JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A REVIEW ON DIAGNOSTIC AND SURVEILLANCE TECHNIQUES FOR CORAL ECOSYSTEM HEALTH

[1]Varshini, [2]Sudarshan K, [3]Sanvi S Shetty, [4]Swathi , [5]Harshini P K
[1]Second year B.E Student , [2]Associate Professor, [3]Second year B.E Student , [4]Second year B.E Student Student, [5]Second year B.E Student
[1]Department of Information Science and Engineering
[1]Srinivas Institute of Technology, Mangaluru, India.

Abstract **:**Coral reefs cover less than 0.2% of the ocean floor, but don't let their small size fool you—they're some of the most important ecosystems in the sea. Not only do they support over a third of all marine life, but they also provide huge ecological and economic benefits to us humans. Unfortunately, pollution, climate change, and unsustainable human activity are posing an increasing threat to these ecosystems. Conventional techniques for assessing the health of reefs are frequently laborious, necessitate professional advice, and are difficult to scale.

Recent advances in remote sensing and AI are transforming how we monitor coral reefs. By leveraging deep learning models like CNNs, transfer learning (VGG19, DenseNet-169), object detection (YOLOv8), and SVMs, researchers can now classify reef images, segment underwater scenes, and analyze satellite data with impressive accuracy. These tools are proving especially powerful for tracking coral bleaching, assessing reef health, and detecting long-term changes in reef coverage—helping us protect these vital ecosystems more effectively than ever before.

Even in remote marine environments, real-time, affordable reef monitoring is made possible by the combination of image enhancement methods, geolocation information, and optimisation for low-power edge devices like the Jetson Nano. There are still obstacles to be addressed, such as standardising the metrics used to measure coral reef health (such as the Coral Reef Health Index), increasing the variety of training datasets, and taking into account ecological elements that are invisible in photos, like fish biomass.

In order to make coral reef conservation initiatives more scalable and sustainable, this review addresses the present advantages and disadvantages of AI-driven approaches to coral reef monitoring and suggests future directions, such as hybrid modelling, combining various data sources, and creating lightweight solutions.

Index terms- Coral Reef Monitoring, Deep Learning, (CNNs) Convolutional Neural Networks, Transfer Learning, VGG19, DenseNet-169, YOLOv8, Support Vector Machines (SVMs), Remote Sensing, Semantic Segmentation, Detection of Coral Bleaching, Image Enhancement, Edge Computing, Jetson Nano, Coral Reef Health Index (CRHI), Protection of the Environment, Underwater Image Analysis, Marine Biodiversity, and Multimodal Data Fusion.

I.INTRODUCTION

Coral reefs are among the most vibrant and intricate ecosystems on Earth. Though they cover less than 0.2% of the ocean floor, they support a staggering 35% of all marine life. Beyond their ecological importance, they act as nature's coastal shields, protecting shorelines from erosion, while also fueling fisheries, tourism, and biodiversity. Millions of people rely on these underwater wonderlands for their livelihoods, making them indispensable to both marine health and human economies.

However, a combination of natural and human stressors is posing a growing threat to coral reefs [1][2]. Widespread reef degradation and more frequent and severe coral bleaching have been caused by rising ocean temperatures, acidification, pollution, sedimentation, and unsustainable tourism [8]. In the Nature Recreation Park of Sangiang Island, Indonesia, for instance, the increase in marine tourism has put additional strain on already delicate reef systems, underscoring the urgent need for continuous and sustainable monitoring [7]. Since it is estimated that more than 40% of reef systems worldwide are in danger, it is more crucial than ever to implement efficient monitoring and protection measures.

Diver-based visual surveys, which continue to be an important technique for gathering in-situ data, have historically been used to evaluate the health of reefs [4]. However, the availability of divers, changing environmental conditions, and scalability problems make these surveys limited. Additionally, they take a lot of time, are prone to human bias, and are challenging to repeat reliably over extended periods of time or over wide areas. Interest in technology-driven solutions that provide standardised, scalable, and real-time monitoring has increased as a outcome of these difficulties.

