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Article

Satellite image-based AI system for monitoring coral bleaching in Hawaii

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Abstract

Coral reefs play a critical role in sustaining marine biodiversity, supporting fisheries, and protecting coastlines. However, climate change and anthropogenic pressures have led to widespread coral bleaching, threatening ecological and economic stability—especially in tourism-dependent regions like Hawaii. Despite the urgency, current monitoring methods often lack real-time responsiveness and scalability. This study proposes an AI-based monitoring system that leverages satellite imagery to detect and track coral bleaching in Hawaii. The system integrates deep learning techniques for semantic segmentation of coral regions, temporal change detection to identify bleaching progress, and spectral analysis to estimate reef health. By visualizing high-risk areas through heatmaps, the framework enables early intervention and data-driven conservation planning. While the current focus is on the core detection and analysis functionalities, the system is designed with extensibility in mind—allowing future integration of automated reporting tools and real-time alert mechanisms. Our approach aims to provide an efficient and scalable solution for reef monitoring that bridges the gap between environmental science and AI technology. It offers both ecological insight and practical utility, contributing to the sustainable management of Hawaii's vital coral reef ecosystems.

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Introduction

Coral reefs, often referred to as the "rainforests of the sea," host approximately 25% of all marine species despite covering only a small fraction of the ocean floor. These ecosystems are not only vital habitats for marine life but also serve as breeding grounds, support coastal fisheries, and contribute directly to food security and local economies. Additionally, through the formation of their calcium carbonate skeletons, coral reefs absorb carbonates from seawater, contributing to long-term carbon sequestration and playing a meaningful role in global climate regulation.

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In recent decades, however, coral reef ecosystems have faced severe threats due to global warming and increased human activity. One of the most critical issues is coral bleaching, a phenomenon triggered by rising sea temperatures, which leads to the expulsion of symbiotic algae and ultimately results in large-scale coral mortality. Coral bleaching is further exacerbated by ocean acidification, pollution from land runoff, unsustainable tourism, overfishing, invasive species, and the spread of diseases. The degradation of coral reefs has far-reaching consequences—not only for biodiversity, but also for regional economies, food systems, and the global carbon cycle (Spalding, 2001; Hughes, 2018).

Figure 1. A panoramic view of coral reefs near Hawaii

Clear reef structures are visible beneath the shallow coastal waters, visually highlighting the ecological diversity and habitat functions of the coastal ecosystem. These coral reefs serve as critical components of the marine environment—contributing to shoreline protection, fishery formation, and tourism. However, due to recent climate change and human activities, coral bleaching has intensified, underscoring the growing need for reef preservation and monitoring.

As shown in Figure 1, coral reefs are densely distributed along the coastlines of Hawaii. This region is a representative case where the urgency of reef preservation is especially prominent. Hawaii's coral reefs are heavily impacted by marine tourism, including snorkeling and diving activities that physically damage reef structures. Given the state's high dependence on external food and resource supplies, reef degradation also poses direct threats to fishery stocks and local food security. These regional characteristics highlight the pressing need for effective coral reef protection in Hawaii.

However, current conservation efforts remain fragmented and slow to respond. There is a notable lack of real-time systems capable of linking tourist activity with ecological impacts to enable early detection and intervention (Peters et al., 2018). In particular, there are no comprehensive technological frameworks for systematically monitoring coral conditions and bleaching progression in high-traffic marine areas. This underscores the need for a new approach that integrates satellite imagery and artificial intelligence (AI).

To address this gap, this study proposes an AI-powered monitoring system that utilizes satellite imagery to regularly assess coral reef conditions in Hawaii. The system detects bleaching progression, structural damage, and relative reef health in near real time. Specifically, it incorporates semantic segmentation to isolate coral areas (Ronneberger et al., 2015; Chen et al., 2017; He et al., 2017), change detection across temporal satellite data (Zhou et al., 2018; Du et al, 2024), spectral analysis to estimate health conditions, and visualization to map high-risk zones. In the future, this framework may be expanded to include automated reporting tools for continuous updates and real-time alerts.

