



Sea Land Segmentation of East Java's North Coast Using Landsat 9 and ResNet50

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Abstract

Coastal regions are among the most vulnerable ecosystems due to the combined impacts of natural processes and human activities. Climate change, population growth, and coastal development accelerate shoreline dynamics, increasing the need for accurate and efficient coastal monitoring. Satellite-based remote sensing, combined with deep learning techniques, provides a promising solution for large-scale and continuous shoreline analysis. This study proposes a deep learning-based approach for coastal land-sea segmentation using the ResNet50 architecture applied to Landsat 9 OLI imagery of the North Coast of East Java, Indonesia. The dataset consists of multispectral images processed into 224×224 pixel tiles, accompanied by manually generated ground truth segmentation maps. Two optimization strategies, Adam and Stochastic Gradient Descent (SGD), are evaluated to determine the most effective optimizer for improving segmentation performance. Experimental results demonstrate that the Adam optimizer outperforms SGD across multiple training epochs, achieving the highest segmentation accuracy with mean Intersection over Union (IoU) and Dice coefficient values of 0.888 and 0.934, respectively. These findings indicate that optimizer selection significantly influences the performance of ResNet50-based coastal segmentation. The proposed approach shows strong potential for supporting automated and large-scale coastal monitoring applications using medium-resolution satellite imagery.

Keywords: optimizer adam; optimizer sgd; resnet50; segmentation; shoreline

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1. Introduction

Coastal regions are among the most important ecosystems from both environmental and economic perspectives, with more than half of the world's population living within 100 km of the coastline. These areas are increasingly threatened by land-based pollution, maritime activities, and climate change, making effective coastline monitoring essential for coastal management and erosion mitigation [1] - [3]. Although in-situ measurements provide accurate observations, they are costly, time-consuming, and unsuitable for large-scale or high-frequency monitoring. Consequently, satellite remote sensing has become the primary tool for coastal observation, particularly for regions that are difficult to access. However, the growing volume and complexity of satellite data require automated and accurate image

analysis techniques to improve monitoring efficiency and reliability.

A crucial component of coastal geomorphology is the research of coastal forms, which offers important insights into the underlying mechanisms and forces that form coastal habitats. Researching the geometry of coastlines, researchers can deduce details about the processes that shaped and evolved these varied landscapes. This is a multi-factor reasoning-based intelligent decision-making technique. The research of shoreline shapes is important for reasons other than academic ones; it has important applications in the fields of planning, management, and conservation. For an extended period, scholars and coastal administrators have acknowledged the need to precisely categorize coasts according to their geometric characteristics, as this aids in detecting trends, mitigating risks, and

improving understanding of the elements influencing coastal development [4].

Though commonly used, traditional image segmentation approaches have certain drawbacks, such as their inapplicability to certain image types. Object-based segmentation approaches have drawbacks, including over and under-segmentation, whereas edge detection-based methods are highly image-dependent and noise-sensitive. Consequently, segmentation techniques that are object-based, pixel-based, or integrated can yield results for mix classification. Shoreline segmentation has also been done using machine learning techniques. Deep learning (DL) algorithms have emerged as cutting-edge techniques in remote sensing research. Deep learning (DL) is a machine learning technique that mimics human learning. When compared to machine learning techniques, the primary benefit of deep learning is autonomous feature extraction [5] - [9]. When compared to machine learning techniques, the primary benefit of deep learning is autonomous feature extraction. As a result, deep learning reduces development issues related to problem-based feature extractors. Unlike machine learning, which handles the problem by dividing it into separate portions and integrating them, deep learning (DL) offers an end-to-end answer. After training the architecture, any research region can implement DL-based techniques, which are critical for long-term coastal area monitoring. Therefore, DL-based coastal monitoring systems can be effective for temporal and real-time analysis. Although conventional image processing techniques can be applied for coastline segmentation, they prove ineffective for large data sets and require the creation of new parameter values for each image [10] - [15].

These days, deep learning research is using remote sensing technology, which has several benefits, such as multi-sensor, multi-temporal, and high-resolution images. Research projects have successfully employed remote sensing (RS) and geographical information systems (GIS) to produce findings for coastal management and evaluate coastal erosion. Prior research has frequently used mid-resolution satellite pictures (such as Landsat, SPOT, and Sentinel-2) to examine the coastal erosion process by separating land and sea in general, with imprecise and less reliable conclusions. Remote sensing devices such as unmanned aerial vehicles (UAVs) and Google Earth photos can provide clear views of coastlines and shorelines to tackle this issue. Deep learning technology has made it possible for people to teach a computer to distinguish between shorelines and shorelines that have other items nearby. This knowledge enables the computer to identify the shoreline and coastline immediately upon the acquisition of remote sensing photos, facilitating real-time monitoring models that display changes to the coast. Medical, geographic, and environmental domains are using a wide range of deep learning models, including Support Vector Machines (SVM), Convolutional Neural Networks (CNN), Unet,

DeepUNet, Semantic Segmentation, FusionNet, and DeepLabV3+ [16]- [24].

