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SATELLITE IMAGE PROCESSING TECHNIQUES FOR MONITORING COASTAL EROSION AND CLIMATE CHANGE IMPACT

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ABSTRACT:
Coastal erosion and climate change are increasingly altering shoreline environments, creating risks for ecosystems, infrastructure, and coastal communities. Satellite remote sensing and deep learning offer promising approaches for improving large-scale and repeatable coastal monitoring. This study aimed to develop a deep learning–based semantic segmentation framework for coastal satellite imagery to classify major coastal features and support more efficient shoreline monitoring. A supervised semantic segmentation approach was implemented using a U-Net model. The dataset consisted of labeled coastal satellite images with four classes: water, surf, sediment, and other. RGB inputs were resized, normalized, and divided into training, validation, and test sets. The model was trained using categorical cross-entropy with class weights and evaluated using pixel accuracy, Intersection over Union (IoU), Dice coefficient, confusion matrix analysis, and qualitative visual assessment. The model achieved a pixel accuracy of 0.8007, a mean IoU of 0.6006, and a mean Dice coefficient of 0.7449. The highest class-wise performance was observed for water and other, with IoU values of 0.7059 and 0.7062 and Dice coefficients exceeding 0.82. Lower performance for surf and sediment reflects the complexity of transitional shoreline zones and spectral overlap between adjacent classes. Qualitative assessment indicated that the model preserved overall shoreline morphology, although some boundary-level errors remained. Deep learning–based semantic segmentation demonstrates reliable performance for coastal feature classification and shows potential for scalable shoreline monitoring. Further improvements may be achieved through the incorporation of multi-spectral inputs, expansion of datasets, and the development of boundary-sensitive model designs.

KEYWORDS: coastal erosion, semantic segmentation, satellite imagery, deep learning, shoreline monitoring

1. INTRODUCTION

Coastal sites are dynamic terrestrial-marine boundaries and play a role in supporting the human population, biota, and economic activities, such as trade, tourism, and fisheries. However, these areas are now facing the threat of coastal erosion that is causing the coastline to shrink, leading to the loss of habitats and the destruction of structures. The waves and tides, transportation of sediment, human activities, urbanization and coastal engineering processes are some of the natural processes that influence the erosion, making it difficult to manage the coast [1]. These problems have also been worsened by climate change, which has increased the rate of increase of the sea-level, intensification of storms and alterations of sediment patterns. These have enhanced risks on the coastal ecosystems as well as communities, thereby complicating the coastal management and requiring the integrated and adaptive approaches [2]. Both nature-based and traditional methods have been employed in an attempt to reduce erosion. The conventional hard engineering systems, such as seawalls and groynes, will provide temporary protection and can also disrupt the natural systems. In comparison, an ecosystem-based solution, e.g. the mangroves and dunes, would offer more sustainable solutions to implement, i.e., natural resilience and ecological balance [3]. The successes of such strategies are, however, pegged on closely monitoring changes along the coast. The necessary tool in this direction has become remote sensing using satellites, which can enable the assessment of the shoreline processes and land cover changes in massive and uninterrupted quantities [4]. The establishment of satellite image classification has also helped in extracting and analyzing the features of the coast to help in better and more efficient coastal monitoring [5].
The analysis of satellite imagery has been changing in recent years with the introduction of artificial intelligence, and, most notably, the use of deep learning. Deep learning models can automatically extract complex patterns using large datasets, and therefore, they are very useful in applications to the environment. The methods have effectively been used

