. These limitations and challenges highlight areas where advancements can be made to improve the accuracy, efficiency, and generalizability of existing systems.

Limitations/Problems in Existing Systems:

- **Noise and Inconsistencies:** Existing methods struggle to handle noise and inconsistencies in SAR images, particularly in diverse environmental conditions.
- **High Computational Cost:** Many deep learning-based methods, such as Dense-Coordinate-Feature-Concatenate networks, require significant computational resources, limiting their scalability.
- **Overfitting Risks:** Models often face overfitting issues, especially when trained on small datasets, reducing their reliability across diverse datasets.
- **Limited Generalization:** Existing frameworks, particularly those tailored for specific environments (e.g., urban or wetland), fail to generalize effectively to other contexts.
- **Boundary Detection Challenges:** Precise boundary delineation remains a challenge, especially in regions with complex water-land transitions.
- **Dependence on High-Quality Data:** Many solutions depend on high-quality, labeled datasets, which are often scarce, limiting the applicability of these methods.

1. **Gaps addressed in Phase I**
   - **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 FCN, U-Net, and HRNet, to enhance performance across multiple conditions.
2. **Gaps that will addressed in Phase II**
   - **Diverse Datasets from Various Sources:** Expand the dataset by incorporating additional data from different regions and sources, improving model robustness and generalization.
   - **Improving Model Accuracy:** Focus on improving the model's accuracy by fine-tuning the existing architectures and experimenting with more advanced models.
   - **Boundary Detection Challenges:** Work on refining boundary detection, particularly in complex water-land transition zones, to achieve more accurate delineation.
   - **Limited Generalization:** Aim to develop models that generalize better across different environments (urban, rural, wetlands) by enhancing training datasets and model adaptability.

2.2 Problem Statement and Contributions

1. Problem Statement: Right now, we're focusing on how well we can find water bodies using just SAR images.This means we're figuring out how to make the most of SAR technology to solve problems that other methods have. For example, sometimes current methods make mistakes, like thinking a non-water area is a water body, and we want to reduce those mistakes.

   Looking ahead, we plan to explore using not just SAR images but also other kinds of data, like optical images or other sensors. By combining these different types of information, we hope to make our tools even better. This means our methods could work in more situations and help us keep track of water bodies more effectively. For instance, this could be useful for monitoring floods or managing water resources in real-time, making it easier to respond quickly in emergencies and protect our environment.

2. Research Contributions:

   - Advancing Water Body Detection: Developed an improved approach for accurately detecting water bodies in SAR images, addressing challenges like noise and environmental inconsistencies, leading to enhanced performance.
   - Integrating Multi-Source Data: Combined SAR and optical imagery to improve water body detection accuracy, reducing false positives and enhancing model robustness across different environmental conditions.
   - Implementing Novel Architectures (FCN, U-Net): Applied and compared various deep learning architectures, including FCN and U-Net, for effective water body extraction, demonstrating their capability to handle complex scenarios.
   - Validating Model Robustness across Types of Data (SAR, Optical): Validated the proposed model on diverse datasets, including both SAR and optical data, ensuring the approach's robustness and scalability across different data sources.

Chapter 3

Proposed Work

3.1 Proposed Work

This is a problem of identifying water bodies from Synthetic Aperture Radar imagery, challenging the system with noise in SAR images, inconsistency, data inconsistencies, boundary issues in detection, and inadequate generalization across different settings. As discussed in Literature Study chapter, these issues have become some of the main deterrents to the development of water body detection frameworks that would be more robust, accurate, and scalable.
Our proposed work covers these research gaps by using by deep learning architectures, such as Fully Convolutional Networks and U-Net, and adapting these to different forms of imagery for segmentation tasks. By incorporating both SAR and optical imagery from different sources, our method tries to improve the precision of water body detection and improves model robustness across different environments.

3.1.1 Objectives of the Proposed Work

The primary and secondary objectives of the proposed work are as follows:

Primary Objectives

- Develop a strong framework for water body detection over noisy and inconsistent data with Synthetic Aperture Radar (SAR) imagery: Construct a reliable and robust detection framework capable of accurately identifying water bodies in SAR images, even in the presence of noise, inconsistencies, and environmental challenges such as varied land cover, cloud interference, or vegetation. This framework aims to enhance the reliability of water body detection across diverse scenarios.

- Design and implement advanced deep learning architectures such as Fully Convolutional Networks (FCN), U-Net, etc., for the precise segmentation of water bodies: Leverage state-of-the-art deep learning methodologies to segment water bodies with high precision. By incorporating models like FCN and U-Net, the work aims to address complex challenges such as edge detection and transitions between land and water, providing detailed and accurate delineation of water bodies.

- Improve the generalization capability of the detection model by synergizing SAR and optical imagery from different sources: Develop a synergistic approach that combines the strengths of SAR and optical imagery. This will involve integrating data from multiple sources to enhance the model's adaptability and effectiveness across diverse environmental conditions, such as urban areas, wetlands, and agricultural landscapes.

- Achieve measurable improvements in detection accuracy, boundary delineation, and overall segmentation performance: Establish performance benchmarks and strive for significant improvements over existing methodologies in terms of detection accuracy, edge delineation, and overall segmentation quality. The goal is to provide a dependable framework that outperforms traditional approaches.

Secondary Objectives

- Validate the proposed model across multiple datasets representing diverse environmental conditions, ensuring scalability and robustness: Conduct comprehensive validation by testing the model on datasets obtained from various geographical regions and environmental conditions. This ensures that the framework is scalable and reliable for global applications, including different climates, terrains, and ecological settings.

- Explore the impact of incorporating environmental metadata, such as vegetation and land cover data, to complement SAR and optical imagery: Investigate how additional contextual data, such as vegetation indices, land cover classifications, and other environmental metadata, can improve the model's segmentation accuracy and adaptability. This exploration will help create a holistic framework that leverages all available data sources.

- Optimize the computational efficiency of the framework to facilitate its application in resource-constrained environments: Focus on reducing the computational demands of the detection framework by employing efficient algorithms and lightweight architectures. This ensures that the model can be deployed on low-power devices and used in regions with limited computational resources, such as remote or developing areas.