Thanks to breakthroughs in AI and deep learning, we can now automate coral reef monitoring like never before. Techniques like Convolutional Neural Networks (CNNs) are proving especially powerful, making underwater image analysis faster and more accurate than traditional methods. With remarkable accuracy, models like VGG19, DenseNet-169, and YOLOv8-m are being used to categorise coral health conditions, such as healthy, partially bleached, or fully bleached corals. Every architecture has special advantages. While DenseNet-169 can detect more subtle signs of coral stress, VGG19 is best at detecting broad visual features [6][2]. Furthermore, edge computing-optimized lightweight models such as YOLOv8-m enable real-time classification in field settings with limited resources.

To keep tabs on vast coral reef systems, scientists are now turning to remote sensing—using satellites and drones alongside deep learning. These tools allow researchers to track reef health and structural shifts across huge areas and over decades. A great example? In the Red Sea, machine learning paired with satellite imagery has successfully monitored coral cover changes for nearly 20 years, proving how powerful this combo can be for long-term conservation.

Even with these developments, a number of obstacles still exist. Looking at results across multiple studies and geographical areas is challenging because there isn't enough standardisation in Coral Reef Health Index (CRHI) methodologies [7]. Furthermore, because they can't yet be accurately recorded by photography alone, some ecological variables—such as fish biomass and invertebrate populations—remain largely dependent on manual field surveys.

Tackling these challenges will require collaboration across fields. By weaving together deep learning, remote sensing, marine biology, and image-boosting techniques—like CLAHE, gamma correction, and Bright Channel Prior—we can sharpen underwater visuals and supercharge the AI's accuracy [4]. These techniques facilitate the production of comprehensive reef health maps that aid in evidence-based conservation and policymaking when combined with spatial tagging and geolocation tools such as XML metadata.

Recent advancements in AI-powered coral reef monitoring are compiled in this review paper, with an emphasis on Object localization, Pixel-wise labeling, image classification, and geospatial data integration. It seeks to give a clear picture of where we are now and where we can go in order to create scalable, effective, and dependable tools for coral reef conservation by assessing the upsides and downsides of existing technologies. By doing this, it supports international initiatives to protect these priceless ecosystems from the effects of rapidly changing environmental conditions.

II. LITERATURE REVIEW :

[1]AI is revolutionizing how we monitor ecosystems and environments. Cutting-edge deep learning models—especially CNNs such as VGGNet, ResNet, and Inception—now excel at analyzing images, from identifying wildlife to tracking habitat changes. Marine scientists are also leveraging a clever trick: transfer learning. By fine-tuning models pre-trained on massive datasets like ImageNet, they can achieve accurate results even with limited labeled data—a game-changer for ocean research. CNNs have shown promise in automating the classification of coral health through a number of successful applications in coral reef monitoring and biodiversity assessment. The robustness of these systems is still impacted by issues like data imbalance, a lack of diversity in datasets, and the difficulty of extrapolating models to different marine environments.By addressing these issues through meticulous dataset curation, training optimisation, and thorough performance evaluation, the current study builds on this foundation by classifying coral images into healthy and bleached categories using a transfer learning-based VGG19 model.

[2]Earlier attempts to classify corals in underwater images relied on traditional computer vision techniques, where researchers had to manually define what features to look for. But these methods struggled with the messy, unpredictable conditions of the ocean. Enter deep learning—especially CNNs—which lets models automatically learn intricate patterns directly from images, boosting both accuracy and reliability. Networks like VGGNet have shown real promise in coral health assessments, particularly for spotting the difference between healthy and bleached corals. That said, most early work stuck to simple 'healthy vs. bleached' sorting and didn't account for real-world needs like real-time analysis or running on portable devices. Newer models like YOLOv8 are changing that by delivering speed without sacrificing precision, making them ideal for field use. Our study takes this further: we adapt YOLOv8-m to classify multiple coral health states, supercharge its performance with data augmentation and transfer learning, and optimize it for edge devices like the Jetson Nano—paving the way for live, on-the-spot reef monitoring.

