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Deep Learning-Based Methods for Mapping Mangrove Forests in Bohol, Philippines Using Sentinel-2 Imagery

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Abstract

This study presents a deep learning-based approach for mapping mangrove forests in Bohol, Philippines using high-resolution Sentinel-2 imagery. Given the limitations of traditional mapping techniques and the ecological importance of mangroves, four convolutional neural network (CNN) architectures—U-Net, Attention U-Net, MSNet, and SegNet—were trained and evaluated. The preprocessing pipeline included patch generation, normalization, and random sampling to ensure spatial representativeness. Hyperparameter tuning explored combinations of loss functions and learning rates to optimize model performance. Results showed that U-Net consistently achieved the highest accuracy across all evaluation metrics, with an IoU of 0.93, accuracy of 0.98, precision of 0.966 and F1-score of 0.963. Visual inspections confirmed U-Net and Attention U-Net's superior ability to delineate mangrove boundaries, particularly in complex coastal zones. In contrast, SegNet produced coarser edges but trained significantly faster, offering a practical alternative for rapid assessments or resource-constrained deployments. These findings emphasize the value of skip connections and attention mechanisms not just for performance enhancement but for improving the usability of outputs in real-world conservation. The study recommends U-Net for integration into local government monitoring systems, supporting disaster risk reduction, marine zoning, and restoration planning. Future work may incorporate drone imagery and transfer learning to improve adaptability across other Philippine coastal ecosystems.

1. Introduction

1.1 Mangrove Ecosystems Mapping

Mangrove ecosystems are vital components of coastal environments, providing essential ecological and economic services such as coastal protection, nursery habitats for marine species, and carbon sequestration. However, rapid degradation of mangrove forests - driven by human activities and climate change necessitates accurate and consistent monitoring to support conservation and sustainable management efforts (Sun et al., 2023).

The Philippines, home to extensive mangrove forests, has experienced significant losses over the past decades, with substantial percentage disappearing since 1990 (Bhowmik et al., 2022; Conopio et al., 2021). To address this issue, previous studies have explored mangrove mapping using Mangrove Vegetation Index (MVI) derived from remote sensing technologies (Baloloy et al., 2023). Remote sensing offers a cost-effective and reliable solution for long-term mangrove monitoring, overcoming the limitations of traditional field surveys, which are often constrained by accessibility and resource intensiveness (Nardin et al., 2021). While the MVI demonstrates high index accuracy, its mapping effectiveness is constrained by various biophysical and environmental factors, potentially limiting its applicability in diverse mangrove landscapes (Neri et al., 2021).

Given the ecological and economic importance of mangroves, detailed mapping is crucial for effective conservation and management, particularly in mega-biodiversity hotspots like Bohol (Agduma et al., 2024; Cayetano et al., 2023; Faustino et al., 2020; Giri, 2021; Jose et al., 2022). Bohol's coastal landscape is characterized by intricate shoreline morphologies, including fringing mangroves, tidal flats, estuarine systems, and scattered offshore islets. These geophysical features result in fragmented mangrove patches, frequent water–vegetation mixing, and complex spectral signatures, making accurate classification difficult using conventional methods. This spatial complexity presents a region-specific challenge that underscores the novelty of applying deep learning-based approaches to Bohol. By focusing on this biodiversity-rich and morphologically diverse province, the study contributes not only to the methodological advancement of mangrove mapping but also to localized conservation strategies in one of the Philippines' ecologically significant coastal zones.

1.2 Problem definition and Objectives

This study aims to develop an accurate and efficient deep learning-based model for semantic segmentation of mangroves using Sentinel-2 satellite imagery. Specifically, it aims to: (1) gather remote sensing data from Google Earth Engine (GEE); (2) design, train and evaluate convolutional neural network (CNN) models such as U-Net, Attention U-Net, MSNet and SegNet for semantic segmentation of mangrove and non-mangrove areas; (3) fine-tune hyperparameters to improve accuracy of chosen CNN models; and (4) compare convolutional neural network (CNN) models for semantic segmentation of mangrove and non-mangrove areas.