ResNet50 was selected as the backbone network due to its strong feature extraction capability and proven performance in various image classification and semantic segmentation tasks. The residual learning mechanism enables deeper network architectures while effectively addressing the vanishing gradient problem. Previous studies have demonstrated that ResNet-based encoders provide robust spatial feature representations for remote sensing image segmentation, including land-cover and coastal applications [25], [26].

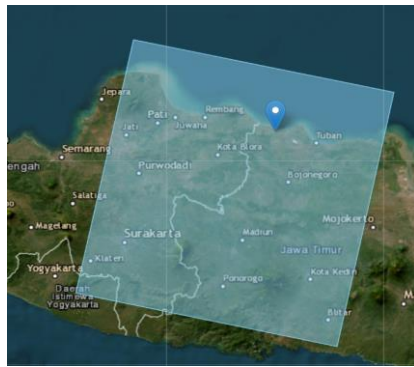
The aims of this research are to (1) develop a deep learning-based framework for accurate land-sea segmentation along the northern coast of East Java using Landsat 9 imagery; and (2) analyze the influence of different optimization strategies (Adam and SGD) on training convergence and segmentation performance using a ResNet50-based architecture. The comparison of optimizers is conducted as an ablation study to evaluate their impact on model stability and segmentation accuracy, rather than as the primary contribution of this research. Based on previous studies [27], variations in optimization strategies can influence training stochasticity and convergence behavior, and may help improve model generalization [28].

2. Methods

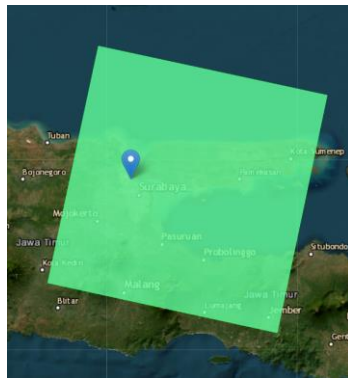
2.1 Dataset

The Landsat 9 image data used in this research is from the EarthExplorer site (usgs.gov) and has the following path and row IDs: the Tuban Scene (path=119, and row=065) and the Gresik Scene (path=118, and row=065), as shown in Figure 1. The first is to download the two data sets before proceeding with further analysis processes. The analysis of coastal land and sea segmentation uses only three bands, namely band 2, band 3, and band 4, out of the 11 bands in each of the two data sets. To download the Landsat 9 image data, we combine bands 2, 3, and 4 for processing (as shown in Figure 2). A deep learning model will then use this processed data for training. The Tuban Scene and the Gresik Scene still separate the merged image data, necessitating a mosaic process to unite these two scenes and facilitate the creation of image tiles with a size of 256x256 pixels. The research area's wide coverage necessitates the implementation of this mosaic, as utilizing a single image scene is not feasible. A mosaic process then transforms the two image scenes of Tuban and Gresik into a single, interconnected scene, as shown in Figure 3.

The length and width of the pixels for each piece of data must determine its entry into the input layer during the data training process. This segmentation analysis of coastal land and sea uses 224x224 pixels of data. This divides the combined (mosaic) Tuban and Gresik scene image data into tiles of 256x256 pixels, which then resize to 224x224 pixels.

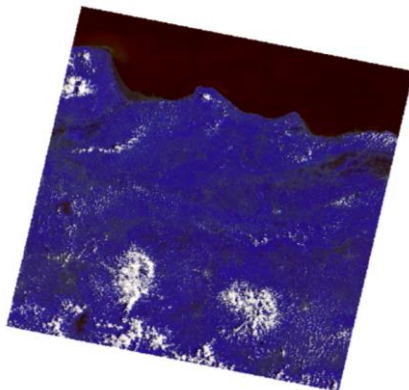


Scene Tuban

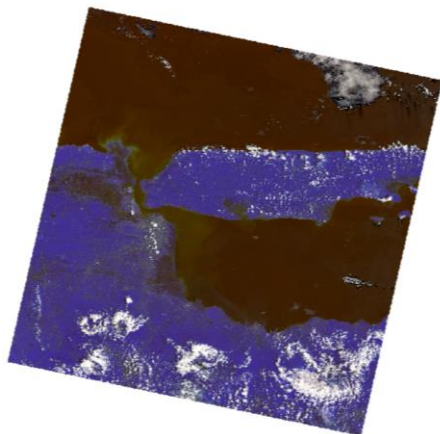


Scene Gresik

Figure 1. Tuban and Gresik scenes



Scene Tuban (band 2,3,4)



Scene Gresik (band 2,3,4)

Figure 2. Scene image of Tuban and Gresik (bands 2,3 and 4)

