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COMPARATIVE EVALUATION OF DEEP LEARNING ARCHITECTURES FOR CORAL BLEACHING DETECTION USING IMAGE RECOGNITION

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ABSTRACT

Coral reefs are vital marine ecosystems supporting biodiversity and coastal communities but face threats from climate-induced coral bleaching. Traditional assessment methods rely on manual visual surveys that are labor-intensive, time-consuming, and difficult to scale. This study presents Smart Coral Diagnostics, an AI-powered web system utilizing Convolutional Neural Networks to automate bleaching detection from underwater images. A mixed-method approach integrates development with expert evaluation, comparing architectures like GoogleNet, EfficientNet, MobileNet, ResNet50, and YOLOv8. Results show GoogleNet achieved the highest classification performance at 81.82% accuracy, surpassing EfficientNet's 79.74%. Implemented via Next.js and FastAPI, the system features automated image analysis, geotagging, and map-based visualization. Evaluation with Coastal Conservation and Education Foundation experts indicates current practices face severe resource constraints. While noting accuracy limitations, experts reported improved time efficiency and reduced labor. Ultimately, the system offers a scalable framework to enhance marine conservation efforts..

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.

To address the limitations of traditional coral monitoring amid rising environmental threats, this study develops an AI-based image analysis model integrated into an open-source web platform. This scalable solution enables both the public and researchers to conduct rapid, large-scale assessments, supporting timely marine conservation interventions.

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

supports 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, The survey results show a clear trend in user feedback across the six value propositions. Respondents strongly agreed on the system's operational benefits, with time efficiency receiving the highest rating at a mean of 4.7, followed closely by ease of use at 4.3. Labor requirements and cost effectiveness both achieved a positive mean score of 4.1, showing that users agree the system reduces traditional workloads and expenses. Scalability also received a positive verdict with a mean of 3.7, meaning users agree the system can be scaled up effectively. However, accuracy revealed a major concern, scoring a mean of only 1.8, which indicates that users strongly disagree with the system's current accuracy levels. Overall, while the software is highly praised for saving time and being user friendly, improving the core AI accuracy remains the main requirement for user trust.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, provides 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 adopts a qualitative research approach focused on the development of an AI-powered image recognition conceptual framework for coral bleaching detection. The research encompasses four primary components: (1) the collection of qualitative insights from documents and operational reports provided by the Coastal Conservation and Education Foundation (CCEF), (2) the assessment of limitations associated with conventional coral reef monitoring through expert diver surveys, (3) the comparative evaluation of existing machine learning architectures, and (4) the design of a conceptual web-based framework refined through expert usability assessment. Rather than employing conventional sample size computation, the study utilizes a total population sampling strategy due to the client-centered and highly specialized nature of the proposed system. Given the limited number of domain experts available, this approach ensures a comprehensive and context-specific evaluation that supports the development of a practical IT-based conservation solution.

The participant group consists of 20 key informant divers actively engaged in marine conservation initiatives across multiple organizations, including six core representatives from CCEF, a recognized institution dedicated to marine ecosystem protection in the Philippines.Data collection was conducted through a structured four-phase methodology aligned with the study's research objectives. The first phase involved an extensive review of secondary data sources, operational protocols, and technical reports from CCEF to establish baseline coral bleaching assessment procedures and monitoring practices. The second phase employed digitally distributed surveys administered to the 20 expert divers to examine the labor demands, operational constraints, and scalability limitations associated with traditional reef assessment techniques. The third phase transitioned to computational experimentation, wherein multiple machine learning algorithms were evaluated and compared using relevant performance metrics to identify the most suitable framework for coral bleaching classification. The fourth phase re-engaged the same cohort of expert participants to conduct usability testing of the proposed web-based system and complete post-evaluation questionnaires measuring perceived efficiency, usability, and overall user experience.

The study further applies a mixed-methods analytical framework integrating both statistical and interpretative approaches to evaluate whether the proposed AI-assisted image recognition system demonstrates improved user acceptance and operational potential compared with existing coral bleaching assessment practices. Descriptive statistical analysis was employed to summarize, organize, and interpret the collected data through measures such as frequency distributions, percentages, means, and standard deviations. This quantitative component provides a structured numerical representation of user perceptions and system performance, enabling the identification of prevailing trends and evaluative patterns that inform the overall assessment of the proposed framework.

3. RESULT AND DISCUSSION

The evaluative findings and survey-derived metrics obtained from marine conservation professionals affiliated with the Coastal Conservation and Education Foundation (CCEF) reveal significant operational patterns, methodological constraints, and system performance indicators relevant to coral reef monitoring practices. A total of 20 practitioners were invited to participate in the assessment of both the field-based monitoring environment and the proposed AI-assisted automated tracking platform, resulting in a 50% response rate ((n = 10)). Despite the limited sample size, the respondents constituted a highly specialized expert cohort, thereby providing contextually rich and domain-specific evaluative data.

The analytical framework synthesizes three principal dimensions of investigation: (1) the operational inefficiencies and scalability limitations associated with conventional coral bleaching assessment methodologies, (2) the computational viability and comparative performance of selected deep learning architectures, and (3) the expert participants' evaluative judgment regarding the system's practical utility, usability, and potential applicability within real-world marine conservation and ecological monitoring initiatives.

