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Automated Detection of Coral Bleaching Using YOLOv8: A Deep Learning Approach for Reef Health Monitoring

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ABSTRACT

Coral reefs are invaluable ecosystems supporting biodiversity and providing essential ecosystem services. However, they are increasingly threatened by various stressors, including coral bleaching induced by rising sea temperatures. Timely detection of bleached corals is critical for effective conservation and management efforts. In this study, we propose a novel approach utilizing YOLOv8, a state-of-the-art deep learning algorithm, for the automated detection of bleached corals from underwater imagery. We collected a diverse dataset of coral reef images encompassing both healthy and bleached corals across different geographical locations. We then fine-tuned the YOLOv8 model on this dataset to accurately identify and delineate bleached corals. Our findings show that the suggested approach outperforms conventional image processing techniques in the precise and recall-rate detection of bleached corals. The developed model offers a promising tool for monitoring coral reef health on a large scale, enabling timely interventions to mitigate the impacts of coral bleaching and safeguard these vulnerable ecosystems.

Introduction

What is Coral?

Coral reefs are diverse marine ecosystems formed by coral polyps secreting calcium carbonate skeletons. They support a plethora of marine life, serve as breeding grounds, and provide coastal protection. Additionally, they sustain livelihoods through fishing, tourism, and pharmaceutical research.

Figure 1:Under Water Coral Reefs

Why are Corals important ecosystems?

Coral reefs are vital marine ecosystems, known as the "rainforests of the sea," due to their exceptional biodiversity and complex habitats. They serve as crucial nurseries and shelters for diverse marine species, supporting nutrient cycling and providing resources like food and shelter. Beyond sustaining marine life, coral reefs play a key role in protecting coastlines from erosion and storm surges, benefiting both ecosystems and human communities. Additionally, they contribute to economic activities such as fishing, tourism, and pharmaceutical research, providing livelihoods for millions worldwide. Overall, the preservation of coral reefs is essential for biodiversity conservation, coastal protection, and the well-being of both marine life and human societies.

What is Coral bleaching and factors contributing to coral bleaching?

Coral bleaching is the expulsion of symbiotic algae from coral tissues due to stress, leading to loss of vibrant colors and increased susceptibility to disease and mortality. The primary trigger is elevated water temperatures, often linked to climate change, while factors like ocean acidification, pollution, and overfishing exacerbate stress. Natural events like El Niño can worsen bleaching by causing widespread temperature anomalies. The frequency and severity of bleaching events have risen, endangering coral

Figure 2:Sample Coral Bleaching

reef ecosystems globally. Understanding these factors is crucial for developing mitigation strategies. Coral reef resilience against bleaching and other stresses can be increased by initiatives to lower greenhouse gas emissions, better water quality, and create marine protected areas, guaranteeing the reefs' survival for future generations.

Understanding the Global Coral Bleaching Crisis

A UNESCO World Heritage Site on Australia's northeastern coast, the Great Barrier Reef (GBR) is seriously threatened, particularly by coral bleaching made worse by warming seas. Coral bleaching disrupts the vital relationship between corals and algae, leading to widespread stress and mortality. This phenomenon not only harms the reef's aesthetic value but also jeopardizes the diverse species dependent on it for habitat and survival.