[3] To monitor coral reefs across vast areas, scientists are increasingly turning to satellites—like NASA's Landsat and the EU's Sentinel—which provide a bird's-eye view of reef health on a scale divers could never achieve alone. Early attempts frequently used site-specific models that worked well in specific locations but had trouble generalising to other reef environments. Classification systems that considers habitat diversity and regional variation are crucial for consistent monitoring across larger ecological areas, according to researchers like Roelfsema (2018), Garza-Pérez (2004), and Stuart-Smith (2021). These observations emphasise the necessity of creating models smart enough to recognize broad environmental trends while mitigating the bias associated with particular sites. The current study builds on this foundation by presenting a more generalised ML approach leveraging SVM's kernel methods for robust classification using depth-invariant indices (DII) obtained from Landsat 7 and 8 imagery. The model's adaptability is evaluated at multiple Red Sea sites and validated against underwater visual census data, providing a more scalable option for coral reef monitoring than site-limited applications.

[4] Thanks to advances in AI-powered image analysis—especially deep learning tools that can pinpoint and label every pixel in coral reef photos—we've radically improved how we study and protect these ecosystems.These methods, which provide higher accuracy in recognising the intricate features present in underwater environments, have mainly supplanted earlier block-based classification techniques. This breakthrough was made possible by open-source datasets like EILAT, UCSD Mosaics, and SSPQICD; however, these datasets have drawbacks, such as limited data across time, sparse annotations, and no geographic references. Data augmentation, photogrammetric preprocessing, and deep convolutional neural networks are examples of tools from mainstream computer vision that researchers have modified to meet the unique requirements of underwater coral imagery in order to get around these problems. Building on these developments, the current study assesses a variety of state-of-the-art and specially designed semantic segmentation models and presents a new, highly annotated, multi-temporal dataset. The goal of this strategy is to offer a more accurate and scalable way to map and track coral ecosystems.

[5] Coral reef monitoring has historically depended on manual surveys and simple photogrammetry, both of which can be laborious and unreliable, particularly in underwater settings where problems like image distortion and inadequate lighting are frequent. Early methods for analyzing underwater images often struggled with accuracy and consistency. But everything changed with deep learning - especially Convolutional Neural Networks (CNNs). These AI systems have dramatically improved our ability to detect and classify marine life, making underwater research far more reliable.However, there are still enduring issues, such as the scarcity of data, the difficulty of extrapolating across different kinds of reefs, and the intrinsically low quality of underwater photos. Even though popular models like U-Net and ResNet have demonstrated promise, they aren't always designed to handle the special qualities of coral reefs, like their intricate shapes and subtle colour variations. Furthermore, although datasets like UCSD Mosaics and EILAT have aided advancements in the field, they frequently have inconsistent geospatial information and sparse annotations. The current study offers a more comprehensive solution to these issues by integrating geospatial visualisation tools, deep learning architecture tailored for coral features, and image enhancement to create an integrated system for precise coral classification and health monitoring.

[6] Coral reef monitoring has evolved dramatically. Early methods relied on manual feature extraction and basic classifiers like SVMs, which often failed to handle underwater challenges—poor lighting, water distortion, and corals' intricate shapes. Today, deep learning (especially CNNs such as AlexNet, ResNet, and Inception) has transformed the field, delivering far more accurate and automated analysis. The capacity of DenseNet and VGG architectures to capture both high-level and detailed visual features has drawn special attention, making them applicable to a variety of medical and environmental imaging tasks. In particular, VGG19 has proven successful in spotting more general contextual patterns, whereas DenseNet-169 has demonstrated strength in identifying subtle indications of coral bleaching.Building on this approach, our study pits two leading AI models—DenseNet-169 and VGG19—against each other, testing them on a curated dataset of coral images. The goal? To identify which system delivers the best blend of accuracy and scalability for monitoring reef health, ultimately supporting smarter conservation efforts.