to determine the level of coastal pollution and health of the environment, which has given good information on the ecological situation and possible risks [6]. Furthermore, the deep learning models have shown excellent performance in the process of identifying coastlines and shoreline boundaries that allow the development of automated and efficient mapping procedures, which minimizes manual interpretation [7]. The use of semantic segmentation, which is one of the important deep learning techniques, has also contributed to the development of coastal image analysis by conducting the pixel-level classification of satellite images. This enables the accurate differentiation and identification of different features of the coastline, including water bodies, sediments, plants and the built environment. This extensive classification is necessary to comprehend the processes in the coasts and aid in the decision-making process in coastal management [8]. Besides this, the growing amount of high-resolution satellite data has improved continuous and large-scale monitoring capacity that has helped to understand the long-term dynamics and changes of the coastline [9]. The ability of deep learning models to detect coastal regions with enhanced robustness and accuracy in diverse environmental conditions is also an indication that they can be applied to real-world problems when associated with benchmark datasets [10]. In addition to the technological changes, recent research has stressed the need to combine scientific instruments with participatory and adaptive management strategies. The involvement of the stakeholders and the integration of the local knowledge can enhance the methods of management of the coastlines, especially when dealing with climate change management [11]. Also, previous studies have indicated the applicability of satellite images in examining the changes in the coastline during the past and obtaining future erosion trends, which highlights the role of time in coastal research [12].

Although there has been a great advance in this field, there are still a few limitations. The few available studies are based on single-source or limited spectral data, which do not permit capturing the complexity of the coastal setting in a comprehensive manner. Differences in environmental factors, including turbidity of water, wave action, and atmospheric influences, may also affect the precision of image categorization and segmentation. Moreover, deep learning models have issues associated with generalizability, since they are usually developed using certain datasets, and they might not work in different coastal environments. The absence of fully developed methods with the potential of incorporating multi-spectral data, such as RGB, near-infrared (NIR) and short-wave infrared (SWIR), to extract and classify features better is also present.

Against these circumstances, this paper is aimed at designing a deep learning-based semantic segmentation model to analyze coastal images. The research will enhance the categorization of coastal objects with the help of RGB satellite imagery to distinguish major classes which involve water, surf (whitewater), sediment and other types of land covers. It also aims to help in the efficient and scalable methods of monitoring and managing the coasts.

2. METHODOLOGY

2.1 Research Design and Data Source

The study uses supervised deep learning that is applied to semantically segment the coastal features on a satellite image. The data preparation, model training and performance evaluation are part of the workflow. The data is a set of satellite images and pixel-level labels of four categories, namely, water, surf, sediment and other. The information was taken out of a publicly available labeled coastal imagery collection [13]. This research employed only RGB bands in an attempt to be consistent between samples. The images were accompanied by their corresponding label mask that showed the membership of the class at the pixel level.

2.2 Data Preprocessing

All the image-label pairs were checked and treated before training. To make the images have the same size in terms of input dimensions, images were resized to 256 x 256 pixels. The values of the pixels in the image were assigned to the range [0, 1], whereas the label masks were coded as integer class indices in a range [0, 3]. The dataset was split into 70:15:15 training, validation and test sets. This enabled the development and testing of the models on different subsets of data.

2.3 Model Architecture

The segmentation task was performed with the help of a U-Net architecture. This model has an encoder-decoder architecture, in which hierarchical features are obtained by the encoder, and the decoder is used to recreate spatial information. The network had convolutional layers, which included batch normalization and ReLU activation. Max-pooling was used for downsampling, and transposed convolution was used for upsampling. Encounter connections between encoder and decoder layers were added in order to maintain the spatial information and enhance the segmentation accuracy. This last layer produces four-class pixel-wise predictions.

2.4 Model Training

A categorical cross-entropy loss function was used in training the model. Class weights were included in the loss in order to compensate for the imbalance in classes. The learning rate was 0.001, and the Adam optimizer was employed. Mini-batches with size eight were used to perform training, and model performance was checked on the validation set. The final model was chosen as the model which has the lowest validation loss.

2.5 Evaluation Metrics

Pixel accuracy, Intersection over Union (IoU) and Dice coefficient were determined as model performance. Each class was computed in terms of IoU and Dice, and mean values were presented as a summary of the overall performance. Common errors between classes were also determined, and classification behavior analyzed by use of a confusion matrix. The model performance was measured both with quantitative measures and by visual outcome.