Satellite Imagery-Based Coral Reef Monitoring Techniques

Traditional coral reef monitoring has primarily relied on underwater photography, diver-based field surveys, and in-situ sensors (Ferrari et al., 2024). While these methods offer high-precision data, they face significant spatial and temporal limitations when applied to large-scale marine ecosystems. They are also labor-intensive and resource-demanding. In recent years, the use of high-resolution satellite imagery has emerged as a promising alternative for observing environmental changes across vast oceanic regions. Satellite-based approaches are particularly advantageous for efficiently analyzing the status of coral reefs, which are expansive and spatially distributed ecosystems (Bhatia et al., 2023).

Satellites such as Sentinel-2 (Goodman et al., 2023), Landsat-8 (Hedley et al., 2016), and PlanetScope (Robinson et al., 2022) offer multi-spectral imaging capabilities with spatial resolutions on the order of a few meters. These platforms enable ecological analysis using reflectance characteristics from different spectral bands. Commonly used spectral indices include the Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974), Blue-Green Index (BGI) (Gamon et al, 1994), and Maximum Chlorophyll Index (MCI) (Gitelson et al., 1996), which are employed to indirectly estimate the vitality of photosynthetic marine organisms and the condition of reef communities. Changes in these spectral indices serve as useful proxies for identifying bleaching events and detecting both short-term environmental shifts and long-term ecological anomalies.

However, these conventional index-based methods are generally limited to single-point or static analyses and tend to be less sensitive to subtle variations in color and structure. Coral reflectance can be significantly affected by various external factors, including water depth, turbidity, surface reflectance, and solar angle, which undermines the reliability of simple index-based approaches for early detection or temporal analysis. Moreover, because corals often exhibit visual similarities to surrounding environments—such as sand, seagrass, or rocks—accurately distinguishing coral boundaries remains a challenging task.

To overcome these limitations, recent studies have increasingly adopted deep learning techniques for satellite image analysis (Bhatia et al., 2023). Since satellite imagery is typically preprocessed with geometric and atmospheric corrections, it is well-suited for integration with AI algorithms, enabling robust analysis under varying conditions. Furthermore, time-series satellite data provide a foundation not only for assessing the current state of reefs but also for quantifying trends over time. These characteristics make satellite data an essential tool for detecting gradual ecological changes such as coral bleaching.

Satellite-based monitoring represents a paradigm shift from localized, manual observation toward scalable, time-series-driven ecological surveillance. Reflecting this shift, the proposed system in this study is designed to ingest high-resolution satellite images as input to an AI-powered analysis pipeline. This enables real-time monitoring of Hawaii's coral reefs and quantitative estimation of change patterns and ecosystem health.

Deep Learning-Based Coral Segmentation Techniques

Accurately delineating coral reef regions within images is a crucial first step in any comprehensive ecosystem monitoring pipeline. Traditional image processing techniques have typically relied on rule-based approaches such as color thresholding, edge detection, or clustering algorithms (e.g., k-means, mean-shift) to identify coral regions. However, these methods often struggle to precisely differentiate corals from visually similar surroundings like sand, seagrass, and rocks. This limitation is further amplified in underwater environments, where image characteristics vary significantly due to factors such as water depth, turbidity, and lighting conditions, resulting in reduced generalization performance.

To address these challenges, recent research has increasingly adopted deep learning-based semantic segmentation techniques. A representative model is U-Net (Ronneberger & Fischer & Brox, 2015), which features an encoder-decoder architecture capable of integrating multi-scale feature information. It also employs skip connections to preserve spatial resolution, allowing for detailed boundary delineation without sacrificing structural integrity. This is particularly advantageous when attempting to distinguish complex coral formations from background elements—making U-Net well-suited for domains like marine ecology and medical imaging, where fine-grained segmentation is essential.

Advanced models such as DeepLabV3+ (Chen et al., 2017) further improve segmentation by employing dilated convolutions and Atrous Spatial Pyramid Pooling (ASPP), enabling the model to aggregate contextual information across multiple receptive fields. Mask R-CNN [He et al., 2017), on the other hand, performs instance-level segmentation by generating masks for individual objects, making it useful when the number of coral structures is distinct and well-separated. These models offer varying strengths depending on the structural complexity and segmentation objectives, and have been successfully applied to coral reef imagery.