3.2 Methodology

3.2.1 Overview of the Approach

The proposed approach for water body segmentation from SAR images follows a systematic methodology to address challenges such as noise, inconsistencies, and boundary detection difficulties. The workflow is summarized below:

- **Dataset Exploration:** The first step involves exploring the dataset to understand its characteristics and limitations. This includes:
  - Assessing the diversity of images in terms of environmental conditions (e.g., urban areas, wetlands, and agricultural landscapes).
  - Analyzing the resolution, size, and quality of SAR images.
  - Examining the masks to ensure accuracy and consistency in identifying water bodies.
  - Identifying potential challenges, such as noise levels and missing data, to guide preprocessing and model design.
- **Preprocessing:** After exploring the dataset, a series of preprocessing steps are applied to prepare the data for training:
  - *Noise Reduction:* Reduce noise in SAR images to improve their clarity and usability.
  - *Normalization:* Scale pixel values to a standard range, ensuring consistency across all images.
  - *Resizing:* Resize images to a uniform resolution, enabling efficient batch processing during model training.
- **Data Splitting:** The dataset is divided into three subsets:
  - *Training Set (70%):* Used to train the model and optimize its parameters.
  - *Validation Set (10%):* Used during training to monitor the model's performance and fine-tune hyperparameters.
  - *Testing Set (20%):* Reserved for final evaluation of the model's performance on unseen data.
- **Model Training:** The training process involves:
  - *Forward Propagation:* Input images are passed through the model to generate predicted masks.
  - *Loss Calculation:* A loss function computes the error between predicted and ground truth masks.
  - *Backward Propagation:* Gradients are calculated, and model weights are updated to minimize error.
  - *Iterative Training:* The model is trained over multiple epochs with periodic validation to refine its generalization capabilities.
- **Prediction and Evaluation:** Once trained, the model generates masks for test images. These masks are compared to the ground truth using metrics such as:
  - Accuracy

– Precision

– Recall

– Intersection over Union (IoU)

These metrics evaluate the model's ability to detect water bodies accurately and delineate complex boundaries effectively.

- **Output and Analysis:** The final step involves analyzing the results to:

  – Identify patterns in model performance across different environments.

  – Pinpoint areas for improvement, such as reducing false positives or negatives.

  – Assess the practical applicability of the framework in real-world scenarios.

This structured approach ensures a comprehensive analysis of the dataset, robust model training, and reliable evaluation, addressing key challenges in SAR-based water body segmentation.

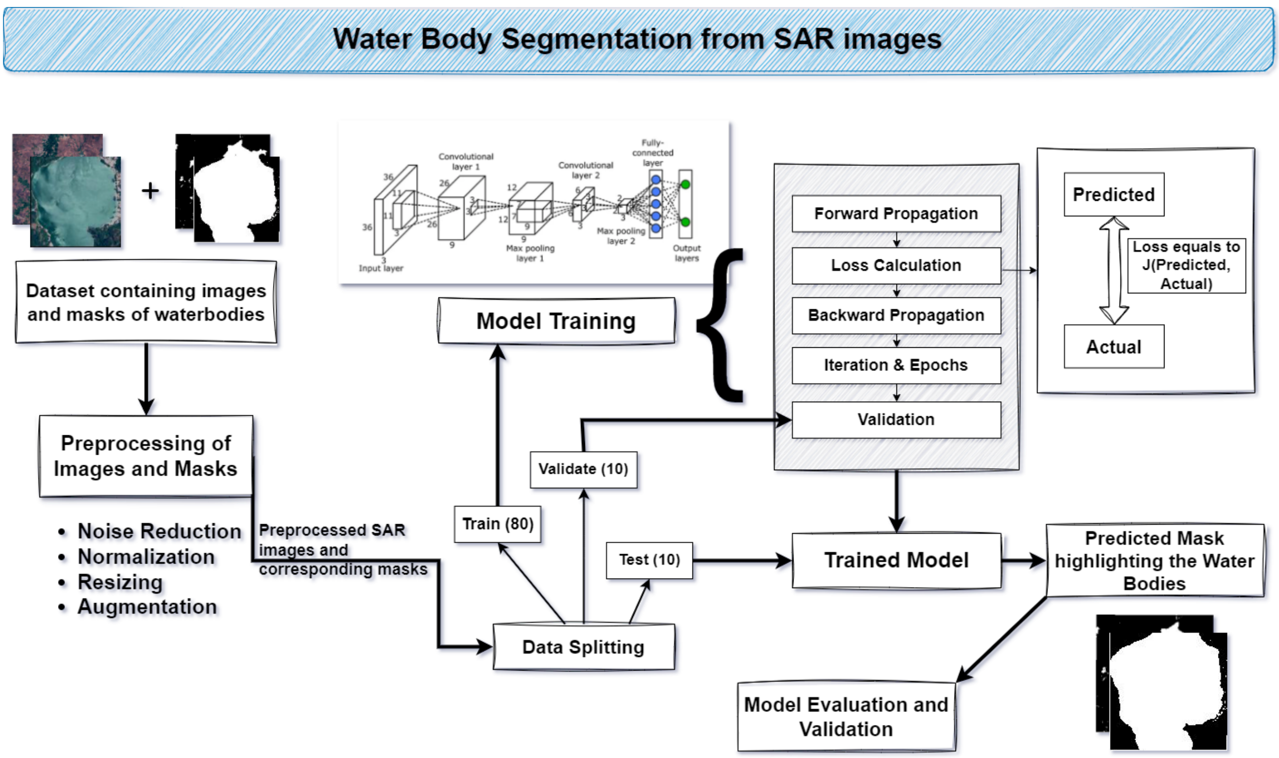

Figure 3.1: Overview of approach for segmentation of Optical Images

3.2.2 Dataset Selection

The dataset used for this study comprises both Synthetic Aperture Radar (SAR) images from KOMPSAT-5 and optical images from Sentinel-2. These datasets have been carefully curated to facilitate the evaluation and development of water body segmentation models. The details for each dataset are as follows:

SAR Images Dataset

The dataset based on KOMPSAT-5 images supports the segmentation of water bodies using radar-based imagery. The details are as follows:

- Real-World Data: The dataset comprises Synthetic Aperture Radar (SAR) imagery captured by KOMPSAT-5. These real-world images represent diverse environmental conditions, including urban areas, wetlands, agricultural regions, and complex water-land transitions.
- Size and Composition: The dataset contains over 3,000 SAR images, each accompanied by a corresponding water body mask. The masks have been manually validated to ensure high-quality annotations for precise model training and evaluation.
- Dataset Diversity: The dataset includes images from various geographical regions, capturing different terrains and environmental scenarios. This diversity is crucial for evaluating the model's generalization ability across heterogeneous conditions.