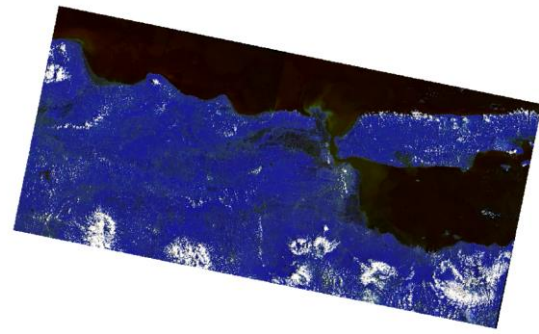
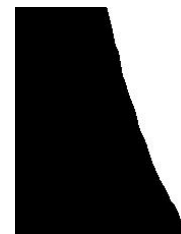


Figure 3. Tuban scene and Gresik scene after being combined (mosaic)

The model creation process does not use all downloaded data. This research selects data that clearly shows land and sea (making it easier to create ground truth segmentation). The training data includes 594 images, each measuring 224x224 pixels. For testing data, a size of 224x224 is used for 218 images. Figure 4 provides an illustration of the input dataset and the ground truth. The input image in light blue or bright blue is land, and dark brown is ocean. Ground truth is the segment's black and white label, with black (0) representing land and white (1) representing sea.



Input dataset



Ground truth label

Figure 4. Example of input dataset and ground truth

This research chooses the ResNet50 [25], [26], [29] method to segment land and coastal seas because the experimental results of the ResNet50 model transfer learning deep learning method have the highest precision results. In addition, this research seeks the best optimizer from adam and sgd in the ResNet50 model, because the way to optimize the model is by replacing the optimizer and learning rate.

The evaluation process of this research is by calculating the jaccard between the segmentation image results and the actual/label data. Image actual/label data get from the download results from the EarthExplorer site (usgs.gov) then processed with photoshop (converted to black (0) representing land and white (1) representing sea).

2.2 Segmentation Using ResNet50

This research proposes a deep learning-based segmentation method to distinguish coastal land and sea areas using a ResNet50 architecture with two optimization scenarios, namely the Adam optimizer (Scenario 1) and the SGD optimizer (Scenario 2), as illustrated in Figure 5. Landsat 9 satellite imagery is used as the input data. All images are resized to 224×224 pixels, and corresponding ground truth segmentation masks are manually generated for each image, as shown in Figure 4. The ground truth creation process relies on the expertise of geomatic engineering researchers to ensure accurate land-sea delineation.

Optimizer selection plays a critical role in deep learning model convergence and generalization. The Adam

optimizer combines the advantages of adaptive learning rates and momentum, enabling faster convergence and stable training, particularly for complex optimization landscapes. In contrast, Stochastic Gradient Descent (SGD) is widely used due to its simplicity and strong generalization capability, although it often requires longer training time to converge [30].

Several studies have reported that adaptive optimizers such as Adam may achieve faster convergence, while SGD often provides better generalization performance under sufficient training epochs. Therefore, this study evaluates both Adam and SGD as an ablation experiment to analyze their impact on convergence behavior and segmentation accuracy [30].

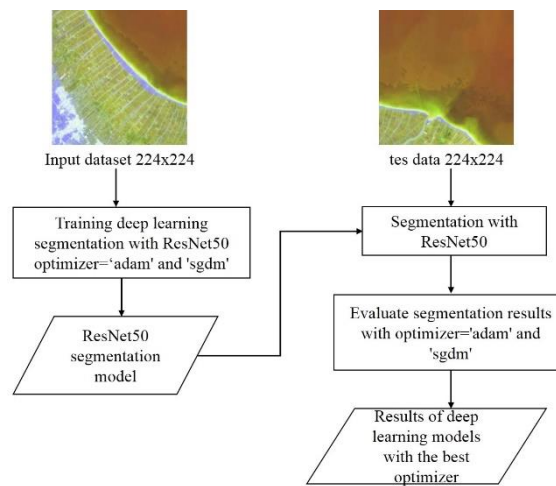


Figure 5. Proposed method

The segmentation model employs a deep learning network based on ResNet50 as the encoder backbone, as shown in Figure 6. ResNet50 consists of 48 convolutional layers organized into convolutional and identity blocks, enabling deep feature extraction while addressing the vanishing gradient problem through residual connections [31]. To adapt ResNet50 for semantic segmentation tasks, the extracted feature maps are followed by a decoding process that upsamples the features to the original spatial resolution, producing pixel-level classification outputs for land and sea regions [32]. The experimental training process is conducted using two optimization scenarios, as summarized in Table 1. Both scenarios are trained with the same learning rate and epoch variations to ensure a fair comparison of optimizer performance.

Table 1. Experiment settings

Parameters	Scenario 1	Scenario 2
Epoch	30, 35, 40	30, 35, 40
Optimizer	Adam	SGD
Learning rate	0.001	0.001

The epoch values of 30, 35, and 40 were selected to evaluate the effect of training duration on model convergence and segmentation performance. In transfer learning-based segmentation tasks using pre-trained

deep CNN architectures, previous studies have reported that stable convergence is typically achieved within a relatively small number of epochs, especially when the dataset size is moderate and data augmentation is applied [25].

By gradually increasing the number of epochs, this study aims to observe potential performance degradation due to overfitting as well as improvements in feature adaptation, providing a balanced analysis of training stability and segmentation accuracy.