3. RESULTS

3.1 Model Performance

The effectiveness of the suggested U-Net model was assessed on a separate test dataset using conventional segmentation indicators. The model attained pixel accuracy of 0.8007, mean Intersection over Union (IoU) of 0.6006 and mean Dice coefficient of 0.7449, which suggests that the model performs well in the segmentation task across the classes of coastal regions. This shows that the general spatial distribution of coastal features can be represented by the model, and the prediction and reference labels have a high degree of agreement. The Dice coefficient is relatively high, indicating good spatial overlap between the ground truth areas and the predicted ones, especially with predominant classes.

3.2 Class-wise Segmentation Performance

In order to further test class-specific behavior, segmentation performance was studied on a case-by-case basis (Table 1), and a visual analysis of the IoU and Dice scores is shown in Figure 1. The waters and other classes were the best performing classes with an average IoU of 0.7059 and 0.7062, respectively, and the Dice coefficients of over 0.82.

Table 1. Per-class segmentation performance measured using IoU and Dice coefficient.

Class	**IoU**	**Dice**
Water	0.7059	0.8276
Surf	0.4767	0.6456
Sediment	0.5137	0.6787
Other	0.7062	0.8278

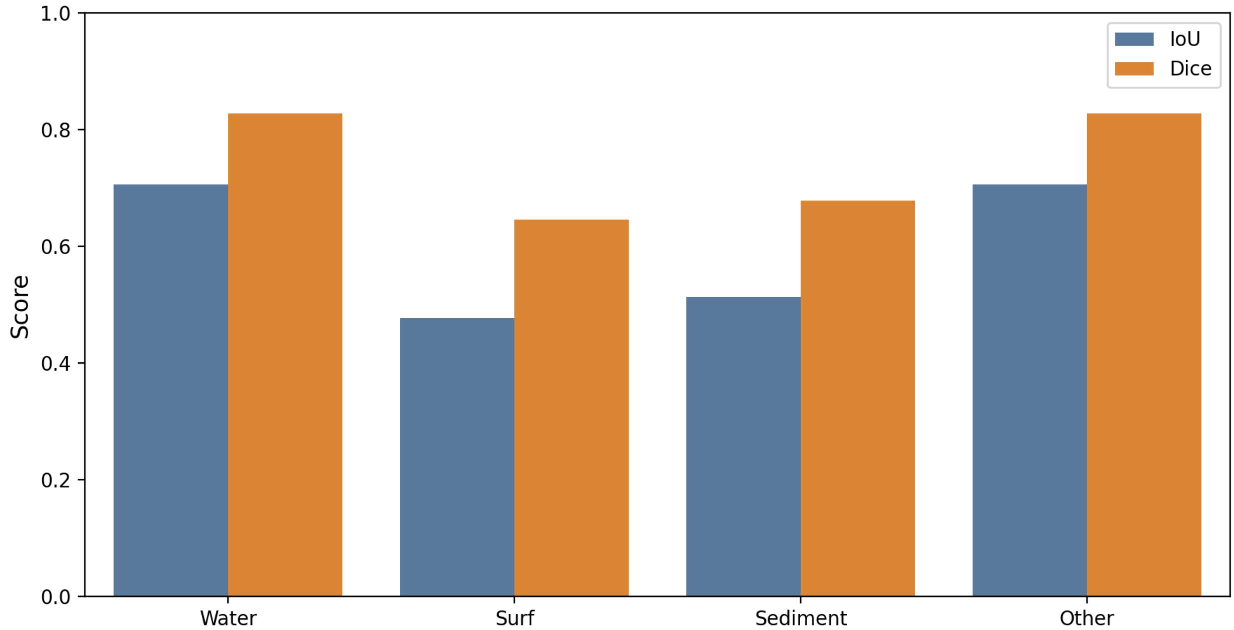

Figure 1. Per-class segmentation performance measured using Intersection over Union (IoU) and Dice coefficient.