In practical applications, these models are often trained on datasets comprising manually annotated coral reef images captured via drones or satellites. The input images typically include not only RGB channels but also multispectral bands such as Near-Infrared (NIR), Green, and Blue. Preprocessing steps such as geometric alignment, color normalization, and atmospheric correction are applied to ensure consistency across inputs. To address limited labeled data, common data augmentation strategies—such as image rotation, scaling, and brightness adjustments—are also employed. Evaluation metrics include Intersection over Union (IoU), mean IoU, Dice coefficient, and F1-score.

Accurate segmentation of coral regions not only improves classification performance but also has a direct impact on the subsequent stages of change detection and health estimation. By isolating only the coral-containing portions of the image, the system can reduce computational load and minimize false detections caused by irrelevant background features. Moreover, the generated segmentation masks serve as critical inputs for visualization modules, enabling clearer and more interpretable mapping of bleaching severity or health indices.

Thus, semantic segmentation serves as a foundational component that directly influences the precision and reliability of coral reef monitoring systems. In this study, U-Net (Ronnenberger et al., 2015) is adopted as the primary segmentation model due to its balance of performance and simplicity. As coral ecology datasets grow and sensor technologies advance, future models may evolve to provide even more adaptive and fine-grained segmentation capabilities.

Time-Series-Based Change Detection Techniqeus

Coral bleaching is a gradual degradation process that is often difficult to detect through single-time-point imagery alone. In its early stages, bleaching manifests as subtle color shifts or slight textural degradation, which are hard to capture using conventional analysis methods. Therefore, accurately monitoring coral reef conditions and enabling early intervention requires time-series analysis that tracks changes over multiple image acquisitions. Change detection based on temporal satellite data is a key technique for this purpose, offering dynamic insights that go beyond static observations.

Traditional change detection methods include image differencing, change vector analysis (CVA), and post-classification comparison. These techniques typically identify differences in pixel values or classification outcomes between two images taken at different times. However, they are highly sensitive to external disturbances such as lighting variations, atmospheric conditions, and surface reflectance. As a result, they often suffer from high false positive rates and lack the precision needed for complex marine environments. Minor color shifts or blurred boundaries—common in early-stage coral bleaching—are usually undetectable by these basic techniques.

Recent research has introduced deep learning-based approaches for temporal change detection. Among them, semantic change detection models like UNet++ (Zhou et al., 2018) are well-suited for identifying large-scale structural changes by aggregating multi-resolution features and preserving spatial information through skip connections. While effective in screening for broad regions of potential change, these models may lack the granularity needed for quantifying or detecting subtle differences.

Siamese CNN architectures (Du et al., 2024) have been employed. A Siamese network processes a pair of satellite images—captured at two different time points—through identical neural branches, enabling it to learn differences at the feature level. This makes the architecture particularly effective for capturing gradual and localized changes such as those seen in early-stage bleaching. Additionally, by balancing positive (change) and negative (no-change) sample pairs during training, the model can generalize well across diverse environmental conditions. Siamese CNNs are also capable of predicting not only the presence but also the type and intensity of detected changes.

Beyond CNNs, recent approaches include Transformer-based models for sequential change detection (Dosovitskiy et al., 2020) and unsupervised contrastive learning frameworks that further enhance robustness to misalignment and noise. These models are increasingly being extended to various input modalities, including drone imagery and low-resolution sensor data, paving the way for integrated frameworks capable of both change detection and condition forecasting.

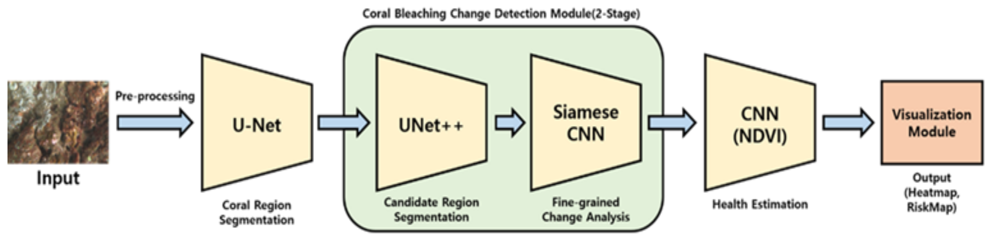

Figure 2. Overall architecture of the proposed coral bleaching monitoring system

Input satellite imagery is first processed by a U-Net model to precisely segment coral regions. Then, potential bleaching areas are identified using UNet++, followed by fine-grained temporal change analysis via a Siamese CNN. A CNN-based regression model estimates coral health scores based on NDVI, and the final outputs—change detection and health estimation—are integrated and visualized as a risk map. Each module is independently designed to ensure both scalability and real-time responsiveness of the system.