The segmentation model evaluation process is calculated using Jaccard and Dice similarity coefficients. Equations 1 and 2 are ways to calculate the Jaccard or Intersection over Union and Dice similarity coefficients.

$$Jaccard(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

$$Jaccard(A, B) = 2 * \frac{|A \cap B|}{|A| + |B|} \quad (2)$$

A is the ground truth image and B is the segmentation image. The ground truth image and segmentation results have a value of 0 and 1, then the intersection value is calculated $\cap$, and union $\cup$.

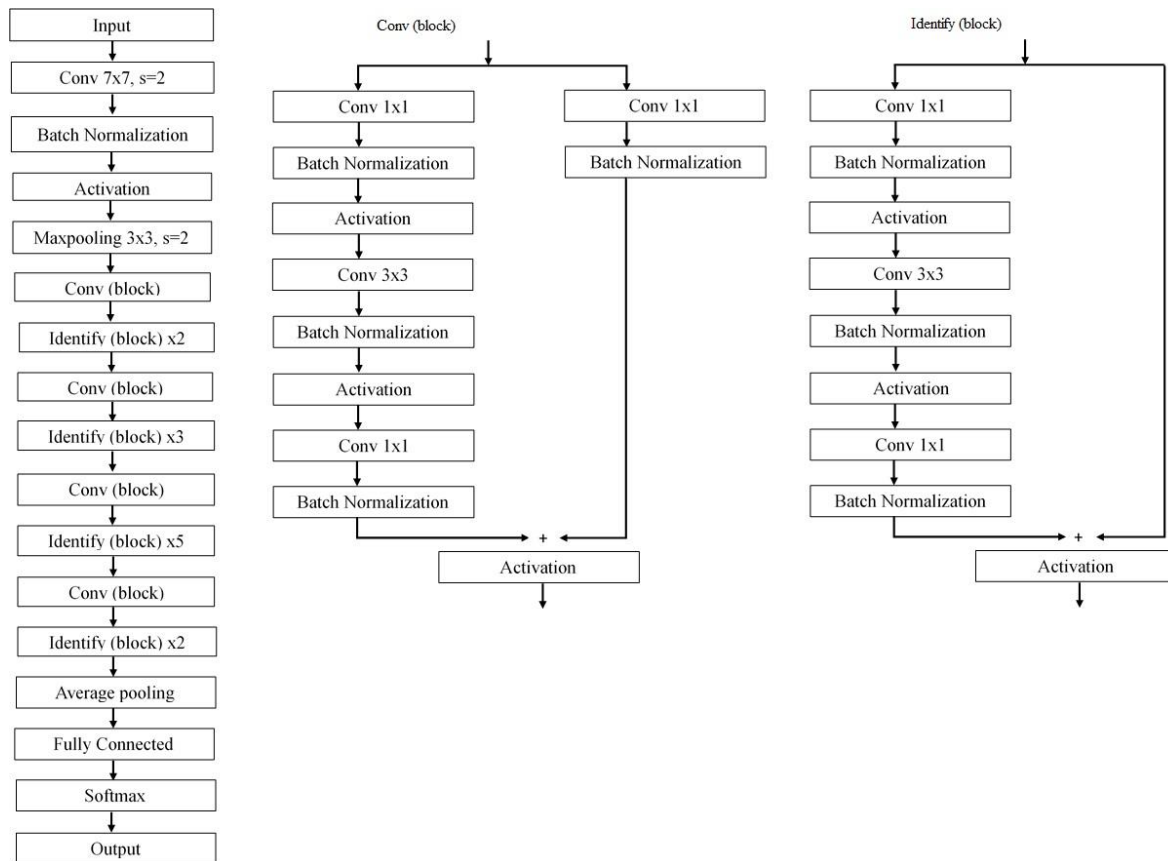


Figure 6. ResNet50 architecture

3. Results and Discussions

Table 2 presents the evaluation results of Scenario 1 using the Adam optimizer with different numbers of training epochs. At 30 epochs, the model achieved a Mean IoU of 0.839 and a Mean Dice coefficient of 0.901, indicating good segmentation performance. However, when the number of epochs was increased to 35, both metrics decreased to 0.757 for Mean IoU and 0.828 for Mean Dice, suggesting a temporary degradation in model performance. This decline may indicate training instability or early overfitting.

Table 2. Evaluation Results Scenario 1

Epochs	Mean IoU	Mean Dice
30	0.839	0.901
35	0.757	0.828
40	0.888	0.934

When the training was extended to 40 epochs, the model showed a significant improvement, achieving the highest performance in this scenario with a Mean IoU of 0.888 and a Mean Dice coefficient of 0.934. These results indicate that the Adam optimizer benefits from sufficient training iterations to reach a more optimal convergence for coastal land-sea segmentation.