Conversely, the surf and sediment classes did not show such high performance, with the IoU of 0.4767 and 0.5137, respectively. They are transitory shoreline zones and overlays of complex textures and smooth bounds of spaces, which are naturally harder to draw accurate boundaries. The summary of observed differences in the performance helps in illuminating the effects of the imbalance in the classes and the vagueness inherent in the point of coastal boundaries.

3.3 Confusion Matrix Analysis

A more detailed analysis of the classification behavior is provided by the normalized confusion matrix (Table 2 and Figure 2). The diagonal factors indicate that the performance in all the classes is good, in particular, sediment (0.880), other (0.822), and surf (0.789).

Table 2. Row-normalized confusion matrix for the four segmentation classes.

True class	**Water**	**Surf**	**Sediment**	**Other**
Water	0.766	0.061	0.011	0.162

Surf	0.033	0.789	0.124	0.054
Sediment	0.003	0.073	0.880	0.044
Other	0.073	0.016	0.089	0.822

Most misclassifications are within neighboring coastal classes, as seen in Figure 2. It is worth noting that water pixels are sometimes incorrectly defined as other (0.162), and surf is often mixed up with sediment (0.124). These distributions are in line with the progressive changes and overlapping spectral features of typical coastal settings.

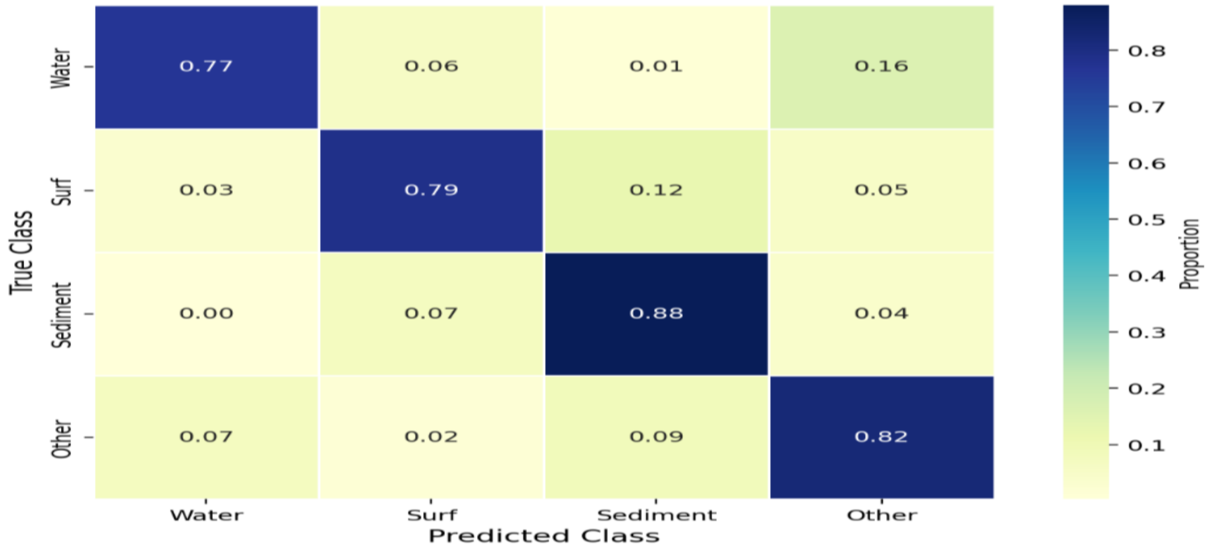

Figure 2. Normalized Confusion Matrix

3.4 Qualitative Evaluation of Segmentation Outputs

The quantitative results are also supported by the qualitative analysis of the segmentation results. Figure 3 provides representative examples, and in each row, the input satellite image, ground truth, predicted segmentation, and overlay visualization are provided.