2. Review of Related Literature

Mangrove forests are critical coastal ecosystems that require accurate and timely monitoring for conservation (Lu & Wang, 2021). With the availability of high-resolution multispectral data from Sentinel-2, recent studies have applied machine learning and deep learning techniques to improve mangrove mapping accuracy. This review highlights recent works that utilize deep learning approaches, presenting their data sources, algorithms and performance metrics as benchmarks relevant to the present study in Bohol, Philippines.

Based from Table 1, previous studies indicate that UNet-based deep learning models remain the dominant approach for mangrove mapping, Various satellite imagery sources, including Landsat 8, ZY-301, ZY-302, GF-1, GF-2, and GF-6, have been widely utilized for this purpose due to their high availability and accessibility (Guo et al., 2021; Wang et al., 2023; Xu et al., 2023, Sun et al., 2023). However, most of these studies have been conducted in China (Sun et al., 2023; Wang et al., 2023), Pakistan (Xu et al., 2023), and other parts of Southeast Asia (Guo et al., 2021; Lomeo & Singh, 2022). Notably, while Sentinel-2 has been used in prior research, only Lomeo and Singh (2022) attempted to apply it for mangrove mapping, explicitly excluding Indonesia and the Philippines. This exclusion was attributed to the complexity of the countries' coastlines and their relatively small land areas, which pose challenges in image processing and class identification.

Study	Data and Study Area	Algorithm	Accuracy
Wang et al. [8]	Satellite images from GF-1 and GF-6 Study Area: northeastern coast of Beibu Gulf, Guangxi, China	Swin-UperNet	98.87
Guo et al. [9]	LandSat 8 images Study Area: Maritime Silk Road	U-Net	81
		Capsuls-UNet	86
Xu et al. [10]	Landsat 8 images (Band 1-7), Landuse data from ESA World Cover project Study Area: Indus Delta in Sindh Pakistan	MSNet	97.64
		U-Net	97.12
Lomeo and Singh [11]	Sentinel-2 data from January – December, 2016 Study Area: South East Asia (SEA)	U-Net	91
		VGG19	90
		ResNet50	73
Sun et al. [1]	ZY-301, ZY-302, GF-1, GF-2, GF-6, satellite images Study Area: Beibu Gulf of Guangxi, China	U-Net	93.29

Table 1. Deep Learning Techniques and Data in Mangrove Mapping

U-Net serves as a strong baseline due to its proven effectiveness and adaptability(Xu et al., 2023). Attention mechanisms can be incorporated into U-Net to improve performance. These mechanisms establish associations between features and explore global context information (Cai & Wang, 2022). MSNet offers a way to address spatial information loss and reduce model complexity (Xu et al., 2023). While SegNet is a more traditional architecture, it provides a useful point of comparison (Xu et al., 2023). By evaluating these models this research can contribute to identifying the most effective techniques for accurate and efficient mangrove mapping.

Bohol stands out as a particularly important study area due to its rich biodiversity and complex coastal ecosystems. Considering the limited research in this region, this study is significant since Bohol is known to have the most diverse mangrove ecosystem in the Philippines (Cuenca-Ocay et al., 2023).

3. Conceptual Framework

This study is anchored on the integration of remote sensing and deep learning technologies to enhance the accuracy and efficiency of mangrove forest mapping. Specifically, it utilizes Sentinel-2 satellite imagery processed through deep learning models for semantic segmentation of mangrove areas in Bohol, Philippines. The conceptual framework (Figure 1) follows a structured flow: (1) Sentinel-2 Imagery Acquisition; (2) Image Pre-Processing; (3) Model Training with Deep Learning; (4) Hyperparameter Tuning; (5) Model Selection; (6) Accuracy Evaluation.

