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AI-BASED IMAGE RECOGNITION FRAMEWORK FOR EFFICIENT CORAL BLEACHING ASSESSMENT

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ABSTRACT

Coral reefs are vital ecosystems that support biodiversity and coastal economies but are increasingly threatened by climate change, overfishing, and pollution. Traditional coral health assessments, while effective, are time-consuming and labor-intensive, limiting their scalability. This study introduces an AI-powered image recognition framework utilizing Convolutional Neural Networks (CNNs) and transfer learning to automate coral bleaching detection with improved accuracy and efficiency. By integrating machine learning experimentation and expert validation, the system ensures reliable classification of coral health conditions, enhancing monitoring capabilities. Evaluation results demonstrate significant improvements in assessment speed, scalability, and reliability, surpassing manual methods. The framework not only streamlines monitoring but also enables real-time data collection for better conservation strategies. Its adaptability supports large-scale environmental applications, offering a scalable tool for proactive reef management. Future advancements could enhance model precision and incorporate predictive analytics, further strengthening AI's role in marine conservation and ecosystem sustainability.

Keywords: Coral bleaching, Image recognition, Artificial Intelligence (AI), Convolutional Neural Networks (CNNs), Marine conservation

1. INTRODUCTION

Coral reefs are vital marine ecosystems that support biodiversity, provide coastal protection, and generate income through fisheries and tourism [1]. However, these ecosystems are under increasing threat due to climate change, overfishing, and pollution, leading to habitat degradation and widespread coral bleaching [1][4][5]. In regions such as Moalboal and Badian in Cebu, Philippines—part of the Coral Triangle—this damage significantly impacts local economies and the sustainability of marine life [2].

Traditionally, coral health assessments have relied on in-situ visual methods such as Line Intercept Transect (LIT) or Point Intercept Transect (PIT) [7]. These methods are labor-intensive, time-consuming, and require specialized expertise. With advancements in technology, artificial intelligence (AI) and image recognition techniques are emerging as powerful tools to enhance the speed and efficiency of coral assessment processes [6][9][10].

The primary problem addressed in this research is the inefficiency and lack of scalability of conventional coral monitoring methods, especially in detecting coral bleaching events promptly and accurately. Constraints in time, manpower, and spatial coverage make traditional methods less suitable for large-scale conservation needs.

As a solution, this study proposes the development of an AI model based on Convolutional Neural Networks (CNNs) capable of analyzing coral health through image classification [3][6][9]. This model will be integrated into a web-based platform accessible to various stakeholders, including divers, marine scientists, and the general public.

The main objective of this research is to design and develop an AI-powered coral bleaching detection system that provides automated, rapid, and accurate assessments. By leveraging this approach, the study specifically aims to (a) define the current methodology used by CCEF in assessing the coral health then eventually identify its limitation; (b) Compare available models and framework to design a new conceptual framework to efficiently assess the health of coral particularly the bleaching and (c) design an AI powered framework capable of detecting coral bleaching. The obtained result will eventually be used to develop an IT solution to support a more responsive and data-driven marine conservation efforts.

Coral bleaching Indicators and Effects

Coral bleaching progresses through distinct phases, reflecting increasing levels of stress on the coral-algae symbiosis. [13] observed that both naturally and experimentally bleached corals exhibit various stages of zooxanthellae degradation, with experimentally bleached corals showing more pronounced effects. These stages likely correspond to the progression from healthy coral tissue with intact zooxanthellae to fully bleached coral with severely degraded or absent symbiotic algae. The primary driver of widespread coral bleaching is the rise in seawater temperatures caused by climate change. An increase of just 1°C above the usual temperature can lead to bleaching events. Additional factors, such as elevated light intensity, changes in nutrient levels, ocean acidification, and 24 alterations in water flow rates, can also play a role in triggering or worsening these events [14][15]. Bleached corals are likely to have reduced growth rates, decreased reproductive capacity, increased susceptibility to diseases, and elevated mortality rates. These effects can lead to changes in coral community composition, affecting the entire reef ecosystem and the species that depend on it.