Table 3 shows the evaluation results of Scenario 2 using the SGD optimizer. At 30 epochs, the model obtained a Mean IoU of 0.758 and a Mean Dice coefficient of 0.837. As the number of epochs increased to 35 and 40, both evaluation metrics improved gradually, reaching

Mean IoU values of 0.775 and 0.777, and Mean Dice coefficients of 0.851 and 0.855, respectively.

Table 3. Evaluation Results Scenario 2

Epochs	Mean IoU	Mean Dice
30	0.758	0.837
35	0.775	0.851
40	0.777	0.855

Unlike Scenario 1, the performance improvement with SGD is more stable and consistent across epochs. However, the overall segmentation accuracy achieved by SGD remains lower than that obtained using the Adam optimizer, indicating that SGD converges more slowly and may require additional optimization strategies to reach comparable performance.

Figures 7-12 present the visual segmentation results of coastal land-sea classification using the ResNet50 model under two optimization scenarios: Scenario 1 (Adam optimizer) and Scenario 2 (SGD optimizer), evaluated at different numbers of training epochs (30, 35, and 40 epochs). Figure 7 shows the segmentation result after 30 epochs using the Adam optimizer. The model is able to distinguish land and sea regions reasonably well; however, some boundary inconsistencies are still observed along complex coastal areas. This is reflected in a Mean IoU of 0.839 and a Mean Dice score of 0.901.

In Figure 8 (35 epochs), the segmentation quality slightly degrades, particularly in areas with mixed pixels and shallow coastal waters. This phenomenon is

consistent with the decrease in quantitative performance, where the Mean IoU drops to 0.757 and the Mean Dice score to 0.828, indicating possible instability during training. Figure 9 illustrates the segmentation result after 40 epochs, where the model achieves the best visual and quantitative performance among all experiments. The land-sea boundary appears

smoother and more continuous, with fewer misclassified pixels. This improvement aligns with the highest Mean IoU (0.888) and Mean Dice (0.934), suggesting that longer training with Adam allows the model to better learn spatial and contextual features of coastal regions.