Operational Limitations of Traditional Coral Monitoring

The initial assessment of the 10 expert practitioners confirmed that current coral monitoring methods are defined by severe operational and administrative bottlenecks. Interestingly, the most significant challenges identified by field teams were not centered around in-water data collection or active diving logistics, but rather the post-fieldwork tasks required to process raw data into actionable intelligence

Table 1: Key fieldwork challenges and workflow bottlenecks ($n=10$)

Category	Monitoring Workflow Challenge	Frequency	Percentage (%)
Post-Field Bottlenecks	Species Identification	90%	90%
	Report Preparation	80%	80%
	Data Entry / Records Management	70%	70%
Scalability Barriers	Time Constraints / Strict Dive Windows	70%	70%

The data underscores that taxonomic Species Identification is the single most intensive task (90%), requiring meticulous evaluation of fine corallite structures. This is closely followed by manual Report Preparation (80%) and tedious Data Entry (70%).These administrative hurdles are heavily compounded by systemic scalability barriers, specifically Time Constraints (70%) and Limited Manpower (70%). This resource-constrained environment creates a critical monitoring gap across regional conservation areas.

As a direct consequence of these manual limitations, 70% of the surveyed respondents reported that more than 50% of their target reef area remains completely unassessed annually. This baseline reality establishes a clear demand for automated image-recognition frameworks to complement existing field expertise.

Technical Evaluation of Machine Learning Architectures

To address the operational bottlenecks of manual identification and color matching, a rigorous technical evaluation was conducted to assess the viability of deep learning models for automated classification. Identifying coral bleaching represents a highly complex, fine grained computer vision task characterized by adverse environmental variables including shifting marine irradiance, water turbidity, and morphological variations within benthic communities.

Consequently, several Convolutional Neural Network architectures were trained and benchmarked to identify the optimal framework for integration into the web application.

Table 2: Performance metrics of evaluated CNN models

Model	Accuracy	Precision	Recall	F1 Score
GoogleNet	81.82%	83.37%	81.82%	81.62%
EfficientNet	79.74%	81.26%	79.74%	79.74%
VGG16	23.90%	33.10%	23.90%	13.91%
AlexNet	17.66%	3.12%	17.66%	5.30%

The empirical evaluation demonstrates a profound performance divergence between modern deep learning frameworks and legacy architectures. Advanced networks exhibited robust feature extraction capabilities, with GoogleNet achieving the highest classification accuracy at 81.82%, followed closely by EfficientNet at 79.74%. These highly optimized frameworks successfully mapped subtle chromatic variations and minor structural changes in coral tissue, allowing for reliable health assessments under variable underwater conditions.

Conversely, legacy architectures such as VGG16 and AlexNet underperformed drastically, demonstrating a complete systemic failure to classify bleaching states effectively. These early generation models lack the structural depth and specialized feature reuse mechanisms, such as residual connections or

inception modules, required to resolve highly complex marine imagery. Their low precision and recall scores render them entirely unsuited for deployment in real world marine conservation or defense operations. Based on these quantitative findings, modern deep learning architectures like GoogleNet provide the necessary computational framework to support automated subsea surveillance.

Comparison with Traditional Methods

This section evaluates the operational viability of the proposed AI framework through a comparative analysis against baseline, manual diver slate methodologies. Target respondents quantified their level of agreement regarding the system's capacity to deliver enhanced performance across six critical operational dimensions: temporal efficiency, labor optimization, scalability, data fidelity, ergonomic utility, and fiscal cost-effectiveness

Table 3. User's agreement on the system performance compared to traditional methods

Statement	Mean	Interpretation
Time Efficiency	4.7	Strongly Agree
Labor Requirements	4.1	Agree
Scalability	3.7	Agree
Accuracy	1.8	Strongly Disagree
Ease of Use	4.3	Strongly Agree
Cost Effectiveness	4.1	Agree

The empirical data delineates a polarized user perception regarding the system current operational efficacy. The AI framework demonstrated exceptional utility in optimizing workflow dynamics, evidenced by the high consensus on Time Efficiency ($\mu = 4.7$) and Ease of Use ($\mu = 4.3$). These metrics suggest that the automation pipeline successfully mitigates the cognitive load and temporal constraints inherent to manual underwater data logging.

Furthermore, positive indications for Labor Requirements ($\mu = 4.1$) and Cost Effectiveness ($\mu = 4.1$) validate the system capacity to reduce resource expenditures and streamline subsea survey logistics. Scalability ($\mu = 3.7$) similarly achieved a favorable consensus, indicating potential for broad deployment across larger marine spatial scales.

However, a critical vulnerability was identified regarding data fidelity. Accuracy received a profoundly low evaluation ($\mu = 1.8$, Strongly Disagree), representing a significant bottleneck for user adoption. In defense and marine research contexts, decision making relies heavily on high precision data; thus, the current margin of error within the AI predictive or classification outputs severely undermines its operational utility.

4. CONCLUSION

This study demonstrates the potential of "Smart Coral Diagnostics" as an AI-assisted framework for enhancing coral bleaching assessment and reef monitoring processes. Although expert evaluation revealed limitations in the prototype's current predictive accuracy and operational efficiency, respondents still recognized its capacity to reduce the labor intensity, time requirements, and logistical burden associated with conventional manual assessment techniques. The findings further suggest that convolutional neural network architectures such as GoogleNet may contribute to mitigating existing monitoring gaps and data bottlenecks that continue to constrain large-scale reef surveillance initiatives.

This research contributes to the emerging body of literature on AI-assisted marine conservation by demonstrating the feasibility of integrating automated diagnostic technologies into coral reef monitoring methodologies. Nevertheless, the results indicate that the system requires further optimization, particularly through improvements in classification accuracy, expansion and diversification of training datasets, and rigorous field validation across varying environmental conditions. Future investigations should focus on model refinement, longitudinal performance evaluation, and real-world deployment testing to further assess the system's reliability, scalability, and applicability in marine conservation and ecological monitoring programs.

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