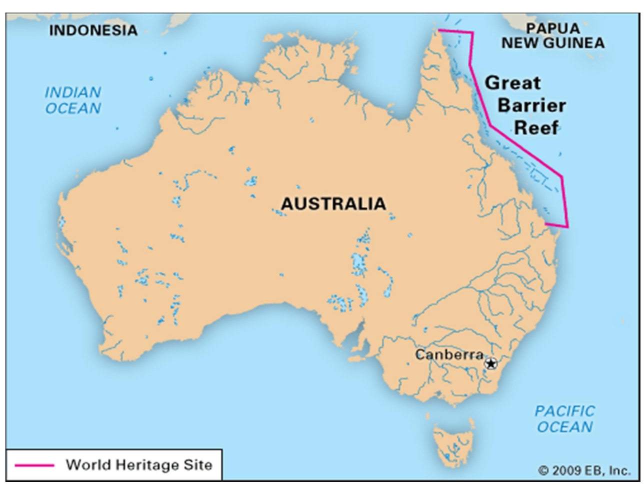

Figure 3: The Great Barrier Reef

Despite efforts, coral bleaching has caused extensive damage to the GBR, surpassing its ability to recover. Urgent action is imperative to address the root causes of coral bleaching and bolster the reef's resilience against future threats, emphasizing the critical need for conservation measures and climate change mitigation strategies. The Coral Triangle, likened to the "Amazon of the Seas," harbors rich coral reefs crucial for millions and diverse marine life. However, it faces unprecedented threats, notably coral bleaching. Rising sea temperatures, a consequence of climate change compounded by local stressors, induce widespread bleaching events. This disrupts the symbiotic relationship between corals and algae, leading to coral loss. Consequently, the intricate marine ecosystem suffers, impacting biodiversity and community livelihoods.

Figure 4: The Coral Triangle

Recent years have witnessed severe coral bleaching, devastating once-vibrant reef ecosystems and endangering marine biodiversity. The decline in coral cover not only diminishes the aesthetic appeal of the underwater landscape but also jeopardizes the socio-economic well-being of coastal communities reliant on reefs for food, tourism, and cultural identity. Despite conservation efforts, the escalating impact of coral bleaching highlights the pressing need for improved monitoring and management

Existing System:

Coral reef health monitoring is a multifaceted approach that employs a combination of techniques

- Field Surveys: Divers and underwater videography are used to directly assess coral cover, bleaching levels, and the presence of predators or diseases. This time-tested method provides detailed information but can be labor-intensive and expensive for large-scale monitoring.

- Satellite Monitoring: Satellites keep an eye on sea surface temperatures, a crucial indicator of coral bleaching risk. By measuring water temperature variations, scientists can identify areas susceptible to bleaching events and warn conservation efforts..

- **Proposed System:**

  Autonomous Underwater Vehicle (AUV) with Deep Learning-based Coral Bleaching Detection

  - Image Acquisition: The AUV will be equipped with a high-resolution camera capable of capturing underwater images of coral reefs.
  - Deep Learning Model for Coral Bleaching Detection: A pre-trained deep learning model, specifically designed to identify coral bleaching from underwater imagery, will be integrated into the AUV's onboard processing unit. A sizable collection of labelled underwater photos with samples of both healthy and bleached coral will be used to train this model.
  - Real-time Analysis and Decision Making: A deep learning model will be trained using the collected photos to analyses them in real time. The observed coral's health status (whether healthy or bleached) will be predicted by the model. Based on these predictions, the AUV can be programmed to follow pre-defined waypoints or adjust its path for further investigation of potentially bleached areas.
  - Data Transmission and Storage: The AUV will transmit the captured images, along with the corresponding bleaching detection results, to a designated onshore station for further analysis, data storage, and creation of coral health maps.

Advantages of the Proposed System:

- Autonomy and Scalability: This system leverages the autonomous nature of AUVs, enabling efficient and large-scale monitoring of coral reefs without relying on human divers.
- Real-time Detection and Response: The deep learning model facilitates real-time analysis of coral health, allowing for early detection of bleaching events and prompting timely intervention strategies.
- Data Richness: The system provides not only bleaching detection but also high-resolution images for further analysis of coral health metrics and reef ecosystems.

Literature Survey

Researchers and conservationists have been paying more and more attention in recent years to the use of deep learning approaches for bleaching coral detection. Deep learning is a kind of artificial intelligence (AI) that uses artificial neural networks to simulate how the human brain functions. It has promising potential for automated image analysis and pattern recognition, which makes it a useful tool for managing and monitoring coral reefs.