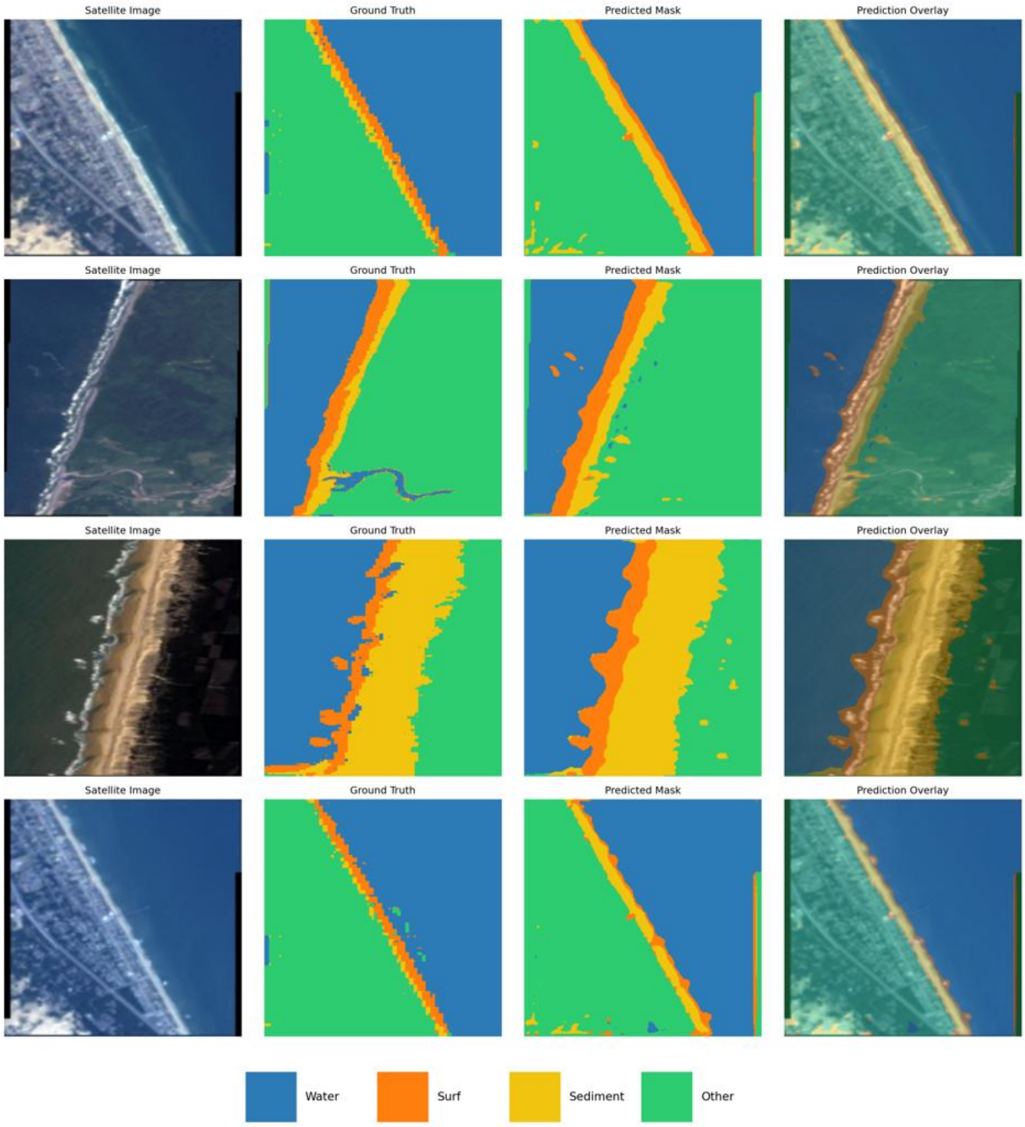

Figure 3. Sample Segmentation Results

The model is highly potent in terms of the substantial scale of capturing the coastal structures comprising continuous water bodies and land areas. The predicted segmentation maps are highly grounded in the morphology of the shoreline and also spatially equal in various geographic locations.