[7] Due in large part to regional variations in environmental threats, monitoring objectives, and data availability, Coral Reef Health Index (CRHI) models have historically varied in their design and input variables. In order to support more comprehensive and scalable assessments, many studies have integrated ecological and biophysical indicators, such as coral cover, algal presence, sea surface temperature (SST), chlorophyll-a levels, and turbidity, while also increasingly integrating data from remote sensing. However, the potential for complete automation is limited because important indicators like fish biomass, coral recruitment, and benthic diversity still mainly rely on in-situ field surveys. Recent studies have responded by favouring the use of sophisticated statistical methods, such as stepwise regression and Generalised Additive Mixed Models (GAMM), to pinpoint what matters most variables influencing reef resilience and health. The Akaike Information Criterion (AIC) is one of these tools that has become well-liked because it simplifies CRHI models by concentrating on what really matters predictors, lowering the necessity of data collection without compromising accuracy. This change reflects a growing effort to develop accessible and accurate CRHI systems, especially for regions with little funding for routine field monitoring.

[8] Key indicators such as fish biomass, species diversity, live coral cover, and the ecosystem's resilience to natural and human stressors are frequently used to evaluate the health of coral reefs. Among these, live coral cover has been widely acknowledged as a key indicator of reef resilience, especially for the delicate but quickly growing Acropora species. Coral growth is severely hampered by sedimentation, particularly close to river mouths, according to studies by Burke et al. and others. Simultaneously, the decrease in herbivorous fish populations, typically brought on by overfishing, is frequently linked to an excess of macroalgae, further upsetting the delicate balance of reef ecosystems. Because unstable rubble can hinder coral larvae's ability to settle and grow, the stability of the seafloor substrate is also essential. On the other hand, strong populations of herbivorous fish, low levels of macroalgae, and firm, stable substrates are characteristics of healthy reefs that indicate a robust, thriving ecosystem. Coral Reef Health Indices (CRHI), which integrate biological and environmental data to produce precise evaluations of reef condition, are based on these ecological insights.

III. CHALLENGES :

The scarcity of high-quality, well-annotated datasets is one of the primary obstacles to applying deep learning for coral reef health monitoring. It is intrinsically challenging to obtain clear, consistent underwater imagery because of things like fluctuating light levels, turbid water, and obstacles from debris or marine life. Furthermore, the quality of photos taken at different times or with different cameras can differ significantly. These discrepancies can have a significant impact on a model's performance and applicability in different contexts.The shape, colour, and species of coral reefs vary greatly depending on where they are found, so a model that has been trained on one reef may not perform well on another unless it has been retrained or adjusted. The challenge is further compounded by the fact that correctly labelling coral images necessitates specialised knowledge and that manual annotation is expensive and time-consuming, which reduces the quantity of training data.

The amount of processing power required to run and train these deep learning models is another significant obstacle. Even though models like YOLOv8 and DenseNet have remarkable accuracy, they require a lot of processing power, which isn't always available in the field, particularly on low-power gadgets like Jetson Nano boards or underwater drones. This results in a difficult trade-off between energy efficiency, speed, and model complexity. A further layer of technical complexity is added when these models are incorporated with other technologies, such as remote sensing, geospatial mapping, and underwater survey techniques, necessitating close interdisciplinary cooperation. Lastly, ethical and practical considerations should be taken into account. AI systems should be developed to minimise disturbance to marine life and to take into account the socioeconomic effects on nearby communities that depend on coral reefs for their livelihoods.

IV. SIGNIFICANCE :

By combining cutting-edge technologies like deep learning, remote sensing, as well as sophisticated image processing, this study holds promise for revolutionise coral reef monitoring. Because they support amazing biodiversity and give coastal communities vital ecosystem services, coral reefs are vital to life as we know it. However, the demand for more effective, scalable, and accurate monitoring has yet not been greater as coral reefs face previously unheard-of risks from pollution, climate change, and human activity. Manual surveys and on-site data collection are examples of traditional coral health assessment techniques that are time-consuming, expensive, and frequently have a narrow scope. This study presents the potential for automated, real-time coral health monitoring by utilising deep learning models, such as convolutional neural networks (CNNs), and incorporating remote sensing data. This would lessen the need for human intervention and increase the parameters of conservation efforts. Large-scale marine conservation can benefit greatly from these models' skill in evolving with unfamiliar and unseen coral reefs thanks to techniques like transfer adaptive model refinement.