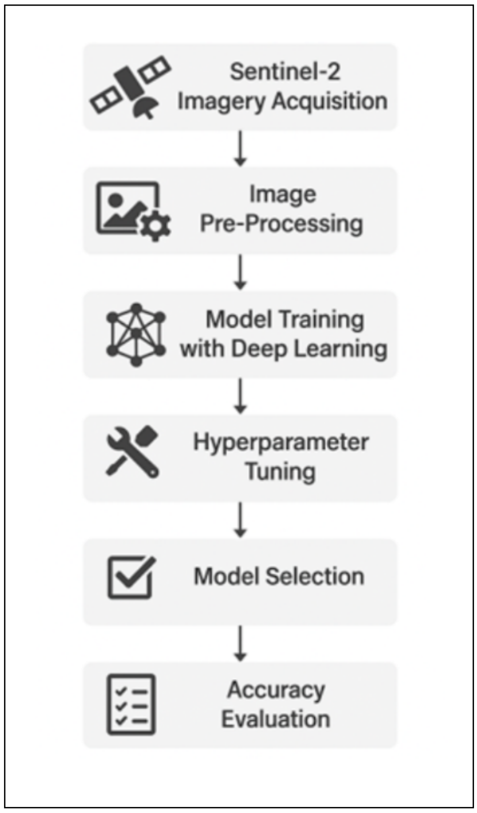


Figure 1. Conceptual Framework of the Study

The process begins with the acquisition of high-resolution Sentinel-2 imagery. These multispectral images are pre-processed through techniques such as band selection, resampling and normalization.

At the core of the framework is the training and optimization of deep learning segmentation models. A key element of the model development is hyperparameter tuning, which involves systematically adjusting parameters such as learning rate, loss function and number of epochs to identify the optimal configuration that yields the highest segmentation performance.

Once the optimal model is selected through validation performance, it is used to generate a classified mangrove map, delineating mangrove and non-mangrove areas. The model's output is evaluated using standard accuracy metrics, including overall accuracy, precision, recall, F1-score, and Intersection over Union (IoU).

4. Methodology

4.1 Study Area

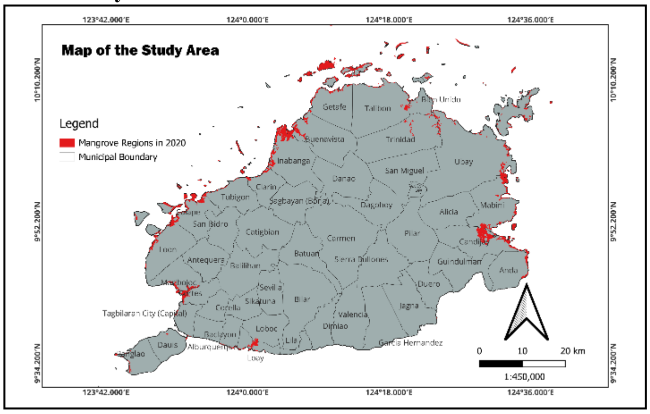


Figure 2. Map of the Study Area

The study was conducted in the coastal areas of Bohol, Philippines (Figure 2), an island province known for its extensive and ecologically significant mangrove ecosystems. These coastal zones were selected due to their environmental relevance and the increasing need for accurate monitoring to support sustainable resource management and conservation.

4.2 Data Acquisition

Multispectral satellite imagery was obtained from the Sentinel-2 satellite mission through the Google Earth Engine (GEE) (Xu et al., 2023). Images were selected based on their spatial coverage of Bohol's coastal zones, acquisition between January 1, 2020 to December 31, 2020 (Figure 3) and minimal cloud cover (less than 10%). Sentinel-2 data was preferred due to its spatial resolution (10-20 meters) and rich spectral bands suitable for vegetation classification tasks, including the identification of mangrove forests.

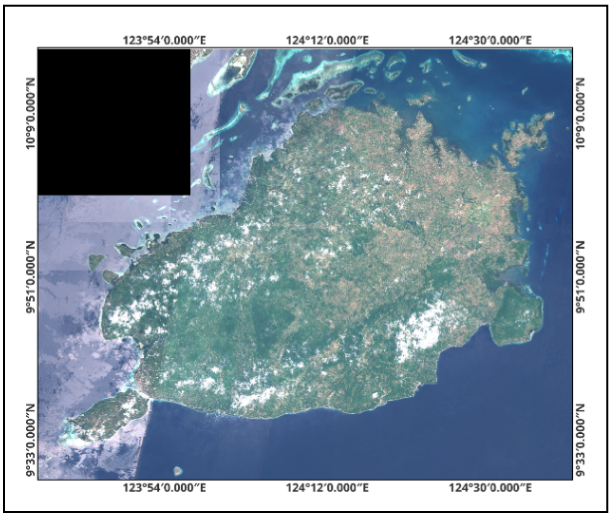


Figure 3. Sentinel-2 2020 Imagery used in Image Processing.

