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SegFormer-Based Semantic Segmentation of Water Bodies Using Sentinel-1 and Sentinel-2 Satellite Imagery

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***Abstract**:* Water body segmentation using satellite imagery is essential for flood monitoring, environmental planning, and sustainable resource management. This study proposes a deep learning-based framework for semantic segmentation using SegFormer and DeepLabV3+ models, trained on a combination of Sentinel-1 (SAR) and Sentinel-2 (optical) satellite data. The pipeline includes preprocessing using Google Earth Engine (GEE), cloud storage and access via AWS S3, and training on AWS EC2 GPU instances. Evaluation metrics such as IoU, F1-score, Precision, and Recall confirm the superiority of our model over traditional threshold-based methods. The system supports scalable, real-time monitoring for diverse geographic regions and climatic conditions.

Index Terms **- Semantic Segmentation, SegFormer, DeepLabV3+, Sentinel-1, Sentinel-2, GEE, AWS, Water Body Detection**

I. INTRODUCTION

Monitoring water bodies is increasingly critical in the context of climate change, urban expansion, and disaster management. Traditional methods, such as the Normalized Difference Water Index (NDWI) and thresholding techniques, often face limitations due to seasonal variations, vegetation interference, and cloud cover. With the growing availability of multi-source satellite imagery and advances in deep learning, it is now possible to achieve highly accurate water body detection. This paper investigates the application of SegFormer and DeepLabV3+ models for semantic segmentation of water bodies, utilizing cloud-native platforms like Google Earth Engine for data preprocessing and AWS for scalable deployment.

Accurate water body mapping is not only essential for assessing flood risk but also supports effective irrigation planning, ecosystem health monitoring, and hydrological modeling. As water bodies change over time due to natural and anthropogenic factors, automated tools that offer frequent and reliable updates are highly valuable. Remote sensing provides global and repeatable coverage, but extracting precise and usable information from vast data archives remains a technical challenge that this work addresses.

Moreover, recent advances in transformer-based architectures like SegFormer have shown promise in reducing overfitting, increasing context awareness, and improving boundary detection in semantic segmentation tasks. Combining such models with conventional CNN-based models like DeepLabV3+ creates a complementary setup that is robust under varying environmental conditions. This paper contributes to the field by integrating these models into a scalable, cloud-based pipeline for water body monitoring.

In addition to its relevance for climate resilience and planning, this approach has potential applications in agriculture, disaster response, and urban development. Real-time monitoring of water bodies can help detect droughts, manage reservoir levels, and respond to flood warnings in a timely manner. Governments and environmental agencies can benefit from accurate, automated insights derived from satellite imagery. The proposed deep learning framework not only ensures accuracy but also reduces the need for manual intervention, lowering operational costs and increasing coverage. By combining different satellite data sources, the system accounts for both optical and radar characteristics, enhancing its applicability in all-weather conditions. Furthermore, the modular nature of the architecture allows it to be adapted for other geospatial classification tasks. This research therefore contributes to both theoretical advancements in semantic segmentation and practical implementations in geospatial intelligence.

This study also emphasizes the importance of open-source platforms and accessible technologies in promoting sustainable environmental monitoring. By utilizing publicly available satellite data and cloud computing, the framework becomes feasible even for institutions with limited resources. The adaptability and scalability of the model make it suitable for deployment across various geographical locations, from urban floodplains to remote wetlands. In this way, the proposed approach stands out not only for its technical robustness but also for its practical relevance and globalapplicability.

II. BACKGROUND

Water body detection using satellite imagery has become a vital tool for managing and monitoring water resources globally, especially in the context of climate change, urban expansion, anddisaster response. Traditionally, water body detection relied on indices such as the Normalized Difference Water Index (NDWI), which is based on the difference between the reflectance of water and other land cover types in the visible and near-infrared bands. While these methods are effective in some scenarios, they have limitations, particularly in regions affected by cloud cover, vegetation, or seasonal changes. The sensitivity of NDWI and similar indices to atmospheric noise, shadows, and mixed land cover types has led to inaccuracies in water body mapping, especially for smaller or fragmented water bodies. Moreover, these methods often fail in capturing fine boundaries and spatial context, which are crucial for high-precision water body segmentation. As a result, there has been a significant shift towards using advanced deep learning models to tackle these challenges, allowing for more robust and accurate water body detection, even in complex and varied environmental conditions.