Figure 3.2: SAR Image and its corresponding mask from the Dataset

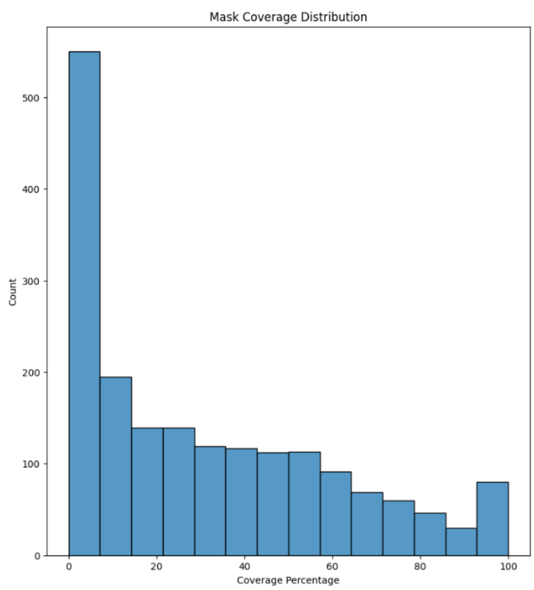

Figure 3.3: Distribution of mask coverage percentages, showing most images have minimal coverage, while a few have significant or full coverage.

Optical Images Dataset

The optical dataset is based on images captured by the Sentinel-2 satellite, aimed at segmenting water bodies using color and spectral information. The details are as follows:

- Context: This dataset consists of water body images captured by the Sentinel-2 satellite. Each image is paired with a black-and-white mask, where white represents water, and black denotes non-water areas.

- Mask Generation: The masks were generated using the Normalized Water Difference Index (NWDI). This index, typically used to measure vegetation, was adapted with a higher threshold to accurately detect water bodies.

- Size and Diversity: The dataset covers a wide range of geographic regions, capturing varied environmental conditions such as rivers, lakes, and coastal areas. This diversity ensures the model's ability to generalize effectively across different water body types.

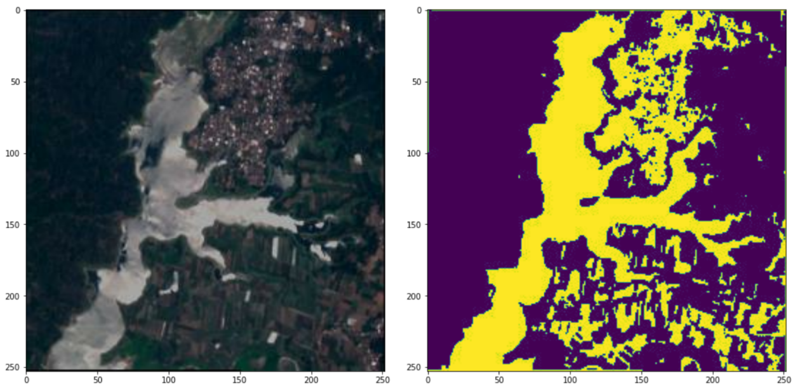

Figure 3.4: Optical Image and its corresponding mask from the Dataset

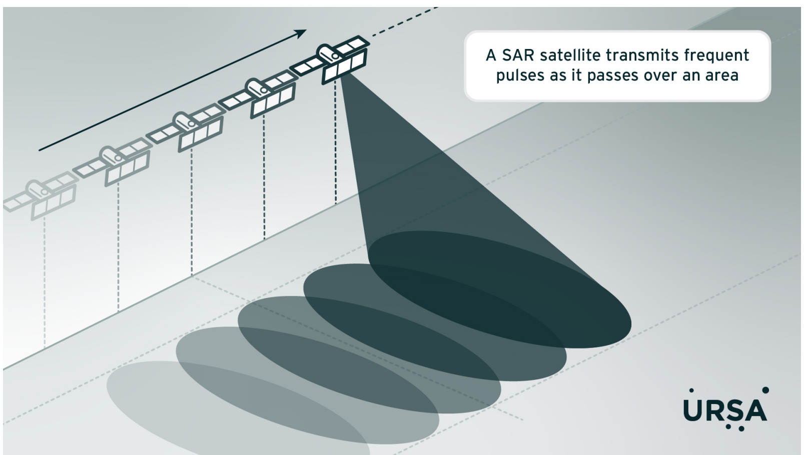

Figure 3.5: A diagram showing a satellite moving through space while transmitting overlapping radar pulses to Earth's surface, illustrated by dashed lines and darkening elliptical footprints.

3.2.3 Algorithm/Model Design

The following tables summarize the models and their architectural details for SAR and optical images. These tables highlight the specialized features of each model, layer descriptions, and the output shapes at various stages.

Table 3.1: Model Architecture Overview

Dataset Type	Model	Special Features
SAR Image	Enhanced U-Net	SkipConnections, Conv2DTranspose for upsampling
Optical Images	Link-Net	Residuals, skip-connections, modularity, efficiency

Usage and Efficiency of Models The **Enhanced U-Net model for SAR images** is specifically designed to address the challenges posed by Synthetic Aperture Radar (SAR) data, such as noise, low contrast, and complex environmental variations. By utilizing skip connections and Conv2DTranspose layers, this model ensures the preservation of spatial information while progressively reconstructing high-resolution segmentation masks. The architecture effectively balances feature extraction and up-sampling, making it highly efficient for SAR imagery segmentation tasks. The model demonstrates robust performance in delineating water bodies, even in regions with complex land-water transitions, achieving high accuracy and Intersection over Union (IoU) scores. Its simplicity and adaptability make it suitable for operational deployment in diverse SAR data environments.

The **LinkNet with Dropout Regularization for Optical Images** leverages the spectral richness of Sentinel-2 imagery to achieve precise segmentation of water bodies. The model incorporates dropout layers strategically placed in both the encoder and decoder paths, enhancing generalization and reducing overfitting. This is particularly beneficial for optical imagery, which often contains high-resolution details but is susceptible to noise and overfitting due to spectral variability. The LinkNet model excels in scenarios where spectral information, such as vegetation indices or water reflectance properties, plays a critical role in segmentation. Its effectiveness is evident in datasets with diverse environmental conditions, consistently achieving high accuracy, recall, and precision.

Together, these models provide a complementary framework for water body segmentation, leveraging the strengths of SAR and optical imagery. While the SAR-based Enhanced U-Net is ideal for scenarios with limited visibility or cloud cover, the optical U-Net model thrives in clear-sky conditions, utilizing rich spectral data to improve segmentation accuracy. By combining the outputs of these models, the framework can achieve robust and reliable segmentation performance across a wide range of environmental conditions.

