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Advancing Coral Reef Identification for Biodiversity and Ecology Assessment: A Color-Invariant CNN–Transformer Hybrid Approach

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Abstract:

Coral reefs are vital ecosystems that support marine biodiversity but are under severe threat. Accurately identifying corals using underwater images is crucial for monitoring their health; however, this task is challenging due to issues such as color distortion caused by water depth and turbidity. Existing methods, primarily based on Convolutional Neural Networks (CNNs), often struggle with these color variations and fail to capture the broader ecological context of a reef.

This paper presents a Dual-Branch CNN-Transformer Hybrid Model that synergistically combines a CNN and a Vision Transformer (ViT) designed to classify coral and non-coral images in underwater environments. This model combines the local feature-detection strength of a CNN (ResNet18) with the global context-understanding ability of a Pre-trained Vision Transformer (ViT). Synthetic color-shift transformations have been applied to simulate various underwater conditions, such as light scattering and water turbidity.

The model was evaluated on a dataset of 1690 images consisting of 1300 coral images and 390 non-coral images. and achieved an overall test accuracy of 93.49%. The results demonstrate that our hybrid approach is a highly effective and reliable tool for automated coral identification, highlighting the potential of deep learning and computer vision in marine conservation and biodiversity protection.

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I. INTRODUCTION

Coral reefs are one of the most important ecosystems on Earth, providing diverse shelter to a wide range of marine species underwater [1]. Healthy coral reefs play a significant role in regulating biodiversity and ecology within the tropical oceans [2]. However, these ecosystems are facing different threats due to climate change, pollution, coral bleaching, and reef degradation. It is crucial to conserve the existence of biodiversity in ecosystems where coral serves as the foundation of marine life and contributes a significant share of marine biodiversity.

The development of effective and accurate identification methods for coral is crucial for understanding their availability, monitoring their health, and promoting sustainable production. However, underwater corals are difficult to identify manually and even with some traditional technologies, especially under different light conditions, water turbidity, and depth [3]. The advantages of Artificial Intelligence, including Deep Learning and Computer Vision, have become a key research area in classification tasks, and they are widely discussed in marine ecology and conservation literature [4].

The majority of existing coral-classification methods are based on Convolutional Neural Networks (CNN) that are made to identify local image features. But these techniques are not successful in working with underwater images that are prone to color distortions under the influence of environmental processing, like light scattering and the depth of water. CNNs are also primarily focused on local features. They can not capture the broader ecological context of the coral ecosystem, which is essential for a comprehensive understanding of reef health and biodiversity. Since all species in these ecosystems are interconnected, there is a need to consider more robust algorithms capable of taking into consideration the intricate associations among corals and other marine plants.

This study proposes an innovative solution to these challenges by developing a dual-branch CNN-Transformer hybrid model. In fact, this model is a spectacular fusion of the Convolutional Neural Network (CNN) and Vision Transformer [5]. The CNN branch will identify local features of pictures, and the Transformer branch will identify global context based on a dataset of underwater photos, which further enhances the model's capability to generalise across various underwater scenarios. The model will present a synthetic colour-shift benchmark to determine the model's resilience.

By classifying Corals under different underwater conditions, such as light scattering and water depth, this research will enhance the process of inspecting the availability of corals for monitoring the impact on biodiversity, as well as the health of available corals, and increase sustainable production. Additionally, the outcomes of this research can also serve as a practical application for marine conservation and environmental monitoring, helping to save biodiversity and protect the underwater ecology.

II. RELATED WORKS

The Coral reefs are very crucial in supporting marine biodiversity and ecological conservation. However, in the case of identifying and classifying corals based on manual surveys and visual inspections, it has proven to be limiting [6]. These techniques are truly valuable, but struggle to efficiently cover large areas, particularly in challenging underwater conditions like varying light levels for depth and water turbidity. This highlights the need for innovative approaches to coral reef monitoring.

In early studies, A. Mahmood et al. used deep learning to classify coral reef images [7]. While these methods worked in clearer waters, they struggled in conditions with high turbidity and fluctuating light, where coral colors change significantly. Similarly, another study by R. Shihavuddin et al. showed that Convolutional Neural Networks (CNNs) can achieve good accuracy over traditional models with dataset of underwater imagery, especially when images were taken under differing light and depth conditions [8].

The botanical surveys have also been part of the traditional coral monitoring methodologies. In these methodologies, researchers observe the prevailing species of corals and their distribution in space through sampling mainly using transects. As a case study, Graham et al. used this research design to determine the coral diversity in heterogeneous reef areas, with the focus that changes in species abundance can be a strong indicator of ecological health shifts [9]. On the same lines, McClanahan examined the impact of overfishing and pollution on coral species richness and found that there is a direct relationship between the anthropogenic activity and a reduction in the reef diversity [10]. These approaches have played an important role in baselining the coral reef ecosystems and biodiversity.

These field-based approaches are very important, but not always practical when it comes to large-scale surveillance because of time and logistical limitations. To overcome these limitations, satellite imagery and remote sensing techniques have been used to monitor coral reefs over broader areas. It was demonstrated by Hughes et al. that aerial and satellite surveys were a quick method of identifying coral bleaching, which could be used as valuable information to understand large-scale ecological effects on coral reefs [11].

Nevertheless, a problem of color variability under the waters is one of the primary problems of coral classification. Li et al. talked about the failure of common methods, e.g., color correction and white balance, in situations with rapidly changing lighting, e.g., turbid waters or deep depths. This renders proper identification of corals a challenge, with the colors of corals usually being distorted [12].

To address this, Ganin et al. introduced the concept of Domain-Adversarial Neural Networks (DANN) to make models more robust in varying environmental conditions. This method assists the model to learn characteristics that are consistent even when the images belong to a different environment, e.g., shallow or deep waters or clear or turbid waters [13]. Nevertheless, this is not a solution that has been embraced by coral reef classification, and a more standardized way of measuring these models in different underwater environments remains necessary.

Though with these developments, it is yet to be seen whether a synthetic color-shift benchmark will be developed, which would make it possible to evaluate the coral classification systems in the real world. There has been little research done on how to determine the strength of the classification techniques in this adverse environmental condition.

This paper expects to address these difficulties by implementing a dual-branch CNN-Transformer hybrid model. This model addresses the difficulty of underwater color difference by applying a synthetic color-shift benchmark [14]. The integration of CNNs to extract local features and the global understanding of the features of Vision Transformers (ViTs) should considerably raise the accuracy and robustness of the model in terms of feature classification, especially in underwater conditions of difficulty. Moreover, it introduces a systematic evaluation protocol for coral classification methods, marking a significant step forward in the field of coral reef conservation and protecting biodiversity.

III. DATA & MEHODOLOGY

A. Dataset

The total dataset comprises 1690 images, consisting of 1300 images from the coral class and 390 from the non-coral class [15]. All the pictures in this dataset have been sourced and manually selected for only the suitable and high-quality clean images from two open-source datasets: the EU Coral Dataset on Kaggle and the Coral Reef Dataset from Images.CV. The whole dataset represents an underwater environment.

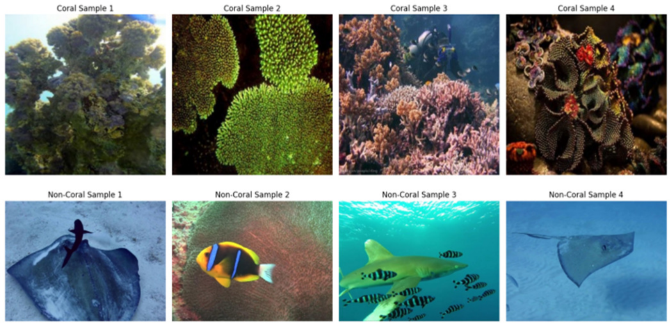

Fig. 1 Sample images from the dataset. The top row shows four examples of coral images, and the bottom row shows four examples of non-coral images.

B. Data Preprocessing

The dataset has been preprocessed by several preprocessing steps to do the proper model training. The processes can significantly help to get better accuracy, overcoming critical situations like an underwater environment.

1) Image Resizing:

All images of our dataset are resized to a consistent shape of 224x224 pixels. This ensures uniform input dimensions for the model, because the CNN and Vision Transformer (ViT) architectures require fixed-size inputs.

2) Normalization:

To make the training process more stable and to help in aligning the dataset with common pretrained models such as ResNet and ViT, the pixel values are normalized using the mean and standard deviation:

Mean: (0.485,0.456,0.406)

Standard Deviation: (0.229,0.224,0.225)

3) Augmentation:

Various augmentation techniques are applied to enhance further the dataset, such as Horizontal and vertical flips, Random brightness and contrast adjustments, Gaussian noise and blurring effects.

4) Colour-Shift Transformations:

A crucial challenge in underwater classification is the variation in colour due to water depth, turbidity, and light conditions. To handle this, synthetic colour-shift transformations have been applied. It can simulate various underwater environments and improve the model's robustness.

These transformations are based on some underwater conditions such as Shallow Water, Medium Depth, Deep Water, Turbid/Green Water, and Low Visibility.

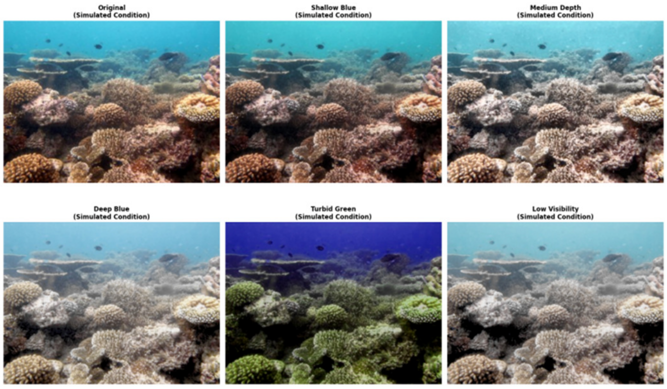

Fig. 2 Color Shift Transformations of Coral Sample under Different Simulated Conditions.

5) *Dataset Split:*

The final dataset is divided into three sets such as train, test and validation using an 80:10:10 ratio. This balanced split intends to ensure that the model is trained on a proper representation of coral and non-coral images.

TABLE I
DATASET DISTRIBUTION ACROSS SPLITS

Class	Total Images	Training Set	Validation Set	Test Set
Coral	1390	1040	130	130
Non-Coral	390	312	39	39

C. Model Architecture

In this research, a dual-branch CNN-Transformer Hybrid model has been employed to distinguish between underwater coral and non-coral species.

The ultimate Hybrid model is a combination of CNN and Vision Transformer. These models feature extraction and capture global context; this combination plays a crucial role in making this model a stronger choice for coral identification.

Below is the description of the structure of our Hybrid Model:

1) *CNN Branch:* The CNN branch utilizes a ResNet18 model, pretrained on the ImageNet dataset, which is selected for its robustness in handling image classification tasks. This will extract the local feature from the coral and non-coral images.

2) *Transformer Branch:* The transformer branch utilizes a Vision Transformer (ViT) model. It is also pre-trained to ensure that the model can efficiently learn global contextual features, such as the overall structure of the reef ecosystem.

3) *Fusion Layer:* For combining the local and global features extracted by the respective branches, the CNN and Transformer branches are fused in a fully Connected layer: This fusion enables the model to make decisions based on both detailed local information (from CNN) and the broader environmental context (from the Transformer).

4) *Classification Head:* After feature fusion, the combined features pass through a classifier (a fully connected layer) to output the final prediction: coral or non-coral.

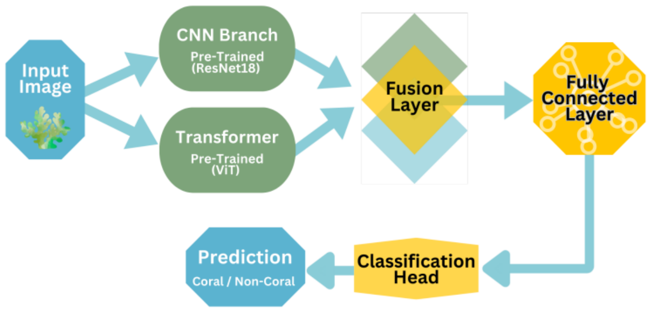

Fig. 3 Architecture of the Dual-Branch CNN-Transformer Model.

D. Model Training

A Dual-Branch CNN-Transformer Hybrid Model has been constructed, trained, tested, and validated throughout the entire procedure. The hybrid model is trained using 80% of the total dataset as the training set. The model is optimised using the AdamW optimiser, with a learning rate of 0.001. For binary classification (coral vs. non-coral), a Binary Cross-Entropy loss function has been used to calculate the error. The batch size is set to 16 to ensure that the model trains efficiently while also managing memory constraints. The model was initiated with a total of 50 epochs, and the model utilises a StepLR scheduler that reduced the learning rate by a factor of 0.5 every 10 epochs, facilitating better convergence during training.

$$\text{New Learning Rate} = \text{Initial Learning Rate} \times (\text{Decay Factor})^{\frac{\text{Epoch}}{\text{Step Frequency}}}$$

For instance, if the initial learning rate is 0.001, the learning rate after 10 epochs would be:

$$\text{New Learning Rate} = 0.001 \times (0.5)^{\frac{10}{10}} = 0.0005$$

The training and validation losses and accuracies have been monitored during the training process. The training loss also continues to decrease, as shown in the plots (Fig. 4) below, indicating that the model in question is learning quite well. The validation loss, however, fluctuates unpredictably, which may suggest that the model is overfitting a specific dataset or simply failing to reach the optimal point within that dataset. The training accuracy is steadily increasing, whereas the validation accuracy is fluctuating, which suggests that the model struggles to generalise to unseen data. The training and validation loss curves are shown as a function of the epochs. The training loss (green line) decreases gradually, while the validation loss (orange line) fluctuates. Although it is moving in a downward trend, these fluctuations indicate that there may be times when it overfits.

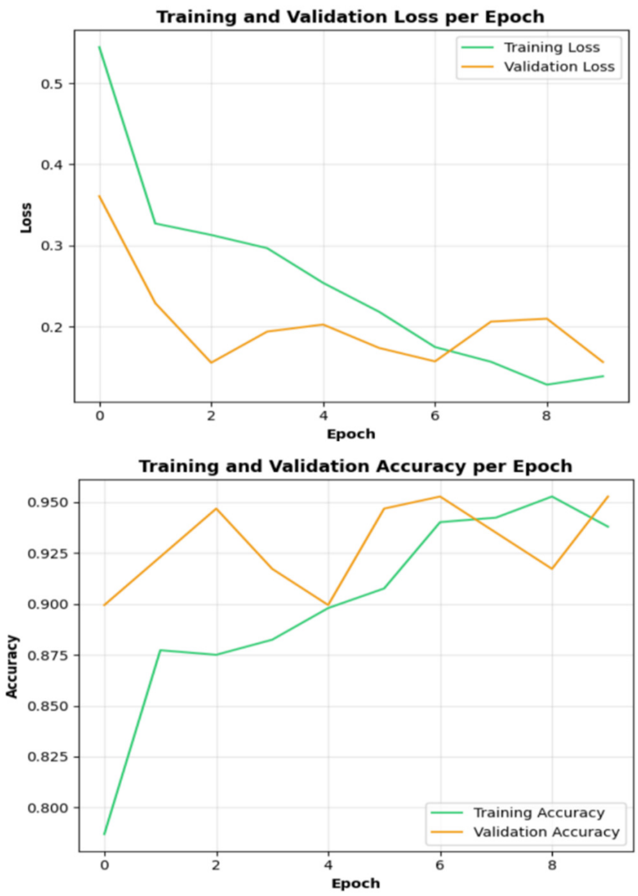

Fig. 4 Training and Validation Loss and Accuracy per Epoch.

E. Model Evaluation

The model's evaluation was conducted on the 10% test set and the 10% validation set. To evaluate the Dual-Branch CNN-Transformer Hybrid Model, we utilised a collection of established metrics and visualisations to ensure the reliability and robustness of the model in differentiating between coral and non-coral images in this study. The assessment metrics were the standard metrics (accuracy, precision, recall, and F1-score) (table 2), whose use is significant in imbalanced classification problems. We also computed AUC-ROC (Area Under the Receiver Operating Characteristic Curve), as a measure of how the model discriminated between the two classes at various decision thresholds.

TABLE 2
MODEL PERFORMANCE EVALUATION ON TEST DATASET

Metric	Value

Accuracy	0.934911
Precision (Non-Coral)	0.850000
Recall (Non-Coral)	0.871795
F1-Score (Non-Coral)	0.860759
Precision (Coral)	0.961240
Recall (Coral)	0.953846
F1-Score (Coral)	0.957529

To assess the model's performance, we also relied on a confusion matrix. The confusion matrix (fig 5) is used to indicate where the model went in the right direction and where it went in the wrong direction. It allows us to visualise the various types of errors that the model can make: true positives, when the model correctly identifies an image as coral or not coral, but it is, and false positives, when the model incorrectly identifies an image as not coral, but it is.

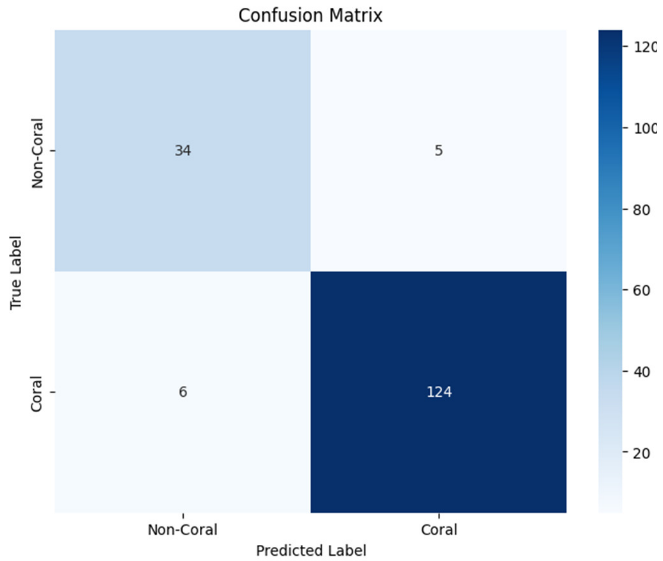

Fig. 5 Confusion Matrix for Coral and Non-Coral

IV. Result and Discussion

The Model Evaluation indicated that the test accuracy is 93.49%, meaning most of the test images were correctly identified. The precision and recall of both the coral and non-coral samples demonstrate that the model can differentiate between the two types. The model's accuracy and recall in identifying coral classes are high, with an F1-score of 95.75%. The non-coral images also scored slightly lower, with an F1-score of 86.08%. Some errors do exist, but by the general recognition of the various photos, the model tends to identify non-coral photos. The precision and recall of the non-coral category, at 85.00% and 87.18%, respectively, indicate that while there might be some false positives, the model is generally effective at detecting non-coral images with a good level of accuracy.

To test the model's robustness under various underwater conditions, we evaluated it on images with different colour-shift transformations. These transformations simulate changes in water depth, turbidity, and visibility. The table below summarises the model’s performance on these transformations:

TABLE 3
Model Performance on Different Color Transformations

Transformation	Accuracy	F1-Score (Coral)	F1-Score (Non-Coral)
Original	0.9349	0.9575	0.8608
Shallow Blue	0.9467	0.9655	0.8831
Medium Depth	0.9408	0.9621	0.8649
Deep Blue	0.9290	0.9538	0.8462
Turbid Green	0.9408	0.9618	0.8684
Low Visibility	0.9290	0.9545	0.8378

As an example of how the model functions in a real-life situation, consider the results of a prediction on a sample image (Fig 6). The dataset that the model was to classify was the image of coral, which it correctly recognised as coral and identified with a high degree of confidence. In this case, the actual class is the coral, and the model predicted it with a confidence level of 95.35. This is further confirmed by the confusion matrix