[1]In their 2022 paper, Gabriel Alejandro Bautista-Hernández, Delond Angelo Jimenez-Nixon, and Alicia María Reyes-Duke from the Faculty of Engineering at Universidad Tecnológica Centroamericana (UNITEC) in San Pedro Sula, Honduras used convolutional neural networks (CNNs) to conduct ground-breaking research on coral disease detection.. Their study aimed to identify healthy corals and those suffering from bleaching by harnessing the capabilities of CNNs. Through an incremental methodology comprising three phases of training, the researchers evaluated the algorithm's performance, achieving significant advancements in automated coral health assessment. With an average accuracy of 94.12% in identifying Stony Coral Tissue Loss Disease (SCTLD), a common coral disease in the Caribbean, they showed encouraging findings by training the algorithm on a dataset of 1,555 coral reef photos. This research serves as a cornerstone in the application of AI-driven approaches to coral reef conservation, offering insights into the potential of advanced technologies in safeguarding these vital marine ecosystems.

[2]In their pioneering work in marine ecology, A. Mahmood, M. Bennamoun, S. An, F. Sohel, F. Boussaid, R. Hovey, G. Kendrick, and R.B. Fisher automated the analysis of large-scale AUV imagery for coral reef annotation. Their 2016 research introduced novel computer vision and deep learning-based algorithms for the quick and precise annotation of underwater photos. The study aimed to address the limitations of manual annotation by developing advanced tools capable of automatically identifying and quantifying marine coral species. By leveraging deep learning techniques, particularly convolutional neural networks (CNNs), the authors proposed a classification method specifically tailored for coral reefs. Their research demonstrated the applicability of the proposed approach in annotating unlabelled mosaics of coral reefs in the Abrolhos Islands, Western Australia, facilitating the quantification of coral coverage and the detection of population trends. This pioneering work represents a significant advancement in coral reef monitoring and ecological research, offering transformative outcomes in terms of cost-effectiveness, speed, and accuracy.

[3]In their 2021 study published in Big Data Cogn. Comput., Sonain Jamil, Muhib Ur Rahman, and Amir Haider developed a Bag of Features (BoF) based deep learning framework for detecting bleached corals. Coral reefs, crucial for biodiversity and coastal protection, are threatened by factors like over-exploitation and climate change-induced bleaching. Their suggested method achieves an impressive 99.08% accuracy in feature extraction from coral reef photos by using deep convolutional neural networks and handmade descriptors. Additionally, they introduced a novel bleached coral positioning algorithm to precisely locate bleached corals within reef images, offering insights for conservation efforts and marine safety measures. This study represents a significant advancement in coral reef monitoring, promising enhanced understanding and protection of these vital ecosystems.

[4] Muthusamy Thamarai from Sri Vasavi Engineering College and S.P. Aruna from Skilltroniks Technologies employed deep learning convolutional neural network (CNN) techniques to identify stressed coral reefs in their study that was published in the Journal of Engineering and Information Sciences.Deep learning, a branch of machine learning, has proven effective in computer vision tasks, offering solutions for challenging problems. Coral reefs, vital ecosystems, have experienced significant degradation, with half of the planet's reefs lost since 1950. Preserving and restoring these reefs are critical for marine ecosystem balance. Using a bespoke CNN model and pre-trained models such as Resnet50 and Inception V3, the study sought to categorise coral reef photos into stressed and healthy groups. Through hyperparameter tuning, including adjustments to dropouts and batch normalization, the accuracy of pre-trained models improved to 70% and 55%, respectively. Additionally, the proposed CNN model achieved a maximum accuracy of up to 90% after optimization. The potential of deep learning in coral reef conservation is shown by this study, which also highlights how crucial it is to optimise neural network topologies for precise stressor identification and mitigation.

[5]Mari Grace Corruz, Emil Filipina, Maria Julia Santiago, Sheila Mae Uy, Cristian Lazana, and Argel Bandala collaborated on a study aimed at improving the accuracy of coral bleaching monitoring methods. Conducted at the Electronics Engineering Department, Polytechnic University of the Philippines, Manila, and the Electronics and Communications Engineering Department, De La Salle University, Manila, Philippines, the research focused on developing and implementing a mobile application capable of classifying bleached coral images from non-bleached ones using convolutional neural networks (CNNs).