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

Table 3.3: LinkNet Architecture for Optical Images

Layer Type	Output Shape	Description
Input Layer	(256, 256, 3)	Accepts RGB optical images
Encoder Block (64 filters)	(128, 128, 64)	Extracts spatial features and downsamples
Encoder Block (128 filters)	(64, 64, 128)	Captures detailed features
Encoder Block (256 filters)	(32, 32, 256)	Encodes complex spatial patterns
Encoder Block (512 filters)	(16, 16, 512)	Captures high-level representations
Bottleneck (1024 filters)	(16, 16, 1024)	Encodes high-level abstract features
Decoder Block (512 filters)	(32, 32, 512)	Decodes and upsamples feature maps
Decoder Block (256 filters)	(64, 64, 256)	Reconstructs features
Decoder Block (128 filters)	(128, 128, 128)	Recovers spatial details
Decoder Block (64 filters)	(256, 256, 64)	Further reconstructs spatial details
Output Layer (Sigmoid)	(256, 256, 1)	Produces the binary segmentation mask

3.2.4 Tools and Technologies

The project utilizes various programming languages, libraries, and software tools to facilitate the processing, analysis, and extraction of water bodies from satellite images. The key tools and technologies involved are outlined below:

Programming Languages

- **Python 3.8:** Python is the primary programming language used for the entire project, including data preprocessing, model development, and evaluation. Python's extensive support for scientific computing and machine learning makes it an ideal choice for this project.

Libraries and Frameworks

The following libraries and frameworks play a critical role in the implementation of the project:

- **TensorFlow and Keras:** These deep learning frameworks are used for constructing and training the Convolutional Neural Network (CNN) models. TensorFlow serves as the backend framework, providing efficient computation and GPU acceleration, while Keras offers a user-friendly API for model development.

- **OpenCV:** OpenCV (Open Source Computer Vision Library) is utilized for image processing tasks such as resizing, normalizing, and augmenting images before they are fed into the deep learning models. It is also employed for preprocessing the satellite images and masks.

- **Pandas:** This library is used for data manipulation and organization, helping with the management of datasets, particularly for handling CSV files containing metadata, labels, or other supplementary data.

- **NumPy:** NumPy is essential for performing numerical operations on image arrays and matrices, making it indispensable for data handling and manipulation throughout the project.

- **Scikit-learn:** Scikit-learn is a key machine learning library used for tasks such as splitting datasets, performing model evaluation, and calculating performance metrics like precision, recall, and F1-score. It also helps in implementing other machine learning models when required.

- **Seaborn and Matplotlib:** These libraries are used for visualizing the performance of the machine learning models, including generating plots, graphs, and confusion matrices to better understand the model's behavior.

- **GDAL (Geospatial Data Abstraction Library):** GDAL is a critical library for handling geospatial raster data. It is used to read, write, and process georeferenced satellite images, which are essential for extracting water bodies from remote sensing data.

Development Environment

- **VSCode or Jupyter Notebook:** These integrated development environments (IDEs) are used for writing, running, and debugging Python code. Jupyter Notebooks is particularly useful for developing machine learning models in an interactive environment.

- **Google Colab:** Google Colab is used for running the project on cloud-based virtual machines equipped with high-performance GPUs. This is especially helpful for training deep learning models, as it accelerates computations and makes collaboration easier.

Version Control

- **Git:** Git is used for version control, allowing the team to track changes to the project code, collaborate effectively, and ensure that all versions of the code are properly documented and accessible.

Hardware Requirements

For efficient execution, the following hardware specifications are required:

- **CPU:** A multi-core processor such as Intel i5 or above is necessary for performing general computations and data processing tasks.
- **RAM:** At least 8 GB of RAM is recommended to handle large datasets and perform intensive computations.
- **Storage:** A minimum of 20 GB of storage is required for storing large datasets of satellite images, model weights, and training logs.
- **GPU:** A high-performance GPU, such as NVIDIA RTX 3080 or higher, is essential for accelerating the training of deep learning models, as these models require significant computational power.

3.2.5 Algorithm or Model Description

U-Net Model Architecture

For this project, the primary model used for extracting water bodies from satellite images is the **U-Net architecture**, which is a specialized type of Convolutional Neural Network (CNN) designed explicitly for **semantic image segmentation**. Semantic segmentation involves classifying each pixel in an image as belonging to a specific class or category, making it a crucial task in applications like medical imaging, autonomous driving, and remote sensing.

The U-Net model is particularly well-suited for tasks that require **precise pixel-level predictions** due to its ability to capture both high-level contextual information and fine-grained spatial details. In the context of satellite image analysis, the goal is to accurately distinguish water bodies from the rest of the image, such as land and other features, which requires high spatial resolution and the preservation of fine details in the segmentation map.

One of the key reasons for choosing U-Net is its architecture, which is designed to be particularly effective in segmentation tasks where the output must have the same spatial dimensions as the input image. This is achieved by the **U-shaped structure** that includes an encoder-decoder framework with **skip connections** that allow the network to maintain and propagate fine spatial details while learning abstract features at higher levels. These capabilities make U-Net ideal for segmenting complex structures like water bodies in satellite imagery, where the boundaries of water bodies can be intricate and require high accuracy.

Furthermore, U-Net's architecture allows it to work well even with relatively small datasets, which is often the case in remote sensing applications where labeled data may be limited. The model's ability to perform **data augmentation** and generalize well from the available training data makes it robust for this type of problem.

- **Contracting Path (Encoder):** The contracting path follows the typical architecture of a CNN, where the image undergoes a series of convolutional layers, followed by pooling layers. The purpose of this path is to capture context and reduce the spatial dimensions of the input image while increasing the depth (number of feature maps). At each step, the network learns more complex features of the image.
- **Bottleneck:** The bottleneck is the central part of the U-Net architecture where the image is represented in the smallest spatial dimensions but with the most abstracted feature representation. Here, the features extracted by the encoder are processed to allow the model to make meaningful predictions.
- **Expansive Path (Decoder):** The expansive path is responsible for upsampling the encoded features to restore the spatial dimensions of the image. This path uses transposed convolutions (also known as deconvolutions) to increase the resolution. It also includes

skip connections from the contracting path, which help retain spatial information and avoid loss of details during upsampling.