As for the mangrove masks, coastal resource map of 2020 were downloaded from the GeoPortal.PH and were manually refined with visual interpretation of the Sentinel-2 imagery using the QGIS software. Figure 4 shows a sample mangrove mask.

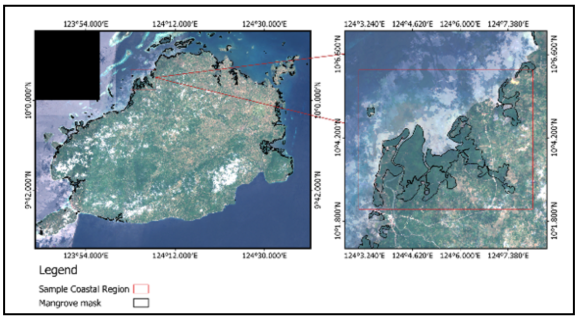
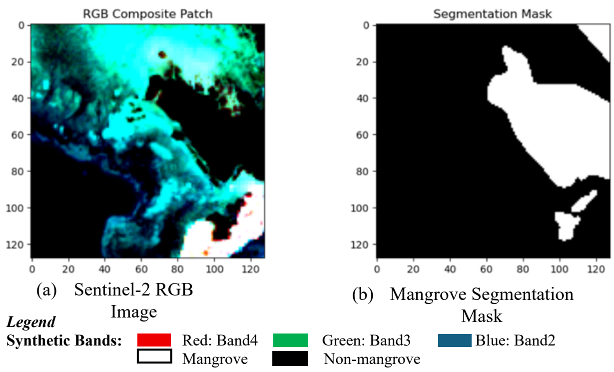


Figure 4. Mangrove Mask in a Sample Coastal Region.

4.3 Image Pre-processing

Prior to model training, the acquired imagery underwent several preprocessing steps using OpenCV and Rasterio in a Jupyter Notebook environment. All images were resampled to a uniform spatial resolution of 10 meters to ensure consistency across datasets. Pixel values were normalized between 0 and 1 to facilitate model convergence (Figure 5a). To generate training data, the satellite image and its corresponding mangrove mask were divided into fixed-size patches of 128x128 pixels. Patches with less than 10% valid mangrove or non-mangrove content were excluded to eliminate mostly empty regions. A total of 836 image-mask patch pairs (128x128 pixels) were generated to represent the mangrove and non-mangrove areas across the coastal region of Bohol. These patches were derived from preprocessed Sentinel-2 imagery and reference ground-truth masks and served as the complete dataset for model training and evaluation. To ensure an unbiased and representative sample, the dataset was randomly split into 70%-15%-15% for training validation and test sets, respectively. This random sampling approach minimizes spatial bias and supports the generalizability of model performance, as recommended in remote sensing accuracy frameworks (Stehman, 2013; Foody, 2002).



(a) Sentinel-2 RGB Image

(b) Mangrove Segmentation Mask

Figure 5. Sentinel-2 RGB Image and Corresponding Segmentation Mask

Ground truth data was prepared using the coastal resource map of 2020 from the Department of Environment and Natural Resources (DENR) as a reference map. Areas identified as mangrove and non-mangrove were labelled and converted into binary mask images (Figure 5b).

4.4 Model Training with Deep Learning

The study utilized four convolutional neural network (CNN) architectures for semantic segmentation: U-Net, Attention U-Net, MSNet, and SegNet. All models were implemented in Jupyter Notebook using TensorFlow and Keras libraries, and their performance was systematically evaluated to determine the most accurate and computationally efficient model for mangrove mapping. The deep learning models were trained using a local machine with an Intel Iris Xe Graphics, Intel Core i5 processor and 16GB RAM. Due to the machine's memory constraints, the training batch size was limited to 16, resulting in each epoch being iterated 73 times (Xu et al., 2023).