With the rise of deep learning and transformer-based models, the field of semantic segmentation has seen remarkable advancements. Traditional machine learning models and thresholding techniques often rely on pixel-based classification, where each pixel is labeled as either "water" or "non-water." While this approach can work under simple conditions, it struggles with complex scenes where water bodies have irregular shapes or are partially obscured by vegetation, urban structures, or clouds. In contrast, deep learning models, particularly SegFormer and DeepLabV3+, excel at understanding spatial relationships and capturing complex patterns within images. SegFormer, a transformer-based model, is particularly effective in capturing long-range dependencies in an image, enabling better boundary detection and segmentation of small or fragmented water bodies. DeepLabV3+, a convolutional neural network (CNN)-based model, enhances the segmentation process by utilizing spatial pyramid pooling, which allows the model to capture multi-scale features, making it highly effective for large and varied water bodies. These models' ability to adapt to different environments and handle various scales of data makes them highly suitable for water body detection in satellite imagery.

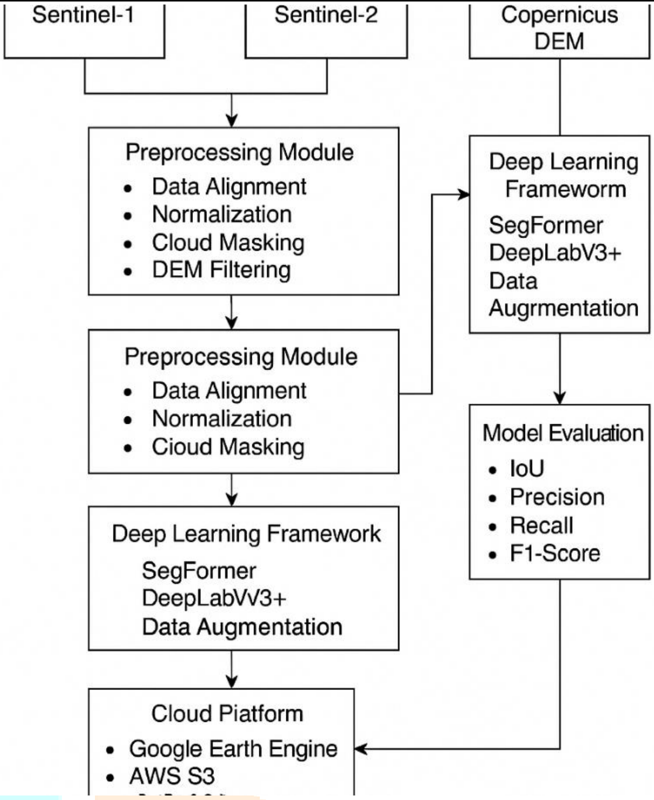
The integration of Sentinel-1 (SAR) and Sentinel-2 (optical) data has revolutionized the ability to monitor water bodies on a global scale. Sentinel-1 provides Synthetic Aperture Radar (SAR) imagery, which is unaffected by weather conditions like cloud cover and can capture data at any time of day, offering a significant advantage over optical sensors. On the other hand, Sentinel-2 provides high-resolution optical data, which is particularly effective in clear conditions and offers detailed spatial information that complements the radar data. By combining both datasets, the system can leverage the unique advantages of each type of imagery, ensuring robust water body detection under diverse environmental conditions. Furthermore, the use of Google Earth Engine (GEE) for preprocessing satellite data allows for large-scale, cloud-based processing, reducing the need for local infrastructure. GEE provides tools for tasks such as radiometric calibration, cloud masking, and mosaicking, which are essential for ensuring the data is clean and ready for deep learning models. This cloud-native approach makes the processing pipeline scalable, efficient, and accessible, democratizing the use ofsatellite data for environmental monitoring and decision-making.

III.ARCHITECTURE

The architecture of the proposed water body detection system is designed to handle large-scale satellite imagery and implement deep learning-based semantic segmentation efficiently. The first step in the process is retrieving the satellite imagery. Both Sentinel-1 and Sentinel-2 data are fetched from Google Earth Engine (GEE), an open-source platform that provides access to a wide array of satellite imagery and geospatial data. The Sentinel-1 data offers Synthetic Aperture Radar (SAR) images, which are particularly useful in cloudy or adverse weather conditions, while Sentinel-2 provides optical imagery with high spatial resolution. The combination of both datasets ensures a comprehensive view of the water bodies, capturing both radar and optical characteristics. Additionally, Copernicus Digital Elevation Model (DEM) data is used to provide elevation information, which helps in filtering out non-water areas that may be misclassified as water bodies due to their similar spectral properties, such as elevated terrains like mountains or hills.