The current work is unique because it uses machine learning and remote sensing to develop Coral Reef Health Indices (CRHI), which provide a more thorough and international method of reef health monitoring. For instance, researchers can continuously monitor large and difficult-to-reach reef areas using satellite imagery and underwater photogrammetry, without being constrained by time or manpower. Decision-makers can more successfully identify at-risk areas and prioritise conservation efforts by integrating this data with geospatial information. Better long-term management strategies can result from our increased understanding of how coral reefs change and evolve, which is made possible by the ability to track coral health over time using historical data and multi-temporal imagery. In the end, this study not only promotes marine conservation but also shows how AI and remote sensing technologies have the potential to be used more broadly in ecosystem observation, providing scalable, easily accessible, and trustworthy instruments to safeguard coral reef ecosystems globally.

V. FUTURE SCOPE:

Deep learning and remote sensing-based coral reef monitoring has a very bright future ahead of it, full of exciting opportunities for advancement and creativity. There is a genuine chance to create more robust, flexible models that can recognise a greater variety of coral species and health states as more high-resolution, well-annotated coral reef datasets become available. Multi-class classification schemes that go beyond the straightforward healthy/bleached categories, such as labels like partially bleached, algae-covered, or disease-affected corals, could be investigated in future studies.These models would also become statically robust and adaptable in various underwater environments if datasets were augmented to incorporate reefs from around the world with different lighting conditions, water turbidity, and habitat types. Furthermore, by supplementing the standard 2D image analysis with depth and topographic information, combining 3D modelling and structure-from-motion techniques may yield a richer, more comprehensive image.

In terms of technology, these models could be used on edge computing devices such as the NVIDIA Jetson series, underwater drones, and autonomous monitoring systems to enable real-time coral health assessments in the field. In remote reef systems or marine protected areas with little human monitoring, this would be extremely helpful. Predictive models that foresee bleaching events may also be developed by combining deep learning with additional data sources, such as temperature, salinity, and pH sensors. Better management techniques and quicker reactions would be possible with these early-warning systems. The protection of coral reefs and biodiversity worldwide will ultimately depend on the cooperation of ecologists, data scientists, and policymakers in transforming these technological advancements into practical conservation measures.

VI. CONCLUSION

Coral reefs rank among the most cost effective and ecologically valuable ecosystems on the planet, but they are also extremely vulnerable. Their survival is in jeopardy due to the frequent bleaching events brought on by pollution, ocean acidification, rising sea temperatures, and human activity. Despite their importance, traditional reef health monitoring techniques are unable to keep up with the scope and urgency of the problem. Manual surveys frequently lack the comprehensive, real-time data required for early warning systems and extensive conservation initiatives, are slow, and are region-specific. Fortunately, developments in artificial intelligence, especially deep learning and remote sensing technologies, have made it possible to monitor, categorise, and track coral reef health at scale in a powerful new way. These automated, real-time solutions have the aptitude to replace or even supplement conventional techniques.

Using Convolutional Neural Networks (CNNs) for image-based classification, object detection models such as YOLOv8, and semantic segmentation for in-depth coral analysis, this review summarises the most recent advancements in the field. It also emphasises how satellite-based remote sensing can be used for extensive, long-term monitoring. The ability to differentiate between healthy, partially bleached, and fully bleached corals has been demonstrated by models such as VGG19, DenseNet-169, and custom deep convolutional networks. Furthermore, even with smaller datasets, methods like data augmentation, transfer learning, and hyperparameter optimisation have contributed to increased model accuracy. The creation of generalised Coral Reef Health Indexes (CRHI) that are adapted to different ecological and geographic regions has been made possible by the invaluable monitoring of reef health indicators such as coral cover, algae spread, sea surface temperature anomalies, and plume intrusion by remote sensing platforms like Landsat and Google Earth Engine.

