Transfer Learning–Based Coral Classification Using Convolutional Neural Networks

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ABSTRACT

Coral reef ecosystems are very important maritime environments, which are experiencing degradation effects due to climate change. Coral reef detection is very essential, though challenging, given the changing dynamics while coral ecosystem data collection processes are sensitive to weather changes. At most times, there have been difficulties in collecting precise data. For coral reef surveys, the processes have been conducted during optimal conditions, which are likely to be absent when individuals are on-site. This is just a small part of the complicated relationships in coral reef modeling. Thus, it is imperative to explore the possibility of using deep learning in classifying coral reefs. This investigation results in exploring the possibility of using non-ideal shoreline photographs for classifying coral reefs. This would give room to increase the scope of other approaches of studying coral reef surveys. For the images in the Coral Reef data set, there is categorization using a segmentation method, which involves a convolution neural network. The categorifications have advanced high accuracy of 92% using MobileNetv2 (Transfer Learning), 89% using Quad-Layer CNN Architecture, while the other portion of 88% using Tri-Layer CNN Architecture. There have been difficulties in classifying the non-ideal images, though with high chances of precise results..

Keywords: Machine Learning, Deep Learning, marine images, corals, classification, convolutional neural networks.

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INTRODUCTION

More and more people throughout the world are starting to notice the threat that coral reefs face. The capacity of coral reef ecosystems to efficiently absorb environmental nutrients, zooplankton, and even phytoplankton makes them very productive. Our knowledge of the human influence on coral reefs is limited and mostly based on short-lived data gathering efforts [1]. In order to better understand how coral reef ecosystems work, coral reef monitoring is crucial for measuring the composition of benthic populations. There are dozens of photos of coral reefs taken every day by different types of cameras [2].

The advent of remote sensing has allowed for the collection of massive volumes of data with fine temporal and geographical resolutions with little interference to all forms of life on Earth. We must determine the long-term and regional patterns of reef community transformation. The most effective method for this seems to be remote sensing [3]. It is better at coral reef classification at lower spatial scales and contains pixels less than 10 m wide. Commercial sources can provide these photographs, although they may be expensive [4]. Lastly, options using UAVs (unmanned aerial vehicles) are available. Compared to satellite photos, newer improvements in UAV remote sensing provide advantages, such as a lower price tag. Thus, UAVs may be used as efficient monitoring instruments for discovering objects on land, in coral reefs, for surveillance, and perhaps even every day. Last but not least, there are reef studies that are known as "traditional" [5]. These studies use scuba divers who have received training in marine ecology to create maps of underwater animals.

One barrier is the analysis of the ever-increasing amount of remote sensing data, which is often done by hand by specialists. Up until recently, conventional machine learning methods were used in conjunction with remote sensing for coastline identification [6]. Beijbom demonstrates that computer scientists using deep learning techniques have attempted to classify underwater coral reef images. Neural networks are the main algorithm of deep learning, a subset of machine learning. Various parts of coral reef categorisation have been the subject of research in computer science and remote sensing. Coastal areas are often classified in remote sensing articles, but underwater imagery is often classified in computer science journals [8].

When comparing different deep learning systems, it is common practice in computer science to classify underwater corals. Most of the prior research either focused only on traditional machine learning methods or compared them to more advanced deep learning approaches. But all of the recent research has focused on neuro. The bulk of computer science articles focus on finding the best model or getting the most accurate results [9]. Aiming for practical, realistic results is the goal of most remote sensing articles. The two fields of research and their respective approaches are often not combined. However, a good outcome may emerge from exploring possible methods of integrating the two areas [10].

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It is feasible to analyse massive volumes of data and improve our understanding of coral reefs by looking at it from many perspectives. Research in these fields has led to classifications of many picture features, which is useful for coral reef photography. But deep learning might provide a geophysical output, in this case bathymetric data. Bathymetric data may usually be retrieved using either active or passive remote sensing.