Time-series-based change detection is essential for monitoring ecological degradation processes like coral bleaching. This study proposes a dual-stage strategy combining UNet++ (Zhou et al., 2018) for broad area detection and Siamese CNN (Du et al., 2024) for precise local analysis. This hybrid approach enables the system to capture both widespread anomalies and early micro-level changes. In the future, such models could be extended to predict recovery trends and bleaching progression rates, ultimately supporting early warning systems and long-term conservation planning.

Method

System Overview

This study proposes a satellite image-based artificial intelligence (AI) monitoring system designed to effectively detect and quantitatively analyze coral bleaching in Hawaii. The system is structured as a sequential pipeline that isolates coral reef regions from satellite imagery, detects temporal changes, estimates reef health conditions, and visualizes high-risk areas. It comprises four key modules: semantic segmentation for coral region identification, time-series change detection, spectral analysis-based health estimation, and a visualization and risk mapping module to display results. Each module is independently designed for modularity, extensibility, and potential integration with other subsequent analysis to relevant areas, improving both computational efficiency and accuracy in later stages. Change detection, the core component of the system, is structured as a two-stage hierarchical process that balances broad detection coverage with localized precision.

UNet++ (Zhou et al., 2018)-based semantic change detection is applied across the entire coral reef area to screen for regions with structural changes potentially caused by bleaching or degradation. This allows for rapid identification of large-scale anomalies. Then, for regions identified as high-risk by UNet++, a second-stage analysis is performed using a Siamese CNN (Du et al., 2024), which compares pairs of satellite images to sensitively detect subtle color changes and early signs of bleaching. This dual-model strategy combines the spatial coverage of UNet++ with the fine-grained sensitivity of the Siamese architecture, enabling robust and accurate change detection.

In the health estimation stage, vegetation indices such as NDVI (Rouse et al., 1974) are used to quantify the physiological activity of coral areas. These indices, derived from the photosynthetic behavior of symbiotic algae (Symbiodinium), are expressed as continuous values between 0 and 1—representing a spectrum from healthy (high reflectance) to severely bleached (low reflectance) corals. This enables not only binary classification but also a graded assessment of bleaching severity and potential recovery.

Results are visualized through heatmaps and risk maps that integrate change detection and health scores to highlight critical areas. The system also supports temporal comparisons, allowing users to track bleaching trends over time.

Built on a modular framework, the proposed system can be extended in the future to include automated reporting, real-time alert mechanisms, or integration with drone imagery. This represents a shift from conventional, reactive reef monitoring approaches to a scalable, data-driven surveillance framework capable of real-time ecological response.

Coral Region Segmentation

To accurately isolate coral reef areas within satellite imagery, this study adopts a deep learning-based semantic segmentation approach. Due to the visual similarity between coral and surrounding marine elements such as sand, algae, and rocks, traditional image processing techniques struggle to distinguish coral boundaries clearly. Thus, a pixel-wise learning-based method is employed to extract coral regions with high precision, thereby narrowing the analysis scope and improving the accuracy and efficiency of subsequent processing steps.

High-resolution optical satellite imagery serves as the primary input, with optional inclusion of multispectral bands depending on the data source. All imagery undergoes preprocessing steps—such as geometric correction, color normalization, and atmospheric correction—to ensure consistent and comparable inputs across time-series datasets. These steps enhance the generalizability of the segmentation model and enable reliable temporal analysis.

Several state-of-the-art semantic segmentation models were considered, including U-Net (Ronnenberger, 2015), DeepLabV3+ (Chen et al., 2017), and Mask R-CNN (He et al., 2017). This study primarily adopts U-Net (Ronnenberger, 2015), which leverages an encoder-decoder architecture with skip connections. This structure allows for multi-scale feature integration while preserving fine-grained spatial details, making it well-suited for separating visually similar marine features like coral from their backgrounds.