- **Skip Connections:** One of the key features of U-Net is the use of skip connections, which transfer high-resolution feature maps from the encoder to the decoder. These connections help the model retain fine-grained information that would otherwise be lost during downsampling in the encoder.

- **Final Layer:** After the expansive path, the final layer is a 1x1 convolution that reduces the number of channels to the number of classes. In the case of binary segmentation (water vs non-water), this layer will output a single channel.

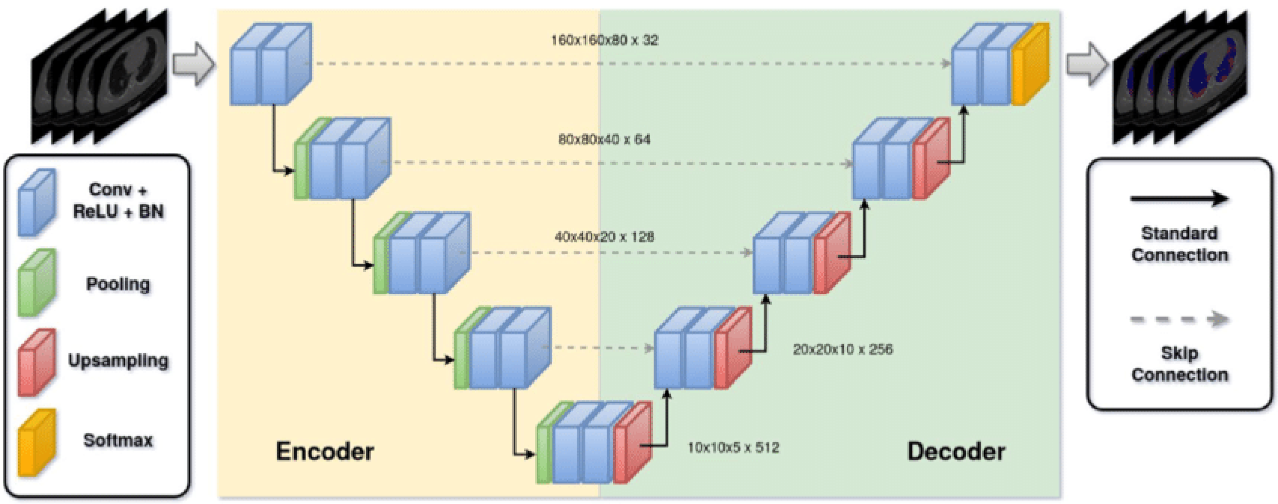

Figure 3.6: U-Net architecture diagram

The U-Net architecture is highly effective for semantic segmentation, making it ideal for tasks like water body extraction from satellite images. Its encoder-decoder structure, with skip connections, allows the model to capture both high-level contextual features and fine-grained spatial details, which is crucial for accurately delineating water bodies. The encoder progressively downscales the image to extract features, while the decoder upsamples the features to match the original image resolution, ensuring pixel-level accuracy. Skip connections between the encoder and decoder help preserve important spatial information, enabling precise segmentation even for complex boundaries. This design is particularly beneficial for tasks with limited labeled data, like satellite imagery, and ensures the model can effectively separate water regions from other features, even in the presence of noise or varying environmental conditions.

3.2.6 Expected Outcomes

The anticipated outcomes of the proposed work are as follows:

- Accurate detection of water bodies in SAR imagery, despite noise, environmental inconsistencies, and challenges like cloud cover, vegetation, and varied land cover.
- Improved segmentation precision and better boundary delineation using the U-Net model, particularly for complex water-body boundaries.
- Scalable solution adaptable to different geographical regions, terrains, and environmental conditions.

3.2.7 Advantages of the Proposed Work

The proposed approach offers several significant advantages over existing methods for water body detection and segmentation:

- Higher segmentation accuracy achieved by using U-Net and FCN architectures for precise pixel-level segmentation, especially in challenging environments.
- Fusion of SAR and optical imagery, allowing the model to leverage the strengths of both data sources, enhancing adaptability across diverse scenarios.
- Practical use in remote sensing, environmental monitoring, and water management, with improvements in accuracy, efficiency, and scalability making the model widely applicable.

3.2.8 Limitations and Assumptions

While the proposed work offers promising solutions for water body detection, several limitations and assumptions need to be considered:

- High computational power required: Training the model, especially with large datasets and complex architectures like U-Net, requires significant computational resources, which may not be available in all settings.
- Data availability: The availability of high-quality labeled datasets is crucial. In some regions, there may be insufficient or poor-quality data, which could limit the model's effectiveness.
- Large datasets: The model needs large datasets for training, which can result in long training times and require substantial memory, making it challenging for resource-constrained environments.

Chapter 4

Experimentation and Result Analysis

4.1 Experimental Setup

Programming Languages

- Python 3.8: Primary language for data preprocessing, model development, and evaluation.

Libraries and Frameworks

- TensorFlow and Keras: For constructing and training CNN models.
- OpenCV: For image processing tasks such as resizing and augmenting images.
- Pandas: For data manipulation and management.
- NumPy: For numerical operations on image arrays.
- Scikit-learn: For dataset splitting, model evaluation, and performance metrics.
- Seaborn and Matplotlib: For visualizing model performance.
- GDAL: For handling geospatial raster data in satellite images.

Development Environment

- VSCode or Jupyter Notebook: IDEs for writing and running code.
- Google Colab: Cloud-based platform for training models with GPUs.

Version Control

- Git: For version control and collaboration on code.

Hardware Requirements

- CPU: Multi-core processor (Intel i5 or above).
- RAM: At least 8 GB of RAM.
- Storage: Minimum of 20 GB of storage for datasets and model files.
- GPU: High-performance GPU (NVIDIA RTX 3080 or higher) for model training.

4.2 Datasets:

The **SAR Images Dataset** consists of real-world *Synthetic Aperture Radar (SAR)* imagery captured by **KOMPSAT-5**, covering diverse environmental conditions such as *urban areas*, *wetlands*, *agricultural regions*, and complex *water-land transitions*. The dataset contains over **3,000 images**, each accompanied by a corresponding *manually validated water body mask*, ensuring high-quality annotations for accurate model training. The dataset's **diversity** includes images from various geographical regions, enhancing the model's *generalization* ability across different terrains.