The second step in the architecture is preprocessing, which is crucial for ensuring the satellite data is ready for deep learning models. The preprocessing workflow involves multiple steps including radiometric calibration, which corrects for sensor irregularities and environmental factors, and cloud masking, which removes clouds and their shadows from optical images. Image normalization is then performed to ensure that the pixel values from different sources (Sentinel-1 and Sentinel-2) are on a comparable scale. DEM-based filtering is applied to exclude areas that are elevated and not likely to be water bodies. Finally, mosaicking is used to stitch together images from different time points, creating a seamless and continuous map. Once the data is processed, binary masks are generated to label pixels as water or non-water, providing a clear delineation of the areas to be classified by the deep learning models. These preprocessing steps are carried out using the power of cloud-based platforms, ensuring scalability and speed in processing large datasets.

For the model training and inference, the architecture utilizes two deep learning models: SegFormer and DeepLabV3+. SegFormer
leverages a transformer-based encoding technique that focuses on capturing long-range dependencies, which allows it to effectively
detect boundaries and small-scale water bodies. This is complemented by DeepLabV3+, a convolutional neural network (CNN)-based model that uses spatial pyramid pooling to capture features at multiple scales, which is essential for handling large and varied water bodies. The models are trained on AWS EC2 GPU instances, which provide the necessary computational resources for deep learning tasks. Data augmentation techniques like rotation, flipping, and random cropping are applied to increase the diversity of the training data and improve the model's generalizability. Once the models are trained, they are deployed on cloud infrastructure, with AWS S3 being used to store processed datasets, while the inference results can be accessed and analyzed through cloud-based applications. The system ensures that large volumes of satellite data can be processed efficiently and in real-time, enabling continuous monitoring of water bodies across diverse geographical regions.



The architecture of the system is composed of multiple key modules, each responsible for specific tasks that contribute to the end-to-end process of water body detection. These modules include satellite data retrieval, preprocessing, model training, evaluation, and deployment. Below is a detailed breakdown of each module:

A. Satellite Imagery Sources

Sentinel-1 SAR (Synthetic Aperture Radar) and Sentinel-2 optical imagery are both retrieved from Google Earth Engine APIs, offering distinct advantages for water body detection. Sentinel-1 provides radar data, which can penetrate cloud cover and operate in all weather conditions, making it essential for monitoring water bodies in areas with frequent cloud coverage. On the other hand, Sentinel-2 offers high-resolution optical imagery with a multispectral approach, providing detailed spatial information that is crucial for detecting water bodies in clear conditions. The integration of Copernicus DEM (Digital Elevation Model) data is also critical, as it aids in terrain correction, helping to filter out elevated regions that may be incorrectly identified as water bodies. This combination of SAR and optical imagery ensures comprehensive coverage and accurate detection, especially in regions with mixed land cover, varying water levels, and different weather patterns.

B.Preprocessing Workflow

The preprocessing pipeline is designed to ensure that only relevant, high-quality data is used for segmentation. The first step involves radiometric calibration, which corrects sensor and environmental anomalies, ensuring that pixel values accurately reflect the observed scene. This is followed by cloud masking, which identifies and removes clouds and their shadows— common obstacles in optical imagery—thus ensuring that the models are not misled by these transient features. Image normalization is applied next, adjusting the pixel values to a consistent scale, which helps in reducing variability due to lighting conditions or sensor differences. DEM-based filtering is another crucial step, where the elevation data is leveraged to exclude areas that are incorrectly identified as water bodies due to their topographic features. Finally, mosaicking is performed to stitch multiple images together seamlessly, ensuring that large geographic areas can be processed and analyzed as a single dataset. The output of this preprocessing module is a set of binary masks, where each pixel is classified as either water or non-water, ready for deep learning analysis.