Effective reef monitoring is crucial for assessing damage extent, evaluating the current state of Philippine coral reefs, and identifying potential areas for conservation efforts. The proposed system utilizes CNNs to classify the bleaching severity of corals and operates on Android phones running versions 4.0 to 11. To achieve a minimum accuracy of 90%, researchers determined that training the CNN with at least 3000 images is necessary. Moreover, specific camera settings, such as 0.92 MP resolution, -1 EV exposure value, and 1600 ISO sensitivity, yielded a 93% accuracy rate.

Additionally, the study evaluated the impact of seawater salinity and turbidity on the system's accuracy, concluding that variations within certain ranges do not significantly affect performance. Furthermore, the study assessed the accuracy of the GPS component used in the system, reporting a 95% accuracy rate. The researchers emphasized the importance of continuously improving the dataset to enhance the application's performance in future iterations.

This study represents a significant step toward leveraging mobile technology and CNNs for efficient and accurate coral bleaching monitoring, contributing to the conservation and management of coral reef ecosystems.

Method And Materials

What is YOLO?

One of the most widely used object detection techniques in machine learning is the YOLO (You Only Look Once) algorithm. It is renowned for its precision and real-time performance in identifying objects in pictures and videos. Here is a broad summary of the YOLO methodology:

What is YOLOv8?

A cutting-edge deep learning model called YOLOv8 was created for computer vision applications that require real-time object recognition. YOLOv8 has transformed object detection with its sophisticated architecture and state-of-the-art algorithms, making it possible to detect items accurately and effectively in real-time situations.

Deep learning models like YOLOv8 have become vital in various industries, including robotics, autonomous driving, and video surveillance. The ability to detect objects in real-time has significant implications for safety and decision-making processes. The YOLOv8 architecture utilizes computer vision techniques and machine learning algorithms to identify and localize objects in images and videos with remarkable speed and accuracy.

YOLO, short for You Only Look Once, made its debut in 2015 with the release of a groundbreaking research paper titled "You Only Look Once: Unified, Real-Time Object Detection." This research paper was authored by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. YOLO represented a significant advancement in real-time object detection, introducing a unified framework that revolutionized the field of computer vision.

Since its inception, YOLO has evolved and undergone several iterations, with each subsequent version building upon the advancements of its predecessors. The initial version, YOLOv1, introduced the concept of real-time object detection by dividing the input image into a grid and predicting bounding boxes and class probabilities. This approach allowed for the simultaneous detection of multiple objects within an image.

Building on the success of YOLOv1, subsequent versions such as YOLOv2 and YOLOv3 further refined the model's capabilities. These iterations introduced improvements in terms of accuracy and speed, incorporating techniques such as anchor boxes, feature pyramid networks, and multi-scale prediction to enhance object detection performance.

Today, the latest release of the YOLO series is YOLOv8. This version represents a significant leap forward in real-time object detection capabilities. With YOLOv8, researchers and developers can achieve state-of-the-art accuracy and speed in object detection tasks, making it a preferred choice for applications in robotics, autonomous driving, and video surveillance.

YOLOv8 Architecture: A Deep Dive

The first step to understanding the YOLO architecture is to understand that there are 3 essential blocks in the algorithm and everything will occur in these blocks, which are: Backbone, Neck and Head. The function of each block is described below

Backbone:

Function: The backbone, also known as the feature extractor, is responsible for extracting meaningful features from the input.

Activities:

- Captures simple patterns in the initial layers, such as edges and textures.
- Can have multiple scales of representation as you go, capturing features from different levels of abstraction.
- Willprovide a rich, hierarchical representation of the input.

Neck:

Function: The neck acts as a bridge between the backbone and the head, performing feature fusion operations and integrating contextual information. Basically the Neck assembles feature pyramids by aggregating feature maps obtained by the Backbone, in other words, the neck collects feature maps from different stages of the backbone.

Activities:

- Perform concatenation or fusion of features of different scales to ensure that the network can detect objects of different sizes.
- Integrates contextual information to improve detection accuracy by considering the broader context of the scene.
- Reduces the spatial resolution and dimensionality of resources to facilitate computation, a fact that increases speed but can also reduce the quality of the model.