For the purpose of studying coral beach areas—which are often conducted under perfect circumstances—this research will look at how deep learning may be used to convert photos into bathymetric data. The hydrodynamic impacts of weather variables including wind, waves, cloud cover, and tides may have a disproportionately large impact on coastal areas. Images may seem distorted due to adverse weather conditions. In addition, there are two main reasons why data collection in coastal locations is so error-prone. At first, features below a depth threshold—which is affected by water turbulence and turbidity—are not discernible due to light absorption. Furthermore, errors are caused by optical distortions and reflections both at the air-water contact and all down the water column. Acquiring subpar data becomes more likely in less-than-ideal settings. Consequently, data that is not optimal is typically thought to be useless. Two datasets were used in this study. A dataset obtained from Moorea, French Polynesia, under ideal circumstances, and another obtained from Curacao, Caribbean, under less than ideal circumstances. Location on an island has a significant impact on the local climate. Important issues in coral reef categorisation are the focus of this study [12].

Challenges

Some critical obstacles exist in the real-world undersea setting that the theoretical model must surmount. Classifying structured pictures of textures and objects is a natural extension of the methods established for image recognition of real-world things. But when it comes to underwater photos taken in the actual world, these methods fall short. picture blurring, picture dispersion, sun flashing, and loss of colour intensity are some of the issues that have been discovered. Consequently, underwater scene categorisation using photographs is a complex and challenging area of study.

We now have a significant opportunity to study the vast and complex ocean environment, thanks to exploration and photography of the bottom. An essential part of comprehending the complex ocean environment is retrieving data from the ocean floor. However, practical problems mean that it is not without limits. The interest in studying the aquatic environment and advancements in underwater cameras have created a pressing need to enhance the image process. Optical imaging is the major tool for studying biodiversity, aquatic biology, seabed geology, archaeological sites, and archaeological activities [1, 10, 11]. The use of ROVs and AUVs, or remotely operated vehicles, to capture digital photographs of the ocean floor has already begun [12]. An essential opportunity to improve the suitability of marine data for exploration exists in the development of an accurate automated annotation method.

The goal of digital underwater photography and computerised species categorisation is quite difficult. Underwater categories with varying shapes, colours, textures, sizes, rotations, illuminations, viewing angles, camera distances, and lighting conditions make up the training datasets. Most notably, the difficulties include: • A great deal of variation in the obtained images both within and across classes and locations • Spatial delineations among classes that are complex and confusing. Specialists' manual annotation styles differ. • Disparities in camera quality, perspectives, and spatial and spectral resolution thresholds. • The obstruction of important things, either partially or entirely. • Degradation of the marine seabed's structure over lengthy periods of time. • Waves and optical characteristics that change with depth-induced refraction artefacts in illumination. • Lighting issues, colour distortions, and water turbidity that may change.

LITERATURE REVIEW

2.1 Automatic Coral Classification using Machine Learning

Coral Classification with Hand-crafted Features

For the purpose of colour description and texture analysis, Stokes and Deane [14] used normalised colour histograms and a feature vector obtained from discrete cosine transform (DCT). Three thousand photos representing eighteen different types of data were used to train the model. For the purpose of categorisation, a new approach known as "probability density weighted mean distance (PDWMD)" has been presented. The procedure is quick and easy to execute.

During feature extraction, the weights of the texture and colour characteristics are manually specified. When it comes to texture descriptors, DCT descriptors aren't very reliable or accurate. Corals are mostly classified based on their colour and texture. Consequently, researchers in the field have focused a lot of attention on how to represent images using attributes based on colour and texture. The corals' variable morphologies and the lack of clear categorisation boundaries make shape-information features less applicable. The majority of people would rather have features that combine colour and texture. For large coral datasets, no specific feature combinations are anticipated to be beneficial. The characteristics that differentiate corals from non-corals in a given dataset are often used to choose features. Important studies on coral image classification using hand-crafted features will be highlighted in this section. The feature vector used by Pizarro [15] was derived using colour histograms, the bag-of-words (BoW) model for scale-invariant feature transform (SIFT), and the normalised cross-correlation (NCC) histogram. We build a Bag of Words (BoW) from a subset of our training data, and then we use this vocabulary to describe the test picture. They used a voting system to sort things into categories and choose the best pairs. There are eight distinct classifications that each picture is given in their method. The training and vocabulary development processes made use of 453 photos in total. When it comes to pixel annotations, this annotation approach falls short and often misses important details. The topic of sub-image level categorisation is not covered