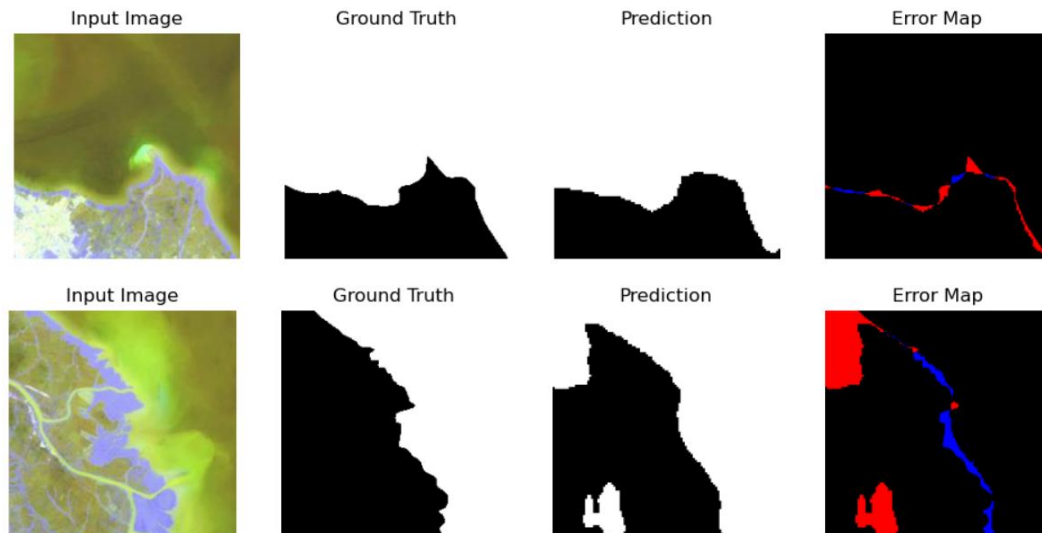


Figure 7. Segmentation results (scenario 1) 30 epochs

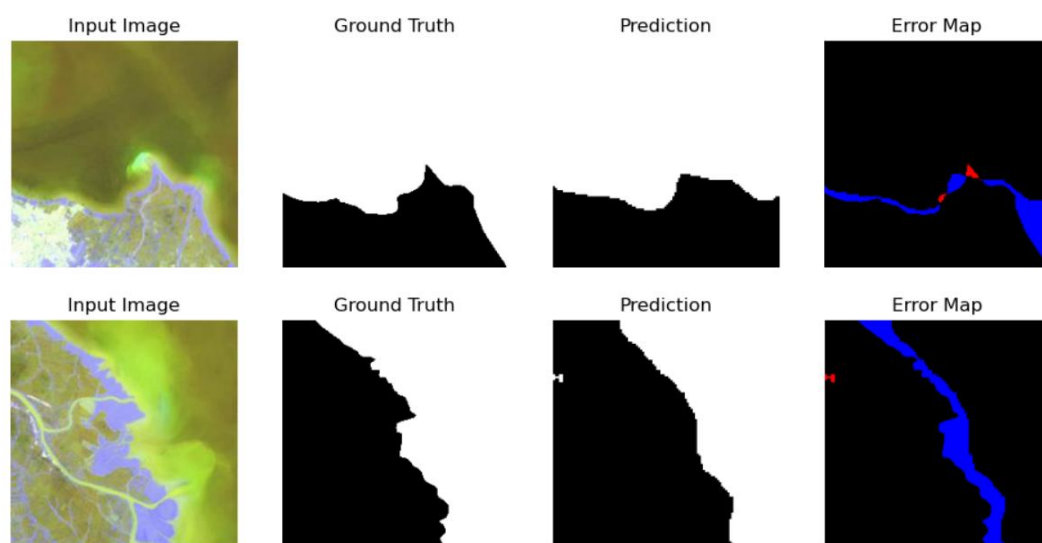


Figure 8. Segmentation results (scenario 1) 35 epochs

Figures 10-12 show the segmentation results obtained using the SGD optimizer. In Figure 10 (30 epochs), the model produces relatively stable segmentation results, although minor misclassifications remain near the shoreline. This result corresponds to a Mean IoU of 0.758 and a Mean Dice score of 0.837. As shown in Figures 11 and 12 (35 and 40 epochs), the segmentation results gradually improve with increasing epochs. The coastline becomes more defined, and noise in offshore regions is reduced. However, the overall improvement is incremental rather than substantial. This trend is consistent with the quantitative results, where Mean

IoU increases slightly from 0.775 to 0.777 and Mean Dice from 0.851 to 0.855.

Overall, Scenario 1 with the Adam optimizer demonstrates superior segmentation performance compared to Scenario 2 with the SGD optimizer, particularly at 40 epochs. While SGD provides more stable convergence across epochs, Adam achieves better generalization and boundary delineation in coastal segmentation tasks. These results indicate that optimizer selection and training duration play a crucial role in improving land-sea segmentation accuracy in high-resolution satellite imagery.