4.5 Hyperparameter Tuning

To identify the most effective model configuration for mangrove segmentation, a systematic hyperparameter tuning process was conducted. This involved training each of the four CNN architectures – U-Net, Attention U-Net, MSNet, and SegNet – under different combinations of loss functions and learning rates. Two loss functions were evaluated: binary cross-entropy (BCE), and a composite loss combining BCE with Dice loss. Each model was trained using two initial learning rates, 1 x 10^-3 and 1 x 10^-4, resulting in a total of 16 training configurations.

Each model variant was compiled using the Adam optimizer, with evaluation metrics including accuracy, precision, recall, F1-score and Intersection over Union (IoU).

4.6 Model Selection

Model selection was guided by performance comparisons across multiple training configurations. Model training was monitored using callbacks such as *ModelCheckpoint* to save the best-performing weights based on validation loss, *ReduceLROnPlateau* to adjust the learning rate dynamically, and *EarlyStopping* to prevent overfitting by halting training when no improvement was observed after eight consecutive epochs.

To ensure fairness and reproducibility, all models were initialized and trained independently for each configuration, and training histories were logged and stored for comparative analysis. The final model selection was based on a combination of metrics – training loss, Intersection over Union (IoU), and F1-score. This allowed identification of the most accurate and robust model for mangrove semantic segmentation.

4.7 Accuracy Evaluation

The classification performance of each model was assessed using a held-out test dataset, independent from the training and validation sets. Evaluation metrics included overall accuracy, precision, recall, Intersection over Union (IoU), and F1-score, which are widely used in both machine learning and remote sensing for assessing segmentation quality at the pixel level. These metrics were computed using TensorFlow's built-in metric classes and custom functions integrated into the training pipeline. While commonly applied in deep learning, these pixel-wise metrics are particularly relevant for remote sensing applications where precise delineation of land cover classes—such as mangroves—is essential. Beyond numerical evaluation, model performance was further validated through side-by-side visual comparisons of RGB images, ground truth masks, and predicted segmentation results from each model's best configuration—aligning with standard remote sensing practice for qualitative accuracy assessment.

5. Results and Discussion

5.1 Model Performance Comparison

Figure 6 illustrates the training loss curves for the best configurations of U-Net, MSNet, SegNet and Attention U-Net. The curves reveal distinct convergence behaviors. U-Net demonstrated the fastest and most consistent convergence, rapidly reducing its training loss and achieving the lowest final loss value among all models. This suggests that U-Net's skip connections and balanced architecture enabled it to learn spatial features more effectively while minimizing overfitting (Lomeo & Singh, 2022; Xu et al., 2023).

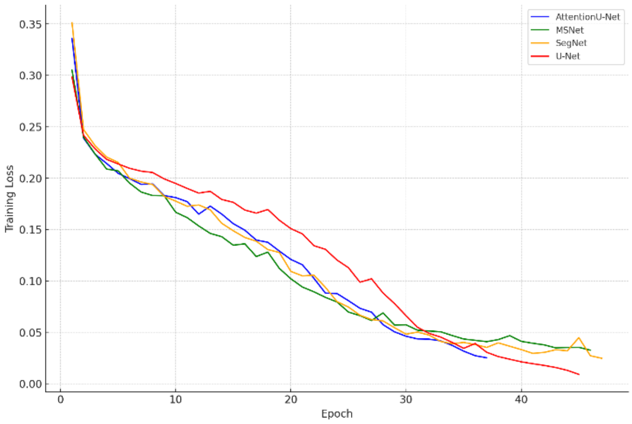


Figure 6. Training Losses of Attention U-Net, MSNet, SegNet and U-Net.

Attention U-Net also showed a steady decrease in training loss but plateaued at a slightly high loss value compared to U-Net. MSNet achieved a moderate convergence rate, reflecting its ability to capture multi-scale features (Xu et al., 2023). SegNet, while comparable in final loss values, exhibited slower convergence due to its simpler pooling-based decoder (Guo et al., 2021). The consistently decreasing training losses and relatively low final values across all models highlight the effectiveness of the preprocessing pipeline and hyperparameter tuning strategies. In particular, U-Net's performance reinforces its suitability for mangrove mapping in coastal landscapes with limited computational resources (Sun et al., 2023).