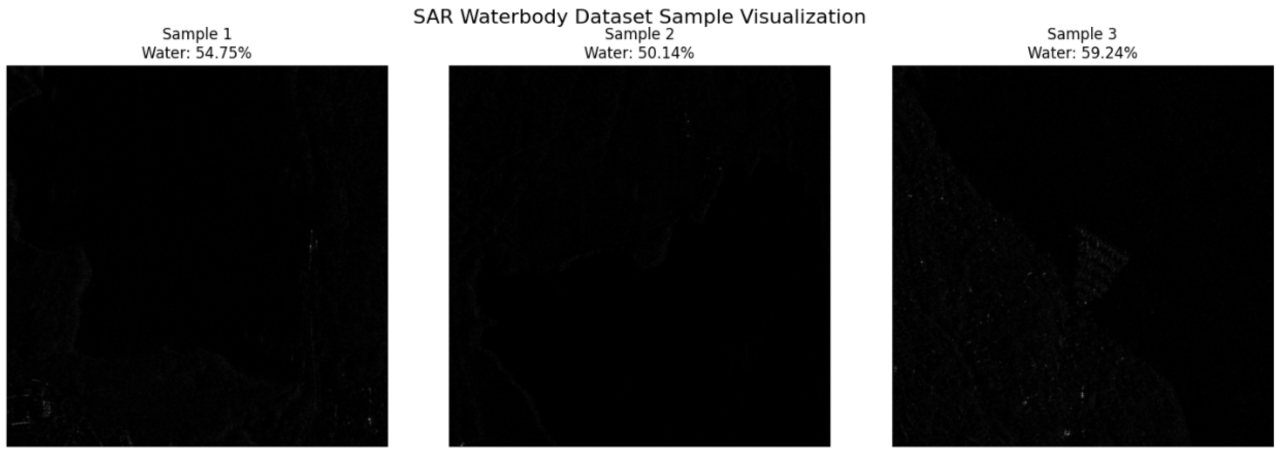

Figure 4.1: Amount of water percentage present in data samples

- **Average Mask Pixel Percentage:** 31.20%
- **Total Mask Pixels:** 608,469,784
- **Total Pixels:** 1,950,351,360

The **Optical Images Dataset** is based on images captured by the *Sentinel-2 satellite*, with each image paired with a black-and-white *mask* where white indicates *water* and black denotes non-water areas. The masks are generated using the *Normalized Water Difference Index (NWDI)*, adapted with a higher threshold for accurate water detection. This dataset covers a wide range of geographic regions, including *rivers*, *lakes*, and *coastal areas*, ensuring the model can generalize across various water body types.

4.3 Evaluation Metrics

To assess the performance of the proposed framework and ensure accurate evaluation for a segmentation task, the following metrics were utilized:

- **Test Set Accuracy**: Measures the overall percentage of correctly classified pixels in the test set, providing a high-level view of model performance.
- **Precision**: Evaluates the proportion of correctly predicted positive pixels to all predicted positive pixels, emphasizing the accuracy of water body detection.
- **Recall**: Assesses the proportion of correctly predicted positive pixels to all actual positive pixels, highlighting the model's ability to detect water bodies comprehensively.
- **Intersection over Union (IoU)**: Calculates the ratio of the intersection to the union of predicted and ground truth masks, providing a robust measure of segmentation accuracy.
- **Dice/F1 Score**: Combines precision and recall into a single metric, offering a balanced evaluation of the model's accuracy and comprehensiveness in segmentation tasks.
- **Confusion Matrix**: Presents a detailed breakdown of true positives, false positives, true negatives, and false negatives, allowing for a comprehensive analysis of classification performance.

These metrics collectively help in evaluating the model's performance accurately for segmentation tasks, ensuring precise and reliable assessment of its effectiveness in detecting and delineating water bodies.

4.4 Experimental Design

The experimental design began with an initial phase of data exploration, where the SAR and optical image datasets were analyzed to understand their characteristics, including distribution, resolution, and variability. Following this, the data underwent preprocessing steps such as resizing, normalization, and augmentation to ensure it was suitable for training the models. The proposed model and baseline methods were trained on the same dataset using identical hyperparameters to ensure a fair comparison. After training, each model was evaluated on a separate test dataset to assess its generalization performance. Performance metrics, including test set accuracy, precision, recall, Intersection over Union (IoU), Dice/F1 Score, and confusion matrix, were computed for all models to quantitatively measure their effectiveness. Postprocessing techniques were then applied to refine the segmentation results, such as smoothing boundaries and correcting small artifacts in the predictions. Finally, the performance of the proposed framework was compared against the baseline methods using the computed metrics, with a particular focus on improvements in segmentation accuracy, boundary delineation, and overall performance.

The experiments were conducted step by step to evaluate the performance of the proposed framework against baseline methods. The key aspects of the experimental design are outlined below:

Baseline Methods

The proposed model was compared against existing segmentation models, including:

- Fully Convolutional Networks (FCN): A widely used architecture for semantic segmentation tasks, serving as a baseline for comparison.
- DeepUNet: An advanced variant of the U-Net architecture, known for its improved segmentation performance on complex datasets.

4.4.1 Experimental Scenarios

The experiments were conducted under various conditions to evaluate the robustness and adaptability of the proposed model. Different dataset sizes were tested by using subsets of the complete dataset, including scenarios where some images and masks were deliberately removed to simulate data scarcity. Additionally, experiments were performed with varying data splits to analyze the impact of training and testing set distributions on model performance. The experiments also considered different batch sizes to study the effect of batch processing on training efficiency and model accuracy. Lastly, variations in the number of layers in the U-Net model architecture were explored to assess the influence of model complexity on segmentation performance.

4.5 Results

In this section, we present the outcomes of our experiments.

Quantitative Results

The performance metrics of our proposed model are summarized in Table 4.1. The key evaluation metrics include accuracy, precision, recall, F1 score, Dice coefficient, and IoU.