The model is trained on manually annotated coral reef datasets derived from satellite imagery. To address data scarcity, various data augmentation techniques—such as image flipping, rotation, scaling, and brightness adjustment—are applied during training. Model performance is evaluated using metrics such as Intersection over Union (IoU), mean IoU, and F1-score. Results indicate that U-Net (Ronnenberger, 2015) effectively segments coral regions with varying shapes and scales, demonstrating both accuracy and model efficiency.

The segmented coral masks are used as direct inputs for both the change detection and health estimation modules. By restricting analysis to coral-containing areas, the system reduces computational overhead and minimizes false detections from irrelevant background features. Additionally, the masks play a crucial role in the visualization module by enabling precise spatial mapping of bleaching severity and health scores.

This segmentation approach goes beyond merely identifying the presence of coral; it establishes a foundation for accurate interpretation and reliable downstream analysis. As satellite sensor technologies evolve and more annotated datasets become available, this model can be further extended to general-purpose segmentation tasks or integrated with drone imagery for ultra-high-resolution applications.

Coral Bleaching Change Detection

Coral bleaching is a dynamic process that evolves over time and cannot be effectively identified using single-point imagery alone. It often progresses gradually over several days or weeks, initially manifesting as subtle color fading or loss of texture. As such, a time-series-based approach is essential for accurately capturing and analyzing bleaching events. This study proposes a change detection strategy that compares two or more satellite images taken at different times to determine the extent and location of coral condition changes.

The change detection process is divided into two main stages. In the first stage, semantic change detection is applied across the entire segmented coral region to quickly identify areas with a high likelihood of change. For this task, the UNet++ (Zhou et al., 2018) architecture is utilized due to its ability to integrate multi-depth features and detect broad structural changes. This step acts as a filter, prioritizing detection coverage over precision, and provides a shortlist of candidate regions for further analysis. In the second stage, the candidate regions identified by UNet++ are examined using a Siamese CNN (Du et al., 2024) for fine-grained change analysis. The Siamese network takes two satellite images from different time points (t, $t+\Delta t$) and processes them through identical branches. It then learns to infer differences based on feature-level comparisons. This structure is particularly effective for detecting minor spectral shifts or early bleaching signs that may be imperceptible to standard segmentation models. Its sensitivity to subtle changes in reflectance makes it a valuable foundation for early warning systems.

To ensure consistent comparisons between images, the preprocessing pipeline includes geometric alignment, atmospheric correction, and brightness normalization to mitigate the influence of external factors such as lighting variations, water surface reflections, clouds, and shadows. During training, both positive (change) and negative (no-change) image pairs are evenly balanced to improve generalization.

The output from both models—UNet++ and Siamese CNN—is used to drive risk estimation and health evaluation. The dual-model design allows the system to simultaneously detect wide-area anomalies and localized bleaching trends. This complementary structure offers a balance between computational efficiency and detection accuracy, enabling the development of a space-time analytical framework suitable for early response and ecological monitoring.

Coral Health Estimation

Coral bleaching is not merely a visual whitening phenomenon but a physiological response triggered by the loss or reduced activity of Symbiodinium within coral tissues. Therefore, rather than a binary classification of healthy versus bleached, a continuous health score is more suitable for accurately monitoring ecological status and enabling timely intervention. To this end, this study designs a health estimation module that leverages the spectral reflectance properties of satellite imagery to quantify coral vitality.

The system primarily utilizes optical satellite data, including RGB bands, and optionally incorporates multispectral bands such as Near-Infrared, Blue, and Green. Coral health is indirectly estimated through various vegetation indices calculated from inter-band reflectance differences. This study applies a modified version of NDVI, alongside additional indices such as GNDVI and BNDVI. GNDVI is particularly sensitive to chlorophyll concentration, making it effective for detecting pre-bleaching stress, while BNDVI is optimized for capturing reflectance changes in underwater environments.

These indices are computed at the pixel level and serve as inputs to a CNN-based regression model that outputs continuous coral health scores ranging from 0 to 1. A score near 1 indicates high photosynthetic activity and healthy coral, whereas a score near 0 reflects severe bleaching and coral vulnerability. The model is trained using annotated reference images from expert-curated datasets such as NOAA CoralNet [20] and the Allen Coral Atlas [21], ensuring generalizability across various timeframes and environmental conditions.