These variations, however, are more concentrated in the border regions. These are trifling errors in classifications of the surf zones in the northern parts, discrepancies in the delimiting of the sediment areas and localities of inaccuracy in the heterogeneous areas of coasts. The observed patterns of error suggest that the errors are not widespread across regions, but are concentrated in thin transition bands, suggesting that the model is good at capturing the overall spatial pattern with few limitations on fine boundary delineation.

Altogether, the results demonstrate that the proposed model is an authentic and reliable approach for defining the coastal sections. The model works particularly well in the cases of dominant and visually different classes and is quite accurate to a reasonable degree in more complex transitional regions.

4. DISCUSSION

The findings indicate that the semantic segmentation structure that was developed could successfully segment even the notable coastal features, and the performance was quite high in visually differentiated classes like water and other classes of land, and comparatively less in the surf and sediment classes. This difference in performance is explained by the very nature of coastal environments, in which transitional regions are mixed spectral/textural. The fact that water classification was relatively more accurate shows that the model was able to capture dominant spectral patterns, and the confusion between surf and sediment can be taken as evidence of the model constraints to differentiate the features that have similar appearance and visual characteristics. The analysis of coastal images is not an exception since such challenges are characteristic of dynamic processes of coastlines and constant interaction between land and water. The fact that the model can conserve the overall morphology of the coast also shows that it was able to learn spatial relationships in the imagery. Nevertheless, the decrease in accuracy along boundaries of the classes is an indication of the challenge of precisely segmenting narrow and heterogeneous coastal areas. These observations imply that deep learning-based segmentation can be used to map the coastline on a large scale, but the fine-scale classification process needs some improvement, especially in the regions affected by the wave action and sediment transport.

The current performance is consistent with the existing literature on machine learning and remote sensing applications in shoreline monitoring, where models have been proven to work well in detecting large-scale coastal features, but have difficulties in detecting complex boundary zones [14]. The investigations of coastal erosion monitoring of climate change conditions have also pointed to challenges that are accompanied by dynamic shoreline settings, whereby the temporal and spatial variability influences the classification accuracy [15]. Other studies that have been conducted on satellite image processing also highlighted the fact that remote sensing methods are efficient in capturing the greater scale coastal pattern, though fine scale delineation is still a challenge owing to the data resolution and variability in the environment [16]. More specifically, the research on shoreline extraction has claimed that adjacent classes of the coast have been found to be difficult due to the similarity of the spectrum and mixed pixels, which is also in line with the misclassification experienced in the surf and sediment areas [17].

Moreover, it has been shown that detection accuracy in shorelines is affected by the environmental conditions and data quality, where high levels of uncertainty exist in a highly dynamic coastal area [18] by the use of multi-temporal satellite imagery. Conventional machine learning algorithms like the support vector machines have demonstrated decent performance in tasks of classifying coastal, but are frequently less able to learn the spatial features of deep learning networks [19]. The recently introduced use of deep learning and remote sensing to analyze coastal variations has demonstrated the relevance of combining the latest computational methods with satellite data to enhance the quality of monitoring, especially in the framework of the effects of climate change [20]. Moreover, studies conducted on the topic of vulnerability assessment in the coastal environment have highlighted the importance of geospatial technologies in decision-making and risk areas [21]. The necessity of effective and dynamic surveillance systems has also been validated by the research on the growth in the effect of climate change on the erosion of coastal areas, especially in areas that are prone to the effects [22].

The implications of the results of this analysis on the monitoring and management of the coasts are also significant to some extent. The fact that the proposed framework may be able to allocate the major features of the coastline with a high level of accuracy demonstrates that it may become a helpful instrument in the large-scale analysis of the coastline and the process of environmental surveillance. In a bid to evaluate the erosion pattern, sediment movement and distribution of the habitat in a more appropriate manner, better classification of the coastal elements could be used. It, in its turn, can help policymakers and researchers to develop knowledge-based steps towards the safeguarding of the coastline and climate change adaptation. Moreover, deep learning-based automated semantic segmentation of satellite images makes it possible to both conduct and process the analysis on a considerably greater scale, as there will be no necessity to analyze the images manually, and the process will be more efficient. Such approaches particularly come into play once the coastal areas are closely monitored all the time, where considerable changes are expected to occur, and the response to the arising risks is to be provided.