Table 4.1: Performance Metrics of the Proposed Model

Metric	**Value**
Accuracy	0.8549
Precision	0.8995
Recall	0.6784
F1 Score	0.7734
Dice Coefficient	0.7734
IoU	0.6306

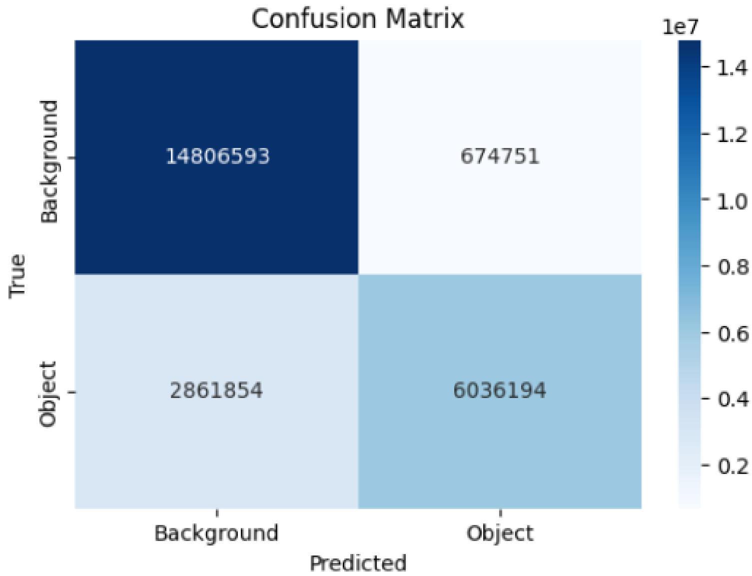

Figure 4.2: Confusion Matrix

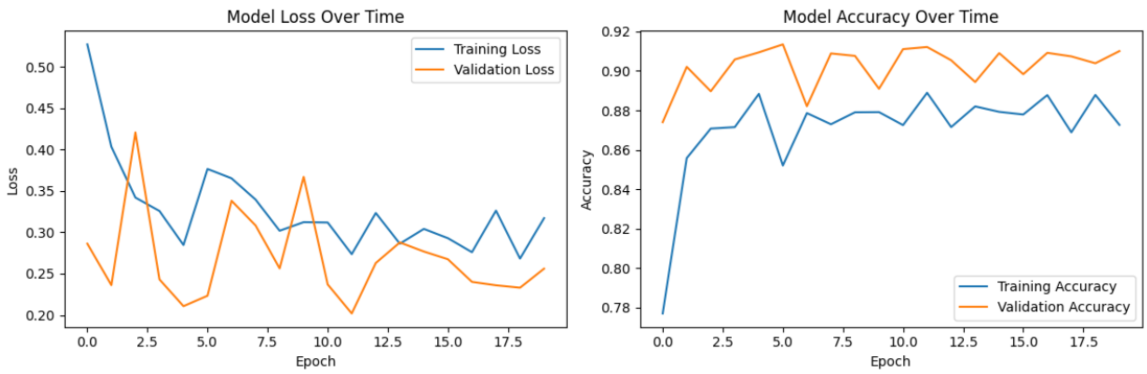

Figure 4.3: Training and Validation Performance Over Epochs

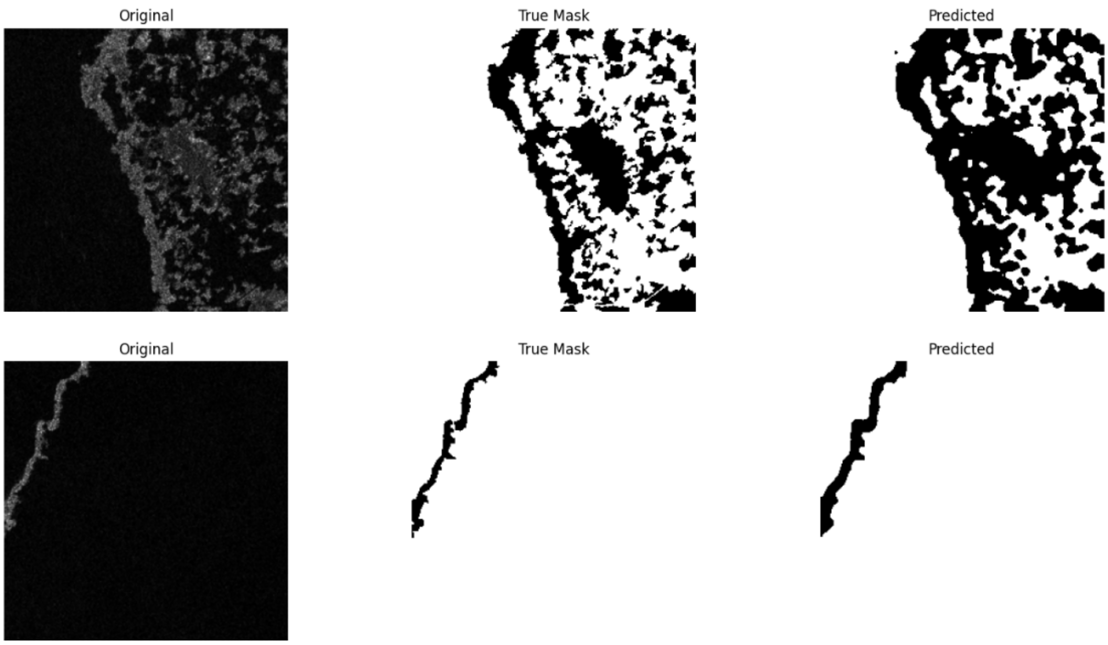

Figure 4.4: Model Predictions

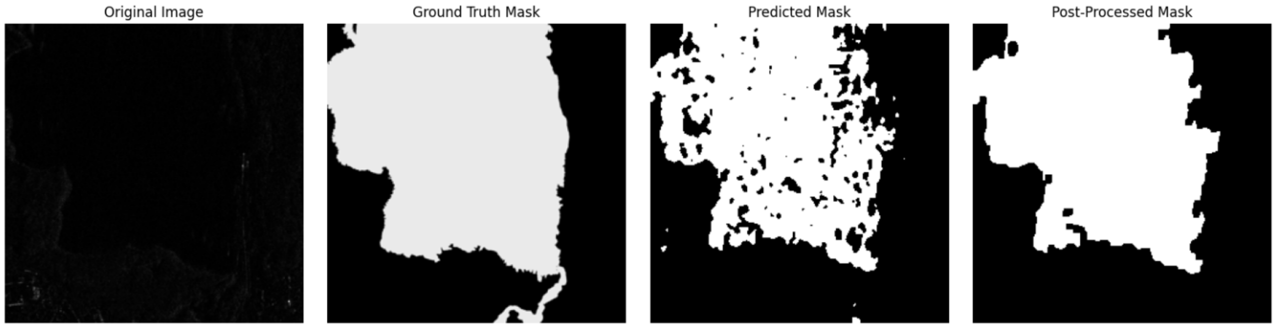

Figure 4.5: After Post Processing

4.6 Analysis of Results

Performance Metrics

- **Accuracy (85.49%):** Indicates the overall correct predictions, but may not fully reflect performance due to class imbalance.
- **Precision (89.95%):** High precision shows that the model effectively avoids false positives, meaning most predicted water bodies are indeed correct.
- **Recall (67.84%):** The recall is relatively low, highlighting that the model misses a notable number of actual water bodies (false negatives).
- **F1 Score (77.34%):** Balances precision and recall, indicating good but improvable segmentation.
- **Dice Coefficient (77.34%) and IoU (63.05%):** Reflect spatial overlap between predicted and ground truth masks. While decent, the values indicate room for improvement in reducing noise and increasing true positives.