Additionally, the review highlights the necessity of combining various approaches, such as combining satellite data with field surveys, applying statistical models like AIC and correspondence analysis, improving underwater images with photogrammetric corrections, and creating simple yet effective reef health indices. The high computational demands of deploying AI models in remote marine environments, the lack of datasets, the quality of underwater images, and the difficulty of generalising models across various reef systems persist despite the advancements. But there is a lot of promise for the future of coral reef monitoring thanks to the convergence of artificial intelligence, computer vision, environmental science, and geospatial analytics.

This review concludes by demonstrating that AI-powered systems are more than just practical instruments; they have the potential to serve as a critical component in international efforts to conserve coral reefs. These technologies can support informed decision-making, early intervention, and public awareness-raising by facilitating real-time, affordable, and repeatable assessments. In the future, combining AI with edge computing, cloud platforms, and citizen science may increase access to coral reef data, enabling governments and local communities to play a more active part in reef conservation. In order to guarantee that these technological developments have a significant ecological impact and help protect one of our planet's most significant ecosystems for future generations, the interdisciplinary nature of this work necessitates constant cooperation between marine biologists, data scientists, remote sensing specialists, and policymakers.

REFERENCES

[1] P. Kaushik, R. S. Rawat, and K. S. Gill, "Deep Diving into VGG19 CNN Model driven Coral Health Monitoring for Sustainable Reef Conservation," 2024 IEEE 3rd World Conference on Applied Intelligence and Computing (AIC), pp. 1–6, 2024, doi: 10.1109/AIC61668.2024.10731097.

[2] V. K. Vyshnav, R. Sooryanarayanan, and T. V. Madhav, "Analysis of Underwater Coral Reef Health Using Neural Networks," The AUV Society, IIITDM Kancheepuram, Chennai, India, 2024.

[3] J. J. Gapper, S. P. Tiwari, S. Maharjan, M. A. Qurban, W. Li, E. Linstead, and H. El-Askary, "A generalized machine learning model for long-term coral reef monitoring in the Red Sea," Earth Systems Science and Data Solutions Lab, Chapman University, Orange, CA, USA, and collaborating institutions in Saudi Arabia and Egypt, 2024.

[4] M. Li, H. Zhang, A. Gruen, and D. Li, "A survey on underwater coral image segmentation based on deep learning," State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, China, and ETH Zürich, Switzerland, 2024

[5] S. Prathibha, V. G. Vivekanandan, R. S. Kamathe, H. V. Vijaykumar, G. Bhuvaneswari, G. Manikandan, G. Sabarinathan, and M. N. S. Mustafa, "Reef Vista: Deep Learning-Powered Underwater Coral Reef Monitoring," 2024.

[6] G. P. M., P. K. G., B. T., P. T. Manur, and S. V. Kumar, "Exploring Machine Learning Models for Coral Reef Classification from Images," Department of Artificial Intelligence & Machine Learning, Jyothy Institute of Technology, Bengaluru, India, 2024.

[7] M. Hafizt, N. S. Adi, M. Munawaroh, S. Wouthuyzen, and A. S. Adji, "Coral Reef Health Index Calculation from Remote Sensing Data: A Review," International Journal of Conservation Science, vol. 14, no. 1, pp. 267–284, Jan.–Mar. 2023. doi: 10.36868/IJCS.2023.01.17.

[8] Idris, A. R. Putri, C. Adiwijaya, M. Gilang, P. Santoso, B. Prabowo, F. Muhammad, W. Andriyani, D. F. Lestari, W. A. Setyaningsih, and N. P. Zamani, "Assessment of Coral Reefs Health in Nature Recreation Park (TWA) Sangiang Island, Banten," Marine Science and Technology, IPB University, and Indonesian Coral Reef Foundation (Terangi), West Java, Indonesia, 2024.