in this research. Underwater environments are too complicated for texture characterisation using Bag of Words on SIFT features.

When analysing colours, Marcos [13] used Normalised Chromaticity Coordinate (NCC), and when analysing textures, he used Local Binary Pattern (LBP). The five types of corals were identified using a three-layer feed-forward backpropagation neural network: live, dead, corals with algae, abiotic materials, and algae. It is claimed that the NCC colour characteristics are light-insensitive, whereas LBP shows resistance to changes in lightness. The discriminative potential of the NCC and LBP features is insufficient for complicated underwater photos, however. After that, we used only 300 photos to evaluate the technique across all three types of coral. Instead of using only LBP and NCC, a combination of the two yielded better results.

Beijbom [8] presented the Moorea Labelled Coral (MLC) dataset, which comprises five coral and four non-coral categories. To extract features at various sizes, the authors used a Maximum Response (MR) filter bank in conjunction with textual annotations on maps. A texture dictionary was built using a set of training photos and k-means clustering. Before processing photos in RGB, they showed that L*a*b colour space performed better. The classifier used for this task was a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel. In order to create coral maps for the reef sites, photos of corals taken at different times of year were automatically annotated.

In order to attain the best possible classification accuracy for different benthic datasets, a combination of features that were created manually and numerous classifiers were studied in [16]. Finished Local Binary Patterns (CLBP), Gabor features, grey level co-occurrence matrix (GLCM), opponent angle, and hue channel colour histograms are the descriptors used. The feature vectors used in this investigation were resistant to colour distortion and underlit, and they were also invariant to scaling. Support vector machines (SVMs), k-nearest neighbours (KNNs), neural networks, and probability density weighted mean distance (PDWMDs) were among the classifiers used. To get the best results across all six test datasets, we used a variety of feature-classifier combinations. Problems like finding the best scale for patch extraction and identifying overlapping classes are not addressed in this study.

Coral Classification with Learned Features

Deep neural networks represent a powerful class of machine learning models constructed by stacking multiple neural layers to increase depth and representational capacity within compact architectures. Recent advancements in deep learning have demonstrated exceptional performance in both discriminative and representation learning across a wide range of modern applications. Researchers continue to expand the scope of deep learning by exploring its potential in new domains, including maritime scene analysis and benthic habitat monitoring.

One promising application area is maritime scene classification. However, deep neural networks typically require large volumes of labeled data for effective training. When trained using efficient optimization strategies, these models can distinguish among millions of annotated images with high accuracy. Furthermore, once trained, deep networks can serve as powerful feature extractors, generating meaningful image representations that can be transferred to related benthic or coral reef datasets. Before examining deep learning applications in coral classification, a concise overview of deep learning concepts and advanced architectures is presented.

2.2 Automatic Coral Classification Using Deep Learning

Image and video processing tasks such as classification, object detection, and scene understanding rely heavily on extracting relevant and discriminative features from raw input data. Traditionally, computer vision systems depended on handcrafted feature descriptors specifically designed for particular domains. However, in recent years, machine learning–based feature extraction methods, commonly referred to as representation learning, have significantly outperformed manually engineered features.

Deep learning methods employ complex neural network architectures with multiple layers, enabling hierarchical feature learning. Neural networks containing numerous hidden layers can progressively transform raw input data into increasingly abstract and meaningful representations. Many state-of-the-art computer vision systems achieve superior performance due to their ability to learn such high-level abstractions automatically.