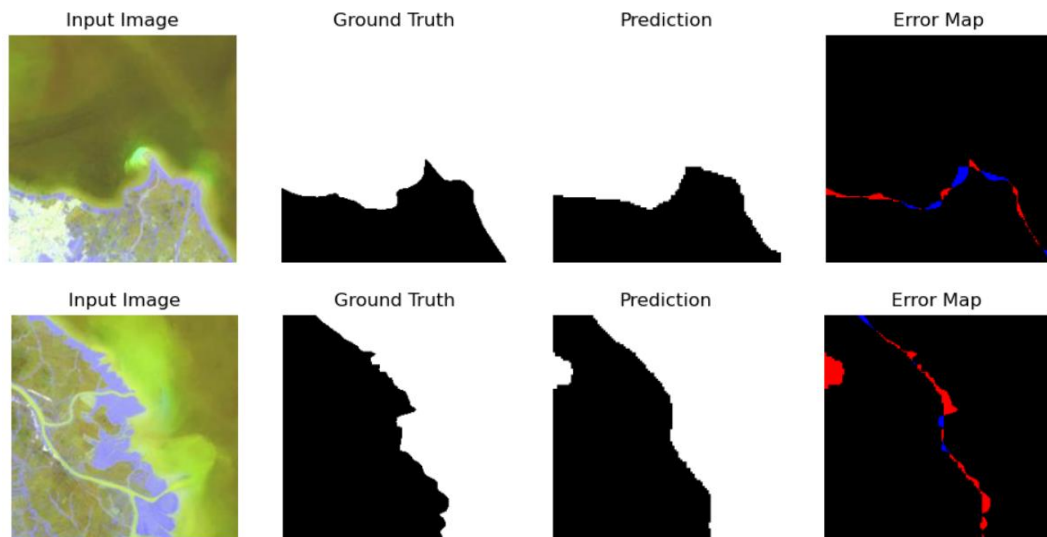


Figure 9. Segmentation results (scenario 1) 40 epochs

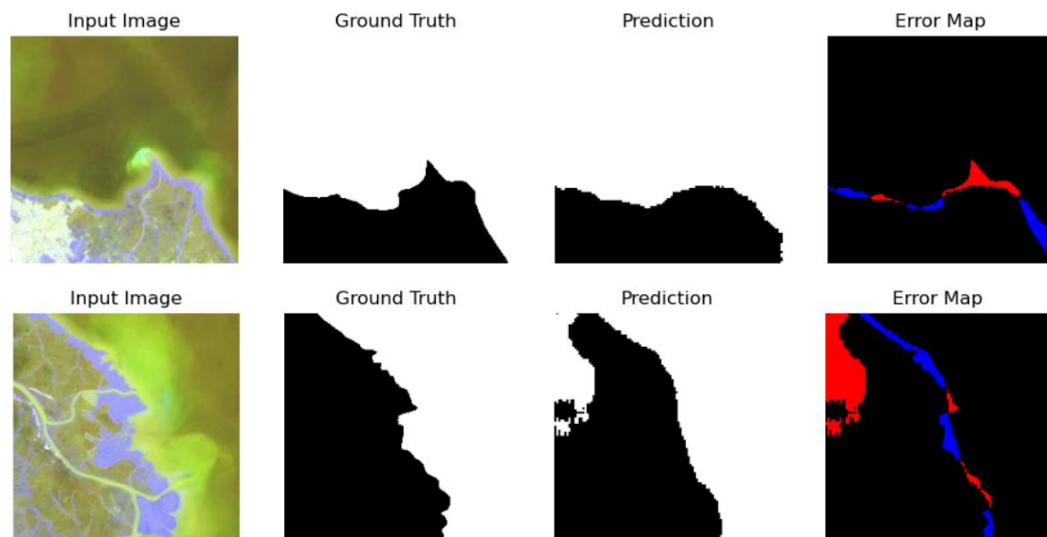


Figure 10. Segmentation results (scenario 2) 30 epochs

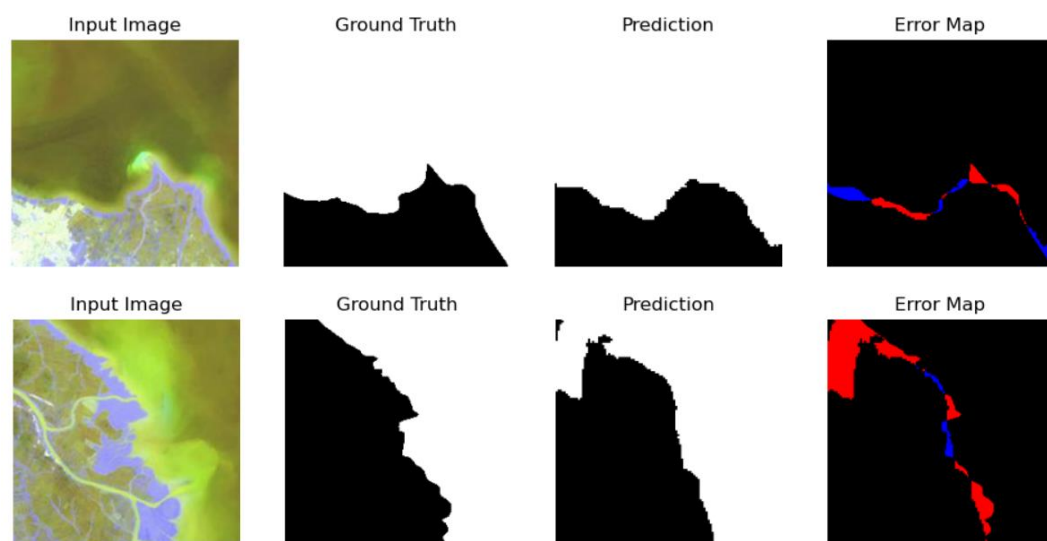


Figure 11. Segmentation results (scenario 2) 35 epochs

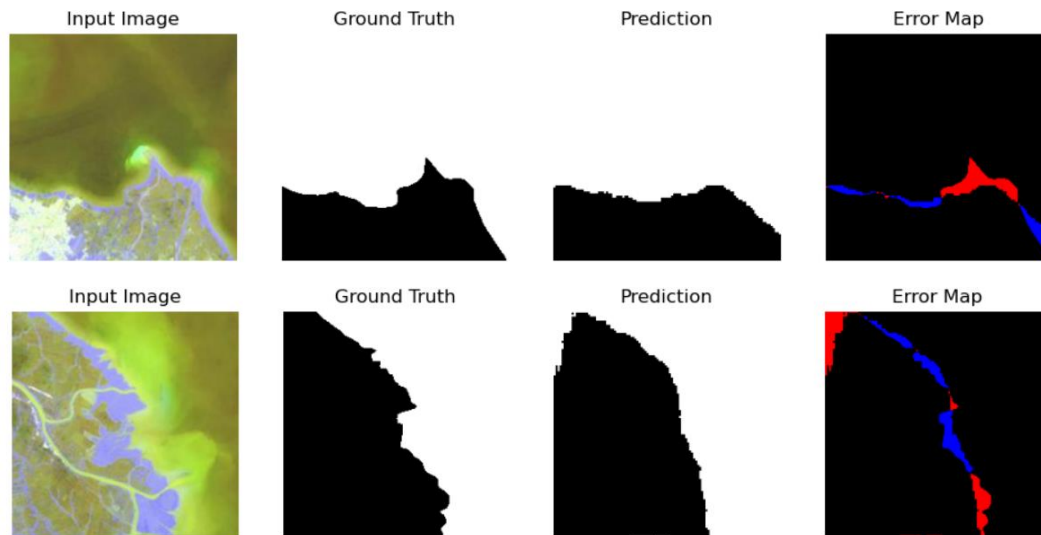


Figure 12. Segmentation results (scenario 2) 40 epochs

Several previous studies have reported varying segmentation performances using different deep learning architectures and datasets. The Hybrid U-Net [6] achieved an mIoU of 65.45% for high-resolution satellite image segmentation. CNN-based sea-land segmentation reached mIoU values of 92.78% and 93.62% on the SLSD and HRSC2016 datasets [27]. A modified U-Net applied to Landsat-8 imagery achieved an mIoU of 84.63% [28], while LANet reported mIoU values of 90.99% and 92.47% on the SLSD and HRSC2016 datasets [33]. STIRUnet achieved an mIoU of 96% on the BSD remote sensing dataset [34].