Health scores go beyond detecting change events; they enable practical applications such as identifying chronically stressed areas, prioritizing conservation zones, and monitoring recovery progress. For instance, regions with consistently low health scores but no recent changes may be classified as long-term degradation zones, while areas showing improved scores post-disturbance may indicate ecological recovery. When combined with change detection results, health estimation provides a more comprehensive and temporal understanding of coral reef status.

The final health scores are used as core metrics in the visualization and risk mapping stages. They are typically rendered as heatmaps or categorized into discrete risk levels to facilitate intuitive interpretation. By enabling users to quickly identify vulnerable areas, the system supports prompt decision-making and resource allocation. This module ultimately enhances the precision and utility of coral monitoring, moving beyond static classifications toward a dynamic and interpretable analytical framework.

Risk Area Visualizaion

The primary goal of coral reef monitoring is not merely data analysis, but enabling decision-makers and field managers to quickly identify high-risk areas and respond accordingly. To support this goal, the proposed system includes a visualization and risk mapping module that integrates results from change detection and health estimation into intuitive, spatially-referenced outputs. This module plays a crucial role in transforming raw numerical outputs into actionable insights that can guide conservation efforts.

Risk area visualization is implemented through two main components. First, a health heatmap is generated based on the estimated health scores for each coral pixel. These scores are visualized along a color spectrum—typically ranging from red (vulnerable) to green (healthy)—enabling users to immediately identify degraded regions at a glance. Second, a risk map is produced by combining change detection results with health scores to quantify the severity of ecological deterioration. Risk levels are defined as a function of change intensity and health score (h), and regions exceeding a predefined threshold are classified as high-risk. These are visually rendered on the map using color-coded overlays, helping managers determine prioritization for intervention.

The visualization module also supports time-series tracking of reef conditions. For example, satellite images captured at 1-month or 3-month intervals can be compared and displayed as animations or change graphs, allowing users to visually follow the progression or recovery of bleaching over time. In cases where detection uncertainty exists, the system provides visual cues—such as adjustable transparency (alpha values) or boundary emphasis—to alert users to ambiguous regions.

Designed with web-based deployment in mind, the module can be expanded into an interactive dashboard using tools such as Dash, Streamlit, or GIS platforms. A user-friendly interface will enable both specialists and the general public to explore risk information more efficiently than static reports. Features such as filtering by marine protected areas or comparing bleaching trends across timeframes can be readily integrated to support diverse user needs.

This visualization stage is also structured to support future integration with automated report generation and real-time alert systems. For instance, the system could automatically generate PDF reports based on periodically updated risk maps or send email/SMS alerts to administrators when high-risk areas are detected. These features greatly enhance the practical applicability of the research outcomes and facilitate their incorporation into policy and field operations.

The proposed visualization and risk mapping module serves as a bridge between analytical output and practical action. By making spatial information more accessible and interpretable, it empowers faster, evidence-based decision-making and provides a robust foundation for implementing effective coral reef protection strategies.

Results

This study evaluates the performance of the proposed system in terms of coral segmentation, bleaching change detection, and health estimation using high-resolution satellite imagery. All experiments were conducted on a workstation equipped with an NVIDIA RTX 3090 GPU, using PyTorch 2.0 as the deep learning framework. Each model was trained for 100 epochs using the Adam optimizer with an initial learning rate of 1e-4. Appropriate metrics were selected for each task to assess model performance and analyze the effectiveness of preprocessing techniques.

Experiment Dataset and Preprocessing

The experiments in this study were conducted using satellite imagery and ecological data compiled from CoralNet (Bejibom et al., 2012) and the Allen Coral Atlas (Hedley et al., 2023). CoralNet provides underwater images annotated for coral classification, while the Allen Coral Atlas offers high-resolution satellite-based maps of coral reef distribution and bleaching conditions. These two datasets are complementary, and were integrated in this study to generate labels for coral region boundaries, bleaching status, and health scores. The data cover diverse geographic locations, time periods, and environmental conditions, making them well-suited for evaluating model generalization.