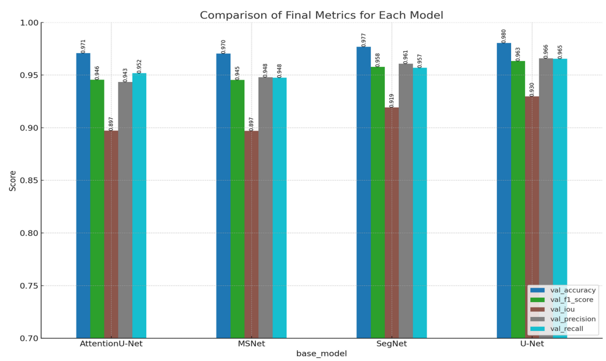


Figure 7. Comparison of Evaluation Metrics for each Model

Figure 7 shows the final validation metrics –F1-score, accuracy, IoU, recall and precision – for the best configurations of each model. U-Net consistently led across all metrics, reflecting its strong capability in accurately segmenting mangrove areas, with particularly high IoU and F1 values. SegNet, while slightly behind, still delivered competitive performance with well-balanced precision and recall, demonstrating its efficiency despite a simpler architecture (Guo et al., 2021). Attention U-Net demonstrated strong F1-score and precision but had slightly lower recall compared to U-Net, suggesting conservative segmentation that might miss some minor mangrove fragments. Nonetheless, its attention gates supported focused and accurate delineation of complex spatial features (Cai & Wang, 2022). Lastly, MSNet's strong precision and recall metrics demonstrate the utility of multi scale feature extraction in heterogeneous coastal scenes (Xu et al., 2023).

These quantitative results align with previous studies highlighting the dominance of U-Net-based architectures for mangrove mapping (Lomeo & Singh, 2022; Wang et al., 2023). The convergence of high validation metrics across all models shows the importance of effective hyperparameter tuning and preprocessing, ensuring robust and generalizable models for remote sensing applications.

5.2 Segmentation Results of Mangroves

To gain deeper understanding of the segmentation accuracy of the deep learning models, representative mangrove distribution areas were chosen for qualitative evaluation.

The visual comparison in Figure 8 illustrates how different CNN architectures handle the spatial complexity of Bohol's fragmented mangrove coastlines. The errors for each model output are highlighted in red circles. Notably, SegNet's outputs often appear less refined, with rougher edges (Figures 8-a, 8-c, 8-f) and omissions near water-mangrove interfaces (Figures 8-b,8-d, 8-e). This can be attributed to the absence of skip connections which are crucial for preserving spatial detail during upsampling. In contrast, U-Net, with its encoder-decoder skip pathways, maintains more continuous and accurate boundaries, even in ecotone zones where mangrove patches transition into open water or built-up areas. Similarly, Attention U-Net benefits from spatial attention mechanisms, which allow the model to focus on irregular or narrow mangrove shapes that might otherwise be overlooked (Figures 8-d, 8-e).

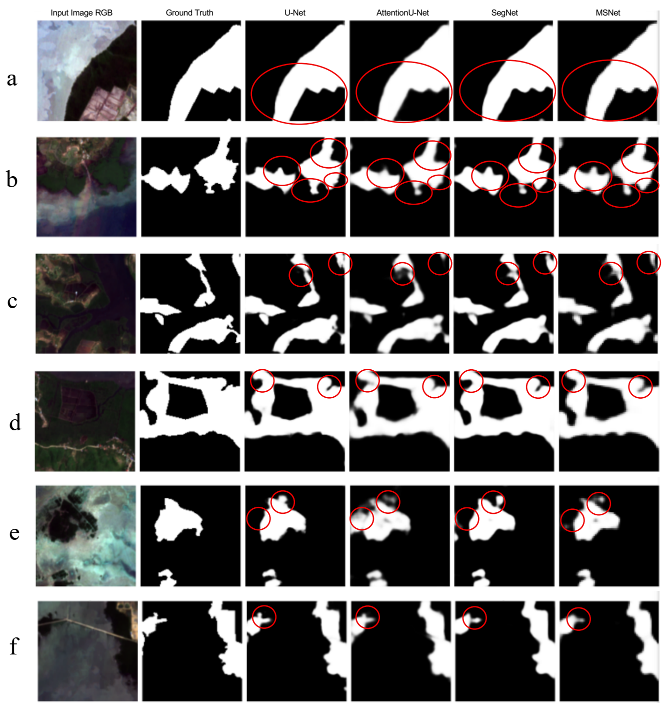


Figure 8. Results of Mangrove Segmentation for the Four Models.