Coral Health Assessment methods

Traditional in-water observation-based methods include visual surveys such as the Line Intercept Transect (LIT) technique and the Underwater Photo Transect (UPT) method, which are commonly used to assess coral health and bleaching extent [7]. The Point Intercept Transect (PIT) method is another traditional approach, where reef life forms are recorded at regular intervals along transects. For instance, some protocols recommend recording reef life forms every 0.5 m along 3 x 50 m transects at 10 m depth at each site. Fish communities are often assessed using a combination of belt transects and long swims, where divers count and measure target reef fish species or families [7]. The Hawaiian Koʻa (Coral) Card, developed by researchers from the Hawaiʻi Institute of Marine Biology's Coral Reef Ecology Lab, provide a simple yet effective color-based assessment tool to determine the health and bleaching status of coral reefs. This method allows for easy comparison between healthy and bleached coral colors, corresponding to the concentration of symbiotic algae in coral tissues. The Koʻa Card was designed for use by a wide range of users, including community members, citizen scientists, researchers, students, and resource managers [16]. Advanced technologies have emerged as effective complements to these traditional methods. Small Unmanned Aerial Systems (SUAS) have been used to assess spatial 26 distributions of coral bleaching on shallow-water patch reefs, providing a more scalable approach to reef monitoring [17]. Hyperspectral imaging techniques, such as PRISMA hyperspectral satellite imagery, have shown promise in effectively discriminating between bleached and live corals [18].

Design Framework and Machine Learning algorithms

Today, Artificial Intelligence (AI) is more commonly understood as a system capable of communicating, reasoning, and operating independently, similar to humans [19]. AI has evolved significantly, transitioning from early rule-based systems to advanced models powered by Machine Learning (ML) and Deep Learning (DL) technologies [20]. These advancements enable AI to simulate human-like capabilities effectively. ML allows systems to learn and improve from data without explicit programming, forming the backbone of applications such as personalized recommendations and predictive analytics. Meanwhile, DL, a sophisticated subset of ML, uses multi-layered neural networks to process information in ways that mimic human brain functions, further advancing AI's ability to perform complex tasks [21]. Another important technique is Natural Language Processing (NLP), which allows machines to understand and generate human language. NLP 32 powers everything from virtual assistants like Siri to chatbots that help with customer service [20].

2. IMPLEMENTATION METHOD

This study is qualitative in nature and focuses on designing an AI-based image recognition conceptual framework for coral bleaching detection. It involves three key components: (1) gathering qualitative insights from a representative of the Coastal Conservation and Education Foundation (CCEF), and (2) comparison available models and framework that uses AI to detect coral bleaching and (3) design a conceptual framework that integrates image recognition principles for future implementation in coral reef monitoring.

This study utilizes the total population instead of a sample size due to the client-based nature of the proposed framework. Given the small number of participants, this approach ensures a comprehensive evaluation to support the future development of an IT solution in the second phase of the study. Participants is are key informants with direct experience in coral reef monitoring and conservation. The chosen participant is a representative from the Coastal Conservation and Education Foundation (CCEF), a recognized organization engaged in marine ecosystem protection in the Philippines corals using photographic data submitted by divers and researchers.

Interview was the primary data collection technique used in data related to research objective #1 and core representative from the Coastal Conservation and Education Foundation Inc. (CCEF) will be the primary participant. Review of secondary resources was also employed to explore the various AI models and frameworks that are being used nowadays for coral bleach detection.

Thematic analysis was used to present the gathered data from the semi-structured interview with the CCEF representative. This method is suitable for identifying, analysing, and interpreting patterns of meaning (themes) within qualitative data.

MAXQDA was used for thematic coding and interpretation through a codebook method.

3. RESULTS AND DISCUSSIONS

The interview findings revealed that the Coastal Conservation and Education Foundation (CCEF) utilizes the Hawaiian Koʻa (Coral) Card as a primary tool for detecting coral bleaching. This color-based assessment method enables easy comparison between healthy and bleached corals, correlating to the concentration of symbiotic algae in coral tissues. The Koʻa Card's accessibility allows a diverse range of users—including researchers, students, citizen scientists, and resource managers—to conduct efficient coral health assessments. This approach provides a simplified yet effective framework for monitoring reef conditions, ensuring consistent evaluation across different environmental settings.

Their procedure generally includes the following steps as shown in figure 1.

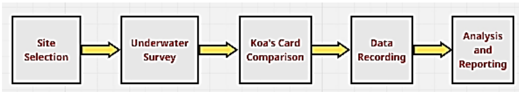

Figure 1. Method of detecting Coral bleach

The assessment begins with site selection, identifying key reef areas based on environmental conditions. Underwater surveys follow, where divers document coral conditions through observations and photography. Images are then analyzed through Koʻa Card comparison, matching coral colors to standardized bleaching references. Findings are logged in data recording, detailing bleaching severity and contributing factors. In the reporting phase, trends are assessed to guide conservation strategies. Finally, intervention recommendations propose solutions like reef restoration and management policies to support coral recovery.

The interview with the CCEF representative, an expert in coral health monitoring and bleaching detection, revealed three major themes that highlight key challenges and opportunities in assessment methods. Table 1 shows the generated themes from the interview.