The dataset was split into 60% for training, 20% for validation, and 20% for testing. Preprocessing steps were applied to generate multiple types of input data tailored to each experimental goal. Unlike conventional RGB or multichannel inputs, this study employed single-channel grayscale images derived from spectral indices that reflect photosynthetic activity and bleaching severity. Specifically, NDVI, GNDVI, and BNDVI were calculated from satellite bands and used to generate grayscale representations that quantitatively capture coral condition. This input format facilitates comparison across time-series imagery and enhances the interpretability of physiological changes.

Additional preprocessing steps included geometric correction, atmospheric correction, and brightness normalization to ensure alignment and consistency between images. Data augmentation techniques such as image rotation, flipping, and brightness adjustment were also applied to improve model robustness. All images were resized to 512×512 pixels and normalized to a [0, 1] pixel intensity range. This preprocessed dataset served as a foundational component for quantitatively evaluating the system's segmentation, change detection, and health estimation modules.

Model Performance Comparison

To evaluate the effectiveness of each module in the proposed system, multiple deep learning models were compared across three core tasks: coral segmentation, bleaching change detection, and health estimation. Each task was experimentally validated using well-established baseline models, and model selection considered not only performance metrics but also resource efficiency for real-world deployment.

For coral segmentation, U-Net (Ronneberger, 2015), DeepLabV3+ (Chen et al., 2017), and Mask R-CNN (He et al., 2017) were compared. As shown in Table 1, U-Net exhibited the most lightweight architecture with approximately 7.8 million parameters and a GPU memory footprint of 512 MB, significantly lower than DeepLabV3+ and Mask R-CNN. According to Table 2, DeepLabV3+ achieved the highest accuracy, with a mean IoU of 0.82 and F1-score of 0.84. Mask R-CNN followed closely with a mean IoU of 0.79 and F1-score of 0.83. U-Net, while slightly behind in performance (0.75 IoU, 0.79 F1), demonstrated superior efficiency in terms of parameter count and memory usage. This makes U-Net especially suitable for deployment on edge devices or real-time monitoring systems, where resource constraints are critical. Given the trade-off between performance and efficiency, U-Net was ultimately selected as the core segmentation model for the overall pipeline.

For bleaching change detection, a dual-branch structure was implemented to capture both wide-area structural changes and localized color shifts. UNet++ (Zhou et al., 2018) was used for broad semantic change detection, and as shown in Table 3, it achieved an F1-score of 0.87. Siamese CNN (Du et al., 2018) outperformed in detecting subtle variations with an F1-score of 0.88 and higher recall, indicating superior sensitivity to early-stage bleaching. This performance validated the use of the two models in parallel to balance detection coverage and granularity.

In the coral health estimation task, a CNN-based regression model was compared against a lightweight MLP. The CNN model yielded more stable predictions in terms of mean squared error (MSE) and R^2, as summarized in Table 4. While the MLP consumed fewer resources, it suffered from degraded accuracy. Therefore, the CNN architecture was chosen to prioritize precision in estimating coral health conditions.

These experimental results support the structural validity and efficiency of the proposed system. By balancing accuracy with real-time applicability and model size, the final pipeline demonstrates strong potential for deployment in practical coral reef monitoring scenarios.

Table 1. Model-wise computational resource usage

Model	Perams (M)	Memory (MB)
U-Net [4]	7.8	512
DeepLabV3+ [5]	41.2	1150
Mask R-CNN [6]	44.5	1380
UNet++ [7]	9.3	720
Siamese CNN [8]	10.1	840
CNN	2.7	260
MLP	1.2	180

Table 2. Performance of coral segmentation models

Model	Backbone	IoU	Mean IoU	F1-Score
U-Net [4]	ResNet-50	0.75	0.78	0.81
DeepLabV3+ [5]	ResNet-50	0.79	0.82	0.84
Mask R-CNN [6]	ResNet-50	0.76	0.79	0.83

Table 3. Performance comparision of coral bleaching change detection models

Model	Precision	Recall	F1-Score
Unet++ [7]	0.873	0.893	0.87
Siamese CNN [8]	0.908	0.917	0.88

Table 4. Performance comparision of coral health estimation models

Model	Precision	Recall	F1-Score
CNN	0.047	0.039	0.864
MLP	0.024	0.021	0.696

Analysis of Preprocessing Effects with Additional Input Channels

Satellite images used for coral detection and health estimation are highly sensitive to external factors such as atmospheric conditions, sea surface reflections, and solar elevation. These variations can reduce consistency across time-series imagery and compromise detection accuracy. To mitigate this, we conducted experiments incorporating additional preprocessing channels to enhance detection performance and compensate for the limitations of single-channel (grayscale) inputs.