Although neural networks gained attention during the 1990s, their popularity declined in the early 2000s when Support Vector Machines (SVMs) demonstrated better performance in several tasks. However, following landmark research breakthroughs in deep architectures, deep neural networks regained prominence and revolutionized the field of computer vision.

Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a specialized class of deep neural networks designed specifically for image representation learning and visual recognition tasks. Modern deep CNNs consist of multiple layers of linear operations (convolutions) followed by non-linear activation functions, trained jointly in an end-to-end manner. The network parameters are optimized iteratively to minimize a predefined objective function.

CNNs typically follow an alternating structure of convolutional layers and pooling layers. Several architectural characteristics make CNNs highly effective for visual data processing:

Sparse connectivity
Parameter sharing
Sub-sampling (pooling)
Local receptive fields

Sparse connectivity is achieved by using convolutional kernels that are smaller than the input dimensions, reducing the number of connections between input and output neurons. This design significantly decreases computational complexity and memory requirements. Unlike fully connected layers—where each weight is used only once—convolutional kernels are reused across spatial locations, improving efficiency.

In convolutional layers, a set of learnable filters is convolved with the input to produce feature maps. Parameter sharing ensures that the same filter weights are applied across different spatial regions, making CNNs equivariant to translations (i.e., a shift in input results in a corresponding shift in output). However, standard convolutional layers do not inherently provide equivariance to scale or rotation changes.

Pooling layers further reduce spatial dimensions, helping the network achieve partial invariance to small distortions and translations while controlling computational cost. Increasing network depth—by stacking multiple convolutional and pooling layers—enables the model to learn progressively complex features.

Research has shown that deeper CNN architectures using smaller filter sizes (e.g., 3×3 kernels) yield improved performance. A notable example is VGGNet, which increased network depth to 16–19 layers and achieved significant improvements over earlier architectures. It secured top positions in the ImageNet Challenge 2014 for both localization and classification tasks.

HYBRID CNN FOR CORAL CLASSIFICATION

Coral reef imagery is characterized by inconsistent image clarity, complex inter-class boundaries, and significant intra-class variability. The discriminative strength of the features extracted from images plays a crucial role in determining the accuracy of any classification approach. Handcrafted feature extraction methods are limited due to the challenges discussed in Section 2. Typically, handcrafted features capture only one or two aspects of visual data, such as color, shape, or texture. Designing a single, carefully engineered feature representation capable of addressing all the complexities associated with underwater and maritime imagery is extremely challenging. Therefore, employing pre-trained, off-the-shelf CNN features derived from large-scale image datasets is a more practical and effective solution. When applied to new domains, CNN-based features have demonstrated strong discriminative capabilities. A deep learning strategy known as Hybrid CNN combines Convolutional Neural Networks with Transfer Learning, where a pre-trained CNN model is adapted and fine-tuned for a new classification task.

Coral Reef Dataset

The Coral Reef dataset is a carefully curated collection of images gathered from multiple repositories, specifically prepared for coral reef image classification research. It is well-suited for researchers and machine learning practitioners working in marine ecology, image recognition, and environmental conservation. For this study, four coral categories were considered: Pavon Coral, Monti Coral, Acrop Coral, and Brain Coral. Each category contains 309 images, with each image resized to dimensions of 312 × 312 pixels. The dataset is divided into 80% training data and 20% testing data. Figure 1 presents sample images from the Coral Reef dataset.