Head:

Function: The head is the final part of the network and is responsible for generating the network's outputs, such as bounding boxes and confidence scores for object detection.

Activities:

- Generates bounding boxes associated with possible objects in the image.
- Assigns confidence scores to each bounding box to indicate how likely an object is present.
- Sorts the objects in the bounding boxes according to their categories.

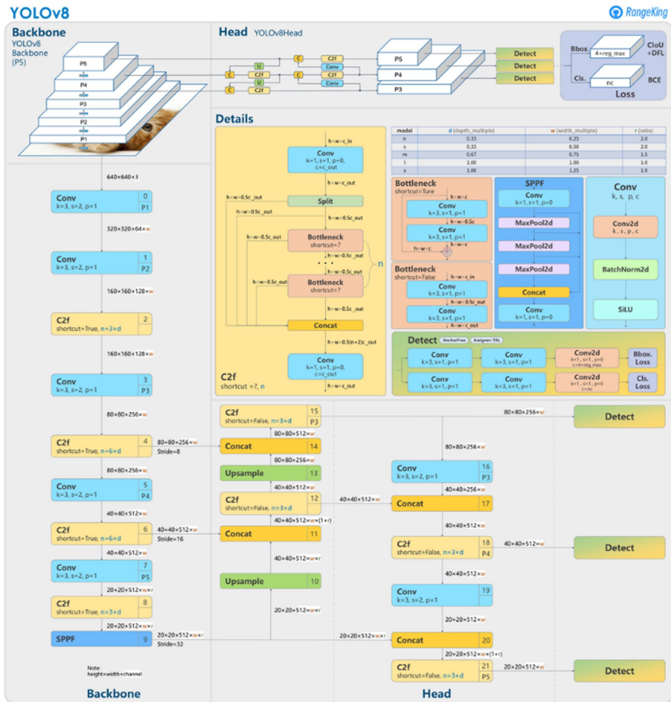

Figure 5: Yolo v8 Architecture

Dataset Description

The dataset utilized in this research paper consists of high-definition images collected from various websites, encompassing a diverse range of coral reef scenes and conditions. Each class within the dataset comprises approximately 70 images, ensuring sufficient representation of different coral species, reef formations, and bleaching conditions. To enhance the dataset's diversity and robustness, data augmentation techniques were applied, resulting in the creation of approximately 1500 images per class.

Furthermore, to facilitate object detection using the YOLO v8 framework, each image in the dataset was manually labelled with bounding boxes specifying the location and extent of coral reefs and bleaching events. The labelling process was conducted using the MakeSense AI platform, ensuring consistent annotation standards and accuracy across the dataset.

Overall, the dataset provides a comprehensive and meticulously curated collection of coral reef images, augmented to enhance variability and labeled to support object detection tasks using YOLO v8. This rich resource enables researchers to train and evaluate deep learning models for automated detection and monitoring of coral bleaching events, contributing to advancements in marine conservation and ecological research.

Training Work -Flow

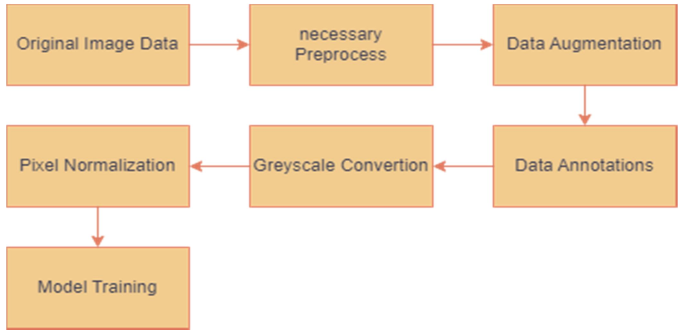

Figure 6: Work flow

images of coral reefs was initially resized to a uniform size of 256x256 pixels to ensure consistency. Subsequently, data augmentation techniques such as rotation, shear, contrast adjustment, and flipping were applied to increase the variability and robustness of the dataset. Annotation of the augmented images was conducted using makesense.ai, wherein bounding boxes were drawn around the annotated objects, namely bleached corals. After augmentation and annotation, the dataset consisted of approximately 1500 images.