Specifically, we compared three input configurations:

- Baseline (Single Channel): Original grayscale image based solely on reflectance data.
- +Sobel: Two-channel input combining the baseline with edge-enhanced output from Sobel filtering.
- +NDVI (Rouse et al., 1974): Three-channel input adding GNDVI and BNDVI spectral indices to the above configuration.

The experiments were conducted using the same model architecture across all configurations. To ensure objective comparison, the same dataset splits and training parameters were applied. The results are summarized in Table 5.

Table 5. Performance comparision with different preprocessing configurations

Input	Segmentation F1-Score	Change Detection F1-Score	Health Estimation R^2
Baseline	0.81	0.87	0.864
+Sobel	0.82	0.88	0.868
+Sobel +NDVI[14]	0.84	0.91	0.876

As shown in Table 5, the baseline configuration achieved reasonable accuracy across all tasks, but adding the Sobel channel improved boundary detection and reduced false positives, particularly in segmentation and change detection tasks where precise edges are critical. The inclusion of NDVI-based vegetation indices further enhanced the health estimation module by capturing subtle reflectance variations associated with physiological stress. This allowed the system to detect early bleaching signs that are difficult to identify through color alone.

The three-channel input configuration yielded the best results in terms of accuracy, model stability, and robustness to environmental noise. It also improved the system's ability to interpret sequential imagery in a consistent manner. For example, F1-scores increased in both segmentation and change detection, and the health estimation model achieved a higher R^2.

However, the multi-channel input setup also increased GPU memory usage by approximately 1.3× and caused a slight 5–8% reduction in inference speed. Despite these trade-offs, the enhanced visual precision and early warning sensitivity justify its adoption. Therefore, this study identifies the three-channel configuration as the optimal balance between performance and efficiency.

These findings provide a valuable reference for extending the system to future input sources such as drone imagery or alternative satellite sensors. The experiments demonstrate how even small changes in input representation can substantially affect end-to-end model performance.

Conclusion and Implications

This study proposes a satellite image-based AI monitoring system capable of detecting coral bleaching in Hawaii and quantitatively tracking temporal changes. The system comprises four core modules: semantic segmentation, change detection, health estimation, and risk area visualization. Each module is designed to process high-resolution satellite imagery, enabling fine-grained detection of spatial and temporal anomalies in coral reef ecosystems.

The proposed change detection pipeline utilizes both UNet++ (Zhou et al., 2018) and Siamese CNN (Du et al., 2024) in parallel, allowing the system to capture large-scale structural changes and subtle color variations simultaneously. The health estimation module employs a CNN-based regression model that leverages NDVI (Rouse et al., 1974) and derived vegetation indices to quantify the physiological state of coral reefs as continuous scores.

The proposed architectures demonstrated higher accuracy and stronger generalization. Notably, using a three-channel input configuration—consisting of reflectance, Sobel edge enhancement, and NDVI(Rouse et al., 1974)—yielded the most robust performance across all tasks. Moreover, the models were designed with computational efficiency in mind, with lightweight architectures and minimal memory footprints suitable for real-time deployment. The risk visualization module translates numerical outputs into intuitive heatmaps and risk maps, supporting rapid interpretation and enabling prompt decision-making by conservation managers and policymakers.

The significance of this work lies in shifting from conventional, fragmented reef monitoring approaches to a unified, real-time digital surveillance system powered by satellite imagery and AI. By enabling early detection and ongoing status assessment, the proposed system can contribute meaningfully to the sustainable preservation and restoration of Hawaii's coral reef ecosystems. Future developments will include automated reporting, real-time alert systems, and integration with drone-based imagery, potentially evolving the platform into a versatile tool for broader marine ecosystem monitoring.

Declarations

Competing interests: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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