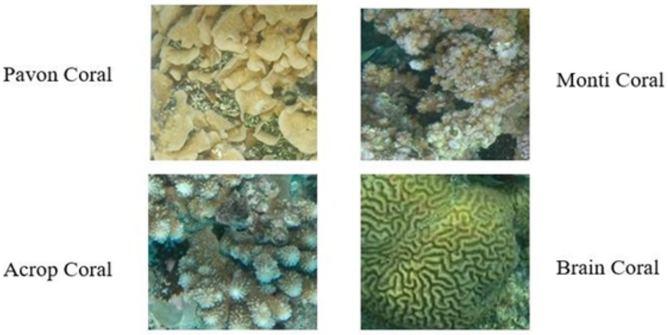


Figure 1: Sample Images of Coral Reef Dataset

Preprocessing

Sharpening: The images exhibit variations in quality, with many appearing blurred or slightly out of focus. To address this issue and construct an enhanced dataset (C), image sharpening techniques were applied. Specifically, overall contrast was increased and fine details were enhanced to improve visual clarity and feature distinctiveness.

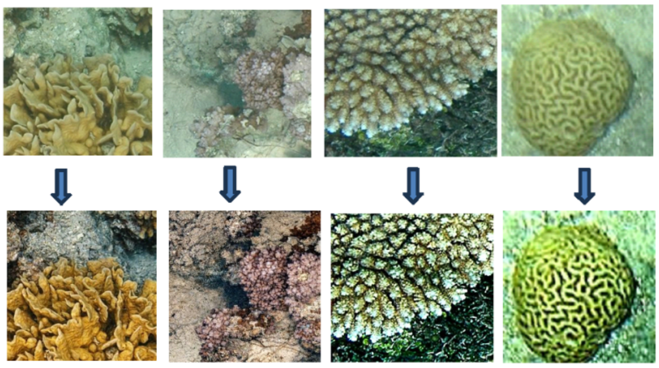


Figure 2: a) Original into Pre-processed Image

For this purpose, each pixel value was substituted with the weighted average of its corresponding 3 × 3 neighborhood. Figure 2(a) illustrates the filter matrix used in the sharpening process, while Figure 2(b) presents examples of the pre-processed images of Pavon Coral, Monti Coral, Acrop Coral, and Brain Coral after enhancement.

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 12 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Figure 2: b) Filter Matrix

Architecture of CNN Model

Computer vision extensively employs deep learning methods, particularly Convolutional Neural Networks (CNNs), due to their structural inspiration from the human visual processing system. As illustrated in Figure 3, a typical CNN architecture consists of an input layer, multiple hidden layers, and an output layer. These layers are generally organized into four primary functional components: the Convolutional layer (feature extraction), the Pooling layer (feature reduction), the Flatten layer, the Fully Connected layer, and the Softmax layer (prediction output).

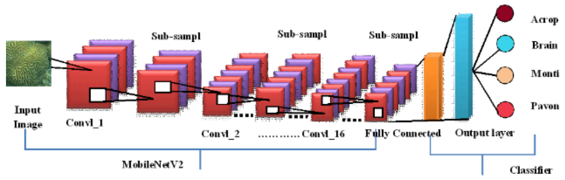


Figure 3: Architecture of CNN Model

RESULT AND DISCUSSION

The performance is calculated with the help of accuracy, precision, recall, f1-score.

Accuracy: The overall correct disease predictions are represented as.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

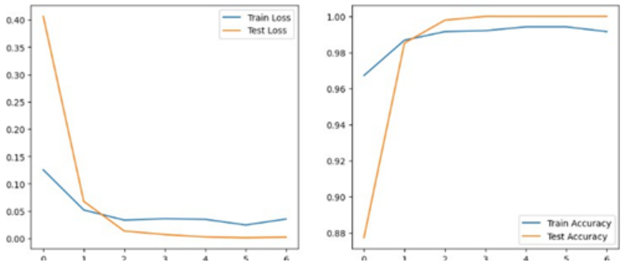


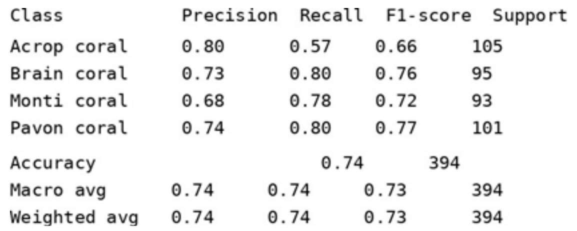
Figure 4: Accuracy and Loss for MobileNETV2 Model