Overall Assessment

The model seems to be learning well with no apparent overfitting (validation metrics seem to be better than training). The learning process seems to have largely converged after about 12-15 epochs The slight gap between training and validation accuracy, with the latter being higher, is a bit unusual and may deserve scrutiny. The model achieves pretty good performance using 90 percent validation accuracy.

4.7 Observations

The model performs well on large water bodies but struggles with thin segments. Before post-processing, cloudy regions are visible, which negatively impact the segmentation accuracy. However, after post-processing, the model demonstrates significant improvement and performs well even on images containing clouds. These results highlight the model's strength in segmenting large water bodies effectively while also underscoring areas for improvement, particularly in handling very thin water segments. The effectiveness of the post-processing step is evident in mitigating the impact of clouds on the segmentation quality. Further statistical significance testing could be conducted to validate these observations and strengthen the claims regarding the performance improvements achieved through post-processing.

4.8 Comparative Analysis

Model	**Accuracy (%)**
DeepUNet	87.73
U-Net (Proposed)	85.49
SegNet	82.30
NDRUNet	84.36

Table 4.2: Accuracy comparison of the proposed model with existing methods.

Discussion: The proposed U-Net model achieves an accuracy of 85.49%, which is slightly lower than DeepUNet but higher than SegNet and NDRUNet. This demonstrates the proposed model's effectiveness in balancing simplicity and segmentation quality. While the accuracy of the proposed model is not the highest, it provides robust performance with a simpler architecture compared to the more complex DeepUNet.

The proposed U-Net model's performance could be further enhanced by addressing limitations, such as handling thin waterbody segments and reducing false negatives. The post-processing step in the pipeline is particularly effective in mitigating challenges posed by cloudy regions, leading to improved segmentation quality in such cases.

Chapter 5

Conclusion and Scope for further Research

5.1 Conclusion

This project introduced a U-Net-based model for waterbody segmentation in satellite images, achieving an accuracy of 85.49%. The model performs well on large waterbodies and improves segmentation in cloudy regions through post-processing. However, it struggles with thin waterbodies and has some false negatives, which shows there is room for improvement.

Waterbody segmentation is important for tasks like disaster management, flood monitoring, and environmental conservation. Advanced models like NDR-UNet and DeepAqua handle complex cases, such as water under vegetation or shadows, by using more complex architectures. Compared to these, the proposed U-Net model provides a simpler and efficient solution with competitive accuracy.

Future work could focus on improving the model by using better architectures, adding more diverse training data, and refining post-processing steps. Despite its limitations, this study contributes a practical and effective approach to waterbody segmentation and offers a strong base for further research in this field.

5.2 Scope for Further Research

This project provides a solid foundation for waterbody segmentation, but there are areas for improvement that can be addressed in the next phase of research:

- **Diverse Datasets from Various Sources:** Expand the dataset by including data from different regions and sources to improve the model's robustness and ability to generalize across diverse environments.

- **Improving Model Accuracy:** Focus on enhancing accuracy by fine-tuning the existing U-Net architecture and experimenting with more advanced models, such as attention-based or hybrid architectures.

- **Boundary Detection Challenges:** Work on improving boundary detection, particularly in complex water-land transition areas, to achieve more precise segmentation results.
- **Limited Generalization:** Develop models that perform consistently across various environments, including urban, rural, and wetland areas, by enhancing training datasets and improving model adaptability.

By addressing these gaps, future research can build upon this work to create more accurate and robust solutions for waterbody segmentation in remote sensing tasks.

References

[1] W. Xue, H. Yang, Y. Wu, P. Kong, H. Xu, P. Wu, and X. Ma, "Water body automated extraction in polarization sar images with dense-coordinate-feature-concatenate network," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 12073–12087, 2021.

[2] L. Bao, X. Lv, and J. Yao, "Water extraction in sar images using features analysis and dual-threshold graph cut model. remote sens. 2021, 13, 3465."

[3] Z. Guo, L. Wu, Y. Huang, Z. Guo, J. Zhao, and N. Li, "Water-body segmentation for sar images: past, current, and future," *Remote Sensing*, vol. 14, no. 7, p. 1752, 2022.

[4] F. J. Peña, C. Hübinger, A. H. Payberah, and F. Jaramillo, "Deepaqua: Semantic segmentation of wetland water surfaces with sar imagery using deep neural networks without manually annotated data," *International Journal of Applied Earth Observation and Geoinformation*, 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.

Papers Communicated

1. Francisco J. Peña, Clara Hübinger, Amir H. Payberah, and Fernando Jaramillo, "DeepAqua: Semantic segmentation of wetland water surfaces with SAR imagery using deep neural networks without manually annotated data," *International Journal of Applied Earth Observation and Geoinformation*, May 2023 (revised December 2023, accepted December 2023).

2. Naga Surekha Jonnala and Neha Gupta, "NDR U-Net: Segmentation of Water Bodies in Remote Sensing Satellite Images Using Nested Dense Residual U-Net," *IIETA*, vol. 38, issue 3, pp. 324, 2024. DOI: https://doi.org/10.18280/ria.380324.

3. Zhishun Guo, Lin Wu, Yabo Huang, Zhengwei Guo, Jianhui Zhao, and Ning Li, "Water-Body Segmentation for SAR Images: Past, Current, and Future," *School of Computer*

and Information Engineering, Henan University, China, 2024. Correspondence Email: hyb@henu.edu.cn.

4. Weibao Xue, Hui Yang, Yanlan Wu, Peng Kong, Hao Xu, Penghai Wu, and Xiaoshuang Ma, "Water Body Automated Extraction in Polarization SAR Images With Dense-Coordinate-Feature-Concatenate Network," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 14, pp. 12073, 2021.

5. Linan Bao, Xiaolei Lv, and Jingchuan Yao, "Water Extraction in SAR Images Using Features Analysis and Dual-Threshold Graph Cut Model," *Remote Sensing*, vol. 13, issue 3465, 2021. DOI: https://doi.org/10.3390/rs13173465. Academic Editor: Piotr Samczynski.