Table 4 presents the segmentation performance of the U-Net architecture using the Adam optimizer across different numbers of training epochs. At 30 epochs, the model achieved a Mean IoU of 0.869 and a Mean Dice coefficient of 0.917, indicating strong segmentation capability.

Table 4. Evaluation Results UNet Optimizer Adam

Epochs	Mean IoU	Mean Dice
30	0.869	0.917
35	0.872	0.919
40	0.899	0.940

When the number of epochs was increased to 35, a slight improvement was observed, with Mean IoU and Mean Dice increasing to 0.872 and 0.919, respectively. This suggests that the U-Net model benefits from additional training iterations when optimized using Adam.

The best performance was achieved at 40 epochs, where the U-Net model obtained a Mean IoU of 0.899 and a Mean Dice coefficient of 0.940. These results indicate that the U-Net architecture, combined with the Adam optimizer, is capable of learning robust spatial features for coastal land-sea segmentation, particularly when sufficient training epochs are provided.

Table 5 shows the evaluation results of the U-Net architecture using the SGD optimizer. At 30 epochs, the model achieved a Mean IoU of 0.883 and a Mean Dice

coefficient of 0.928, demonstrating competitive performance compared to Adam at the same epoch.

Table 5. Evaluation Results UNet Optimizer SGD

Epochs	Mean IoU	Mean Dice
30	0.883	0.928
35	0.851	0.905
40	0.872	0.920

However, at 35 epochs, both evaluation metrics decreased to a Mean IoU of 0.851 and a Mean Dice coefficient of 0.905, suggesting potential instability during training or sensitivity to learning rate when using SGD.

At 40 epochs, the performance partially recovered, with Mean IoU and Mean Dice reaching 0.872 and 0.920, respectively. Despite this improvement, the results remain lower than those achieved using the Adam optimizer, indicating that SGD may require additional tuning or adaptive learning strategies to achieve optimal convergence in U-Net-based coastal segmentation tasks.

When comparing the performance of U-Net and ResNet50-based segmentation models, both architectures demonstrate strong capability in distinguishing coastal land and sea regions. The U-Net model with the Adam optimizer achieved slightly higher segmentation metrics at 40 epochs (Mean IoU = 0.899, Mean Dice = 0.940) compared to the ResNet50 model (Mean IoU = 0.888, Mean Dice = 0.934).

However, the ResNet50-based model exhibited more consistent performance across different training epochs and demonstrated stable convergence behavior, particularly when using the Adam optimizer. This stability is likely attributed to the residual connections in ResNet50, which facilitate deeper feature learning and mitigate gradient degradation during training.

These findings suggest that while U-Net can achieve marginally higher peak accuracy, the ResNet50 architecture provides competitive performance with

improved training stability and transfer learning advantages, making it well suited for large-scale and long-term coastal monitoring applications.

Compared to previous studies, the proposed ResNet50-based approach with the Adam optimizer demonstrates competitive performance on medium-resolution Landsat-9 imagery while maintaining a relatively simple architecture and lower implementation complexity. By incorporating an additional segmentation architecture (U-Net) into the experimental evaluation, this study provides a more comprehensive comparison of deep learning models for coastal land-sea segmentation. The comparative analysis indicates that both architectural design and optimizer selection significantly influence segmentation performance. This extended evaluation strengthens the validity of the proposed ResNet50-based approach and contributes to a broader understanding of deep learning-based coastal segmentation using medium-resolution satellite imagery.

4. Conclusions

This study successfully performed land-sea segmentation on the north coast of East Java using deep learning-based approaches. The primary segmentation model employed was ResNet50, evaluated under two optimization scenarios, namely the Adam and SGD optimizers, to analyze their impact on segmentation performance.

The experimental results indicate that the ResNet50 model optimized with Adam achieves superior performance compared to SGD, particularly at 40 training epochs, with a Mean Intersection over Union (IoU) of 0.888 and a Mean Dice coefficient of 0.934. These findings confirm that optimizer selection plays a crucial role in improving segmentation accuracy and boundary delineation in coastal environments.

To strengthen the experimental analysis, an additional segmentation architecture, U-Net, was also evaluated under the same optimization scenarios. Although the U-Net model achieved slightly higher peak segmentation accuracy in certain configurations, the ResNet50-based model demonstrated competitive performance with more stable convergence behavior, supporting its suitability for coastal land-sea segmentation using medium-resolution satellite imagery.

However, segmentation errors were still observed in coastal areas dominated by swamp or mixed land-water characteristics. Therefore, future research is recommended to explore more advanced architectures, additional spectral features, or post-processing techniques to improve segmentation performance in complex coastal regions.

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