Although the research is a good one, it has several weaknesses. The small quantity of spectral inputs could also have restricted the ability of the model to differentiate between complex coastal types, at any rate in the transitional zones. Environmental influences such as turbidity of the water, turbulence and atmospheric interference would have influenced the classification as well. Further, the data may not be as representative of the diversity of the global sea-coastal environment as it can be, and this may limit the extrapolation of the model.

Further research is required to include the multi-spectral data, e.g. NIR and SWIR bands, in order to identify the features and categorize them better. This kind of increase in the dataset in the form of a wider range of conditions of the coast and geographical regions would also be related to the robustness of the model. Besides, the integration of a time-dependent study that is based on the multi-temporal satellite images can provide deeper information regarding the dynamics of coasts and erosion patterns. The results of the segmentation can also be improved with other higher-level model architectures, such as attention and multi-scale feature extractions, particularly in complicated boundary areas. The additional advancement of deep learning and remote sensing systems will play a significant role in the improvement of coastal monitoring systems and the sustainable use management in the face of the current problem of climate change.

5. CONCLUSION

Coastal monitoring is increasingly playing a greater role in precise and scalable monitoring that needs to be accomplished on a continuous basis, since the problem of corrosion and the power of climate that is re-establishing the shoreline are increasingly defining the coastline. The findings indicate that the semantic segmentation through deep learning provides a credible approach to large-scale segments along the coast with the aid of satellite images, and particular parts, such as water and other land-cover aspects, are very precise. The less success of surf and sediment zones proves that the delimiting transitional shorelines zones remain problematic and that texture mixtures and indistinct boundaries are less precise in delimiting. The overall results have shown that a more efficient method of coastal mapping and strengthening the observation of the process of shoreline changes could be the application of semantic segmentation and satellite image processing. At the same time, the limitations existing in the context of boundary-sensitive classes suggest that one can conclude that further progress would demand more sophisticated spectral inputs, more varied training data, as well as enhanced model designs. Additional RGB, NIR, and SWIR data, as well as time series observation of the coastline, would have the possibility of further feature differentiation and long-term monitoring capabilities. By doing so, remote sensing and deep learning have viable opportunities to assist in managing the coastline, erosion, and climate adaptation planning in risky coastal areas.

REFERENCES

1. Williams, A.T., Rangel-Buitrago, N., Pranzini, E. and Anfuso, G., 2018. The management of coastal erosion. Ocean & coastal management, 156, pp.4-20.