Following augmentation and annotation, common digital image processing techniques were applied, including grayscale conversion and pixel normalization. Grayscale conversion simplifies the data while preserving essential features, and pixel normalization standardizes the pixel values within a specific range, facilitating faster convergence during training.

The YOLO v8 small model was then trained on the preprocessed and annotated dataset for 200 epochs. Despite the relatively small size of the dataset, satisfactory accuracy was achieved by the 73rd epoch. The training dataset comprised 80% of the total data, while the remaining 20% was allocated for validation. Subsequently, testing was performed on new, unseen images to evaluate the model's performance in detecting bleached corals.

GUI

For facilitating bleached coral detection, we have developed a user-friendly Graphical User Interface (GUI) using the PySimpleGUI library. PySimpleGUI is a Python library renowned for its simplicity and efficiency in building GUIs, making it an ideal choice for our application. Our GUI allows users to upload coral reef images for analysis and predicts the presence of bleached corals, visually indicating their location within the image

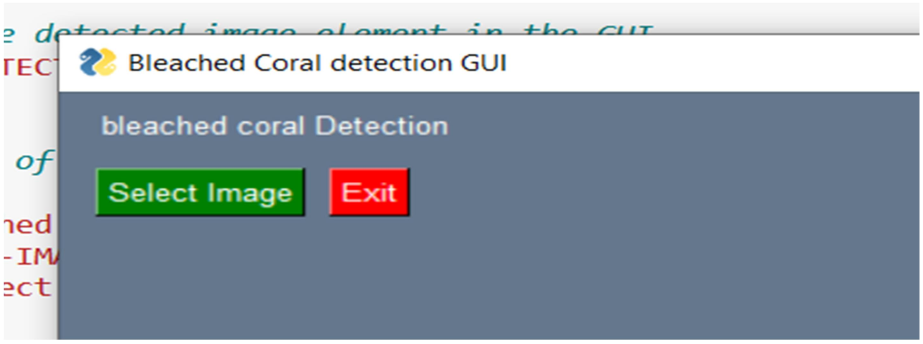

Figure 7: GUI

.The GUI operates as follows: Upon launching, users are presented with an interface comprising image display areas and intuitive buttons for interaction. To initiate the prediction process, users simply select a coral reef image using the "Select Image" button. The chosen image is then passed to the YOLO model, previously trained for bleached coral detection.

Utilizing the YOLO model, the GUI identifies and annotates bleached corals within the uploaded image by drawing bounding boxes around them. Concurrently, the GUI counts the number and type of bleached corals detected and provides this information to the user. This comprehensive analysis offers insights into the severity and extent of coral bleaching within the reef ecosystem.

Furthermore, the GUI incorporates a user-friendly design with clear instructions and prompts, ensuring a smooth and hassle-free experience for users. Upon completion of the prediction process, the GUI displays the annotated image alongside the predicted bleached coral count and type, empowering users to interpret and comprehend the model's findings effectively.

Result

The developed bleached coral detection system showed promising results in our testing. It accurately identified **healthy corals with ahigh accuracy of 94%**, showcasing its ability to recognize healthy coral specimens effectively. For detecting **bleached corals, the system achieved a respectable accuracy of 79%**. These findings demonstrate the system's effectiveness in distinguishing between healthy and bleached corals, providing valuable insights for coral reef conservation efforts. Overall, our results highlight the system's potential to aid marine researchers and conservationists in monitoring coral reef health and implementing targeted conservation measures. Further improvements and refinements to the system could enhance its accuracy and usefulness in real-world applications.