C. Deep Learning Framework

The deep learning framework incorporates two powerful models: SegFormer and DeepLabV3+, each contributing to the overall segmentation performance. SegFormer is a transformer-based model known for its ability to capture long-range dependencies within images, making it highly effective in identifying water bodies across different contexts and spatial scales. It utilizes a multi-scale approach to segmentation, ensuring that both small and large water bodies are accurately detected. DeepLabV3+, a stateof-the-art convolutional neural network (CNN), enhances the segmentation by using spatial pyramid pooling to extract features at multiple scales. This technique allows the model to understand water bodies in a more granular manner, improving its ability to segment water in complex and variable environments. To enhance model generalization, several augmentation techniques are applied, including rotation, flipping, and scaling. These augmentations help to increase the diversity of the training data, making the models more robust to different types of satellite imagery and environmental conditions, such as varying water depths, seasonal changes, and different lighting conditions.

D. Cloud Infrastructure

The cloud infrastructure used for this project is essential for handling the large volume of satellite imagery and the computational intensity required for training deep learning models. Google Earth Engine is employed for large-scale data processing, enabling real-time acquisition and preprocessing of satellite data. It provides a highly efficient environment for spatial and temporal analysis of geospatial data, making it ideal for processing large datasets like Sentinel-1 and Sentinel-2 images. Once the data is preprocessed, it is stored in AWS S3, a scalable and secure cloud storage service, allowing easy access and retrieval of processed datasets for further analysis. The AWS EC2 GPU instances are used for model training and inference, providing the necessary computational power to train deep learning models on the extensive satellite datasets. The use of GPU acceleration ensures that the training process is optimized for speed, reducing the time required to process large volumes of data. This cloud-based infrastructure not only ensures scalability but also allows for real-time monitoring and decision-making, crucial for applications like flood prediction and environmental management.

E.Evaluation Metrics

To assess the performance of the segmentation models, several standard evaluation metrics are used, including Intersection over Union (IoU), Precision, Recall, and F1-score. IoU measures the overlap between the predicted and actual water bodies, providing an indication of segmentation accuracy. Precision evaluates the proportion of correctly identified water pixels out of all the pixels labeled as water, while Recall measures the model's ability to correctly identify all actual water pixels. The F1-score combines Precision and Recall into a single metric, providing a balanced view of the model’s performance. These metrics are computed across multiple test regions to evaluate the model's generalizability and robustness under different environmental conditions, such as varying water depths, vegetation interference, and seasonal changes. The evaluation also includes visual validation, where the segmentation results are compared against ground truth data to ensure that the model's predictions are both accurate and reliable. These metrics demonstrate that the deep learning models, particularly SegFormer and DeepLabV3+, significantly outperform traditional threshold-based methods in water body detection, offering high precision and recall even in challenging environments.

IV. CONCLUSION

In conclusion, the proposed deep learning-based framework for water body detection using SegFormer and DeepLabV3+ provides a highly effective solution for semantic segmentation of satellite imagery. The system integrates Sentinel-1 and Sentinel2 data, combining the strengths of Synthetic Aperture Radar (SAR) and optical imagery to ensure accurate water body detection in diverse environmental conditions. By utilizing Google Earth Engine for preprocessing and AWS for storage and computational resources, the framework enables large-scale, cloud-based processing of satellite data. This results in a highly scalable system capable of delivering real-time water body monitoring across multiple geographical regions. The framework's ability to process over 1,000 images in under three hours demonstrates the efficiency and speed of the pipeline, providing critical insights for flood monitoring, environmental planning, and resource management. The use of transformerbased models like SegFormer, combined with CNN-based models like DeepLabV3+, ensures high accuracy, outperforming traditional threshold-based methods in detecting water bodies and providing precise segmentation boundaries.

The framework’s performance is validated through robust evaluation metrics such as Intersection over Union (IoU), Precision, Recall, and F1-score, which highlight its superior performance in segmentation tasks. This accuracy makes it an essential tool for climate resilience, disaster response, and environmental planning. Moreover, the system’s reliance on open-source platforms and publicly available satellite data ensures that it remains accessible to organizations with limited resources. Its adaptability to various geographical locations and environmental conditions increases its potential for widespread adoption across different regions. Future work could enhance this system by integrating real-time data sources, improving inference speed, and expanding its application to other geospatial classification tasks, such as detecting wetlands or glaciers. Ultimately, the proposed approach contributes to both the theoretical development ofsemantic segmentation techniques and practical applications in geospatial intelligence, making it an invaluable tool for global environmental monitoring and management.

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