2. Pang, T., Wang, X., Nawaz, R.A., Keefe, G. and Adekanmbi, T., 2023. Coastal erosion and climate change: A review on coastal-change process and modeling. Ambio, 52(12), pp.2034-2052.
3. Gracia, A.D., Rangel-Buitrago, N., Oakley, J.A. and Williams, A.T., 2018. Use of ecosystems in coastal erosion management. Ocean & coastal management, 156, pp.277-289.
4. Babbar, J. and Rathee, N., 2019, February. Satellite image analysis: A review. In 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT) (pp. 1-6). IEEE.
5. Dhingra, S. and Kumar, D., 2019. A review of remotely sensed satellite image classification. International Journal of Electrical and Computer Engineering, 9(3), p.1720.
6. Sathish, T., Maheswari, S.U., Balaji, V., Nirupama, P., Panchal, H., Li, Z. and Tlili, I., 2023. Coastal pollution analysis for environmental health and ecological safety using deep learning technique. Advances in Engineering Software, 179, p.103441.
7. Dang, K.B., Vu, K.C., Nguyen, H., Nguyen, D.A., Nguyen, T.D.L., Pham, T.P.N., Giang, T.L., Nguyen, H.D. and Do, T.H., 2022. Application of deep learning models to detect coastlines and shorelines. Journal of Environmental Management, 320, p.115732.
8. Scala, P., Manno, G. and Ciraolo, G., 2024. Semantic segmentation of coastal aerial/satellite images using deep learning techniques: An application to coastline detection. Computers & Geosciences, 192, p.105704.
9. Vitousek, S., Buscombe, D., Vos, K., Barnard, P.L., Ritchie, A.C. and Warrick, J.A., 2023. The future of coastal monitoring through satellite remote sensing. Cambridge Prisms: Coastal Futures, 1, p.e10.
10. Seale, C., Redfern, T., Chatfield, P., Luo, C. and Dempsey, K., 2022. Coastline detection in satellite imagery: A deep learning approach on new benchmark data. Remote Sensing of Environment, 278, p.113044.
11. Coelho, C., Lima, M., Alves, F.M., Roebeling, P., Pais-Barbosa, J. and Marto, M., 2023. Assessing coastal erosion and climate change adaptation measures: a novel participatory approach. Environments, 10(7), p.110.
12. Aryastana, P., Ardantha, I.M. and Candrayana, K.W., 2018. Coastline change analysis and erosion prediction using satellite images. In MATEC Web of Conferences (Vol. 197, p. 13003). EDP Sciences.
13. Buscombe, D., 2022. Images and 4-class labels for semantic segmentation of Sentinel-2 and Landsat RGB, NIR, and SWIR satellite images of coasts (water, whitewater, sediment, other). Zenodo. https://doi.org/10.5281/zenodo.7344571
14. Tsiakos, C.A.D. and Chalkias, C., 2023. Use of machine learning and remote sensing techniques for shoreline monitoring: a review of recent literature. Applied Sciences, 13(5), p.3268.
15. Sarr, M.A., Pouye, I., Sene, A., Aniel-Quiroga, I., Diouf, A.A., Samb, F., Ndiaye, M.L. and Sall, M., 2024. Monitoring and Forecasting of Coastal Erosion in the Context of Climate Change in Saint Louis (Senegal). Geographies, 4(2), pp.287-303.
16. Latella, M., Luijendijk, A., Moreno-Rodenas, A.M. and Camporeale, C., 2021. Satellite image processing for the coarse-scale investigation of sandy coastal areas. Remote Sensing, 13(22), p.4613.
17. Ghorai, D. and Mahapatra, M., 2020. Extracting shoreline from satellite imagery for GIS analysis. Remote Sensing in Earth Systems Sciences, 3(1), pp.13-22.
18. Esmail, M., Mahmod, W.E. and Fath, H., 2019. Assessment and prediction of shoreline change using multi-temporal satellite images and statistics: Case study of Damietta coast, Egypt. Applied Ocean Research, 82, pp.274-282.
19. Schellekens, J., 2022. Coastal erosion detection using Landsat satellite imagery and support vector machine algorithm.
20. Pradeep, J., Shaji, E., Chandran, S., Chandra, S.V., Dev, S.D. and Babu, D.S., 2022. Assessment of coastal variations due to climate change using remote sensing and machine learning techniques: A case study from west coast of India. Estuarine, Coastal and Shelf Science, 275, p.107968.
21. Marzouk, M., Attia, K. and Azab, S., 2021. Assessment of coastal vulnerability to climate change impacts using GIS and remote sensing: A case study of Al-Alamein New City. Journal of Cleaner Production, 290, p.125723.
22. Dong, W.S., Ismailluddin, A., Yun, L.S., Ariffin, E.H., Saengsupavanich, C., Maulud, K.N.A., Ramli, M.Z., Miskon, M.F., Jeofry, M.H., Mohamed, J. and Mohd, F.A., 2024. The impact of climate change on coastal erosion in Southeast Asia and the compelling need to establish robust adaptation strategies. Heliyon, 10(4).