The blue curve in Figure 4 represents the loss of the MobileNetV2 model, while the yellow curve indicates the accuracy of the proposed model. The y-axis ranges from 0 to 1, and the x-axis spans from 0 to 6 epochs. Figure 4 illustrates both the accuracy and loss of the proposed model during training. Figure 5(a) presents the performance metrics of the MobileNetV2 model, whereas Figure 5(b) depicts the model's performance without applying the pre-processing techniques.Finally, Figure 6 displays the confusion matrix of the MobileNetV2 model, providing a detailed evaluation of classification performance across all coral classes.

Table 1: Model Comparison

S. No.	Model	Precision	Recall	F1-score	Accuracy in %
1.	Tri-Layer CNN Architecture	0.85	0.66	0.64	88
2.	Quad-Layer CNN Architecture	0.91	0.87	0.88	89
3.	MobileNetV2 (Transfer Learning)	0.92	0.92	0.91	92

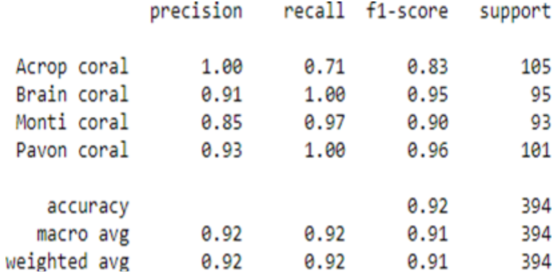
Result Analysis using MobileNetV2



```
Class          Precision  Recall  F1-score  Support
Acrop coral      0.80      0.57    0.66      105
Brain coral      0.73      0.80    0.76      95
Monti coral      0.68      0.78    0.72      93
Pavon coral      0.74      0.80    0.77      101

Accuracy                       0.74       394
Macro avg      0.74     0.74     0.73      394
Weighted avg   0.74     0.74     0.73      394
```

Figure 5: a) Performance Metrics without Pre-processing



```
              precision    recall  f1-score   support

 Acrop coral       1.00      0.71      0.83       105
 Brain coral       0.91      1.00      0.95        95
 Monti coral       0.85      0.97      0.90        93
 Pavon coral       0.93      1.00      0.96       101

    accuracy                           0.92       394
   macro avg       0.92      0.92      0.91       394
weighted avg       0.92      0.92      0.91       394
```