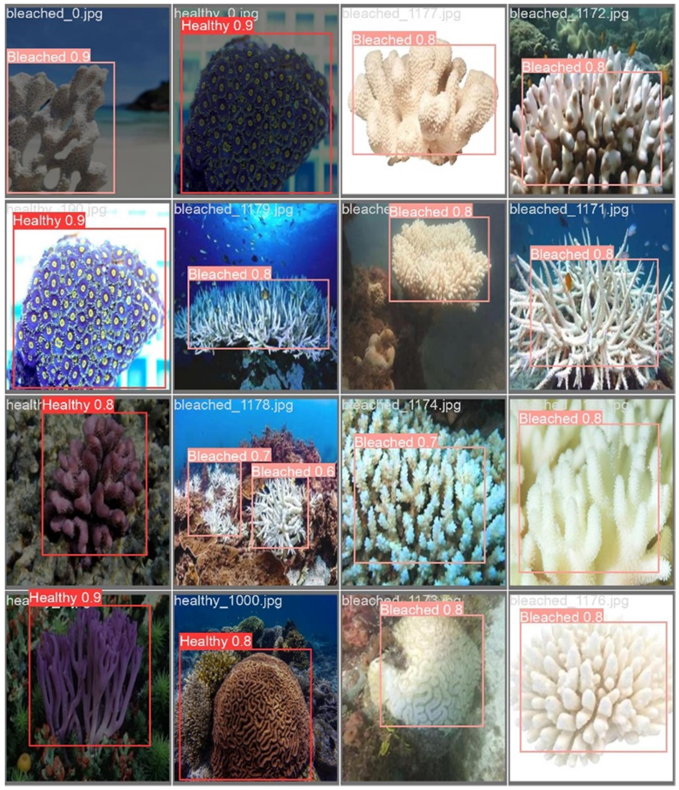

Figure 8 : validation_batch_prediction

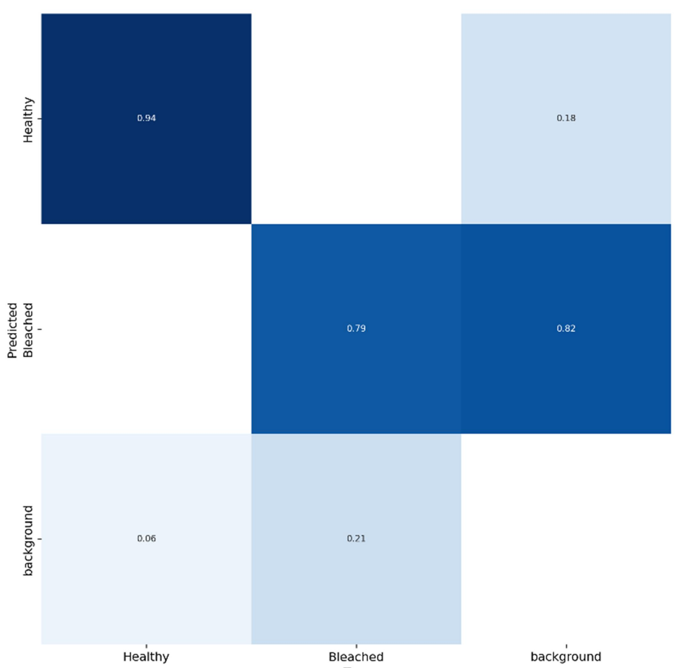

Figure 9: Confusion matrix

Conclusion

As a tool for furthering coral reef conservation efforts, the created bleached coral detection method shows great promise. The algorithm demonstrates the ability to discern between coral health situations with a respectable 79% accuracy in recognising bleached corals and a high 94% accuracy in identifying healthy corals. By facilitating effective coral reef health monitoring, a crucial step in preserving marine ecosystems, these findings demonstrate the system's potential to offer significant assistance to marine researchers and conservationists.

The system's usefulness in practical applications, where precise and fast data are necessary for putting focused conservation measures into action, is highlighted by its capacity to provide trustworthy insights. Even yet, improvements could improve its accuracy, especially in identifying bleached corals, even though the existing performance metrics are praiseworthy. Existing constraints could be addressed and overall system reliability increased by utilising cutting-edge machine learning techniques, adding varied coral species and environmental conditions to the dataset, and incorporating sophisticated algorithms.

In the end, including such a detection system into larger conservation programs may greatly aid in the endeavours to lessen the effects of stressors like climate change on coral reefs. This technology has the potential to be extremely important in maintaining the biodiversity and biological processes of these crucial marine environments by enabling proactive and data-driven decision-making.

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