These architectural differences are not merely reflected in metric performance; they have tangible implications for real-world usability – particularly for local conservation planning, where accurate boundary delineation is essential for monitoring deforestation, zoning rehabilitation areas, and enforcing protection policies in fragmented mangrove systems.

In summary, the side-by-side visualization of RGB images, ground-truth masks, and predicted masks across the four models underscores U-Net and Attention U-Net's superior visual consistency which supports data-driven conservation efforts (Baloloy et al., 2023). MSNet's outputs are reliable for general mapping, while SegNet, despite slightly rougher boundaries, still provides coherent and operationally useful masks for large-scale mangrove assessments. These findings have practical implications for scaling mangrove mapping efforts across the Philippines and other Southeast Asian regions, contributing to the global discourse on sustainable coastal resource management (Bhowmik et al., 2022; Neri et al., 2021).

5.3 Computational Efficiency

Beyond segmentation accuracy, computational efficiency is a critical consideration for real-world implementation, especially in resource-constrained contexts such as local government units (LGUs), small NGOs, or academic institutions. Table 2 summarizes the total training time (in seconds) for each model. MSNet exhibited the fastest training time at 1,974 seconds, followed by SegNet (4,884 s), U-Net (6,435 s), and Attention U-Net, which required significantly more time at 13,588 seconds due to the added computational complexity of attention mechanisms. While U-Net achieved the highest segmentation performance across all metrics, its training duration was more than three times that of MSNet and about 32% longer than SegNet's. In contrast, SegNet, despite slightly lower IoU and F1-scores, offers a reasonable balance of speed and segmentation quality, making it a viable alternative for large-area mapping or low-resource deployments. These trade-offs between computational cost and output quality are crucial for informing deployment decisions in practice, especially when regular monitoring or rapid updates are required.

Model	Training Time (in seconds)	Remarks
MSNet	1,974	Fastest, decent performance
SegNet	4,884	Balanced speed and accuracy
U-Net	6,435	Highest accuracy, moderate time
Attention U-Net	13,588	Most accurate in details, slowest

Table 2. Computational Efficiency of each CNN Model

6. Conclusion

This study successfully demonstrated the effectiveness of deep learning-based convolutional neural networks – U-Net, Attention U-Net, MSNet, and SegNet – in accurately mapping mangrove forests in Bohol, Philippines, using Sentinel-2 imagery. The qualitative and quantitative analysis highlight U-Net as the most consistent and precise model, providing highly detailed and visually coherent mangrove boundaries. Attention U-Net also performed strongly, offering nuanced segmentation for complex scenes and multi-scale features, respectively. SegNet, while somewhat less precise at boundaries, still produced operationally useful mangrove masks suitable for rapid mapping applications. The convergence of high validation metrics and visually robust outputs across these models underscores the reliability of deep learning for environmental monitoring tasks in coastal landscapes.

7. Recommendations

Based on the findings, it is recommended that U-Net be prioritized for operational mangrove mapping and regular monitoring by local government units (LGUs), the Department of Environment and Natural Resources (DENR), and other agencies managing coastal ecosystems. Its superior accuracy and spatial consistency make it highly suitable for generating updated mangrove extent maps, which can be integrated with flood hazard maps, erosion-prone zones, and marine protected areas for use in disaster risk reduction (DRR) and coastal zoning plans. For areas with complex shoreline features or fragmented mangrove patches, such as estuaries or river mouths, Attention U-Net offers a complementary solution, enabling more detailed assessment and management at the barangay or municipal level. In cases where computational resources are limited, such as in community-managed or academic settings, SegNet remains a viable alternative for rapid, large-area mapping. To further enhance map accuracy and usability, future initiatives should explore the incorporation of drone or UAV imagery for higher-resolution validation and apply transfer learning techniques to adapt trained models to other provinces with similar coastal characteristics.

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