Figure 5: b) Performance Metrics for MobileNetV2

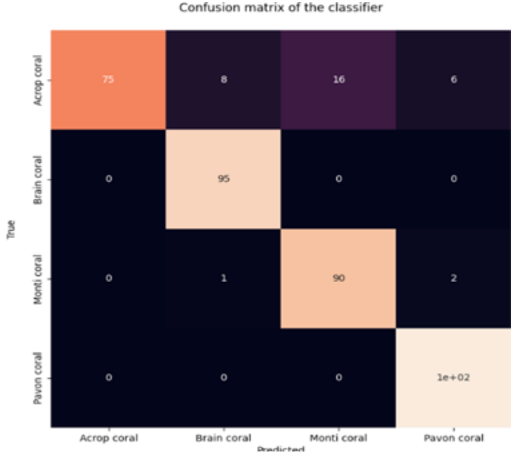


Figure 6: Confusion Matrix for MobileNetV2

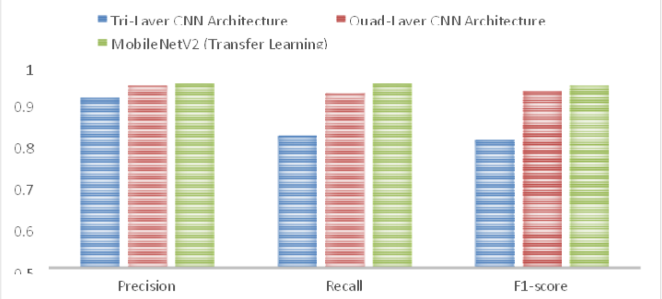
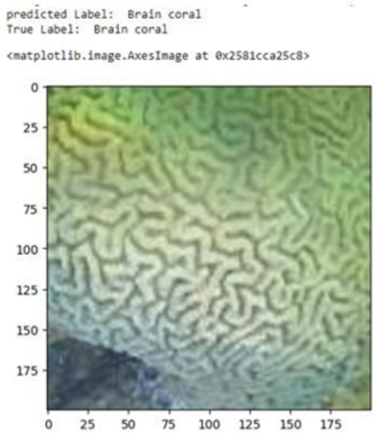
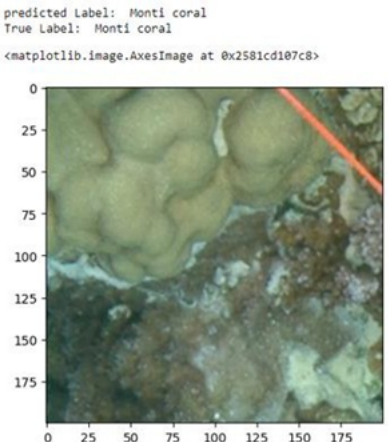


Figure 7: Performance Metrices chart for MobileNetV2



```
predicted Label:  Brain coral
True Label:  Brain coral

<matplotlib.image.AxesImage at 0x2581cca25c8>
```



```
predicted Label:  Monti coral
True Label:  Monti coral

<matplotlib.image.AxesImage at 0x2581cd107c8>
```

Figure 8: Predicted Image using proposed model

MobileNetV2 is designed to achieve high computational efficiency through the use of depth-wise separable convolutions. It incorporates an inverted residual structure with linear bottlenecks, enabling enhanced feature extraction while significantly reducing computational cost. This architecture ensures that the model remains lightweight, yet sufficiently robust to handle the complexity of the coral dataset, particularly considering inter-class variations and potential noise in underwater imagery.

The coral dataset can be effectively optimized for classification tasks by leveraging pre-trained weights within the MobileNetV2 framework through transfer learning. This approach improves overall performance while reducing the volume of training data and computational resources required. The ability of MobileNetV2 to maintain a strong balance between accuracy and efficiency makes it highly suitable for achieving reliable results in coral image classification. Figure 8 illustrates a sample predicted image generated using the transfer learning–based model.

Future Prospects

Deep learning methodologies in ecological research provide an objective and scalable approach for detecting, differentiating, and identifying marine species, including analysis of their morphology and behavioral patterns. The future scope of this research includes:

Developing advanced deep learning frameworks, beyond coral classification, for automated analysis of large-scale marine datasets.

Evaluating and comparing multiple deep learning architectures to establish a robust foundation for accurate marine ecosystem assessment.

Designing automated annotation systems capable of handling diverse datasets, thereby reducing the dependency on manual labeling and conserving human resources.

Investigating the resilience of marine ecosystems to environmental stressors such as global warming, marine pollution, resource exploitation, and coastal development through cost-effective monitoring systems.

Analyzing interspecies relationships and quantifying population dynamics to better understand ecological trends and biodiversity changes.

CONCLUSION

This study presents a streamlined Coral_CNN model that leverages recent advancements in deep learning and modern deep neural network architectures. We examined seabed exploration challenges, particularly those associated with marine data acquisition and preprocessing. A concise review of existing literature on marine image classification techniques was also provided. Furthermore, we explored the potential applications of deep learning in benthic image classification by analyzing experimental results conducted by our research team as well as findings reported by other scholars. The proposed Coral_CNN model was discussed in detail, along with additional research directions in deep learning and underwater image analysis. This book chapter is expected to inspire researchers in both computer vision and marine science domains to undertake similar long-term interdisciplinary research initiatives.

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