Table 1: key challenges and opportunities in assessment methods

Theme	Key challenges
Resource-Intensive Manual Monitoring	Manual observation, time consuming, labor dependent, resource intensive, large scale monitoring challenges
Inconsistences in reporting	Field data variability, human subjectivity, interpretation differences
Openness to AI solution	Accessible, strong support, efficiency, scalability, AI driven monitoring

These findings underscore the value of automating coral bleaching detection to complement, not replace, existing field expertise.

Comparison of existing frameworks and models

To conceptualize a new framework for coral bleaching detection using image recognition, several existing approaches was compared based on their methodologies, accuracy, scalability, and adaptability. Table2 shows a comparative analysis of key models:

Table 2: Comparative analysis of key models

Method	Strength	Constraint
Hawaiian Ko'a (Coral) Card Method	Simple, accessible for citizen scientists, standardized color classification	Subjective interpretation, requires trained personnel for accuracy, lacks automation.
Machine Learning-based Image classification (CNNs)	High accuracy in detecting patterns, scalable for large datasets, eliminates human subjectivity.	Requires large training datasets, computationally intensive, sensitive to image quality.
Transfer Learning Models (ResNet, VGG, InceptionNet)	Reduces training time, enhances accuracy by leveraging existing knowledge.	May require fine-tuning for specific coral bleaching conditions, dependent on quality of initial pre-trained models.
Hybrid AI Approach (CNN + Object Detection Models like YOLO, Faster R-CNN)	Detects bleaching at the coral colony level, provides localized results.	Requires well-annotated datasets, processing-intensive in real-time applications.

The comparison highlights varying approaches to coral bleaching detection, ranging from manual color-based assessments to AI-driven models like CNNs, transfer learning, and hybrid AI techniques. Integrating these methods into a new conceptual framework could enhance efficiency, scalability, and accuracy, bridging the gap between traditional assessments and automated image recognition.

Proposed framework

Based from the comparison made in the previous section, the researchers designed a conceptual framework that integrates possible models that can be adopted. Figure 2 illustrates the web application's user roles and functionality, distinguishing admin and diver as primary users.

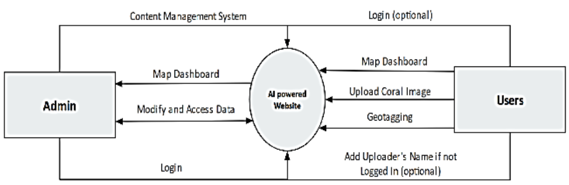

Figure 2: Conceptual framework of a web application

The admin has access to the dashboard, where they manage accounts for divers and oversee content. Both users can modify and manage uploaded data, ensuring flexibility in system operation. Divers, on the other hand, play a crucial role in data collection, as they upload coral images, geo-tag locations, and provide uploader details. Once an image is uploaded, the AI-powered system automatically detects the coral species and bleaching level, streamlining monitoring efforts.

Consequently, Figure 4 showcases the AI model's workflow in detecting coral bleaching.

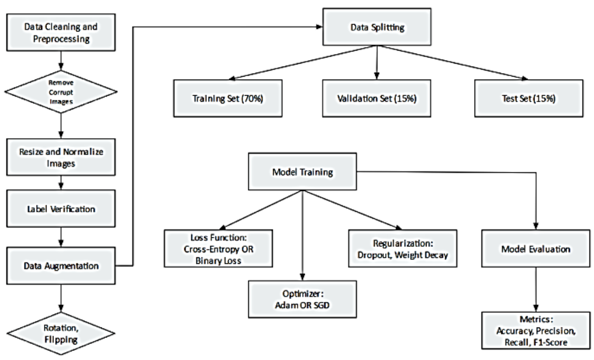

Figure 3 AI model workflow

The process begins with (1) image input, where underwater or satellite images are provided. These images undergo (2) pre-processing, including resizing, normalization, and augmentation, to enhance recognition accuracy. A (3) CNN-based model utilizing transfer learning (e.g., ResNet50 or MobileNetV2) then classifies coral health. The (4) output layer determines whether a coral is healthy, partially bleached, or fully bleached. Finally, (5) result visualization presents the prediction alongside a confidence score, offering reliable insights for conservation efforts.

4. CONCLUSION

This study introduces a conceptual AI image recognition framework for coral bleaching assessment, developed based on insights from a marine conservation expert. It addresses inefficiencies in manual reef monitoring and proposes an AI-driven approach to enhance automation, scalability, and data accuracy in coral health assessments. The framework serves as a foundation for future prototype development, encouraging collaboration between marine conservation institutions and AI practitioners. Additionally, integrating more qualitative data from field experts can improve the realism and effectiveness of the proposed system, ensuring its practical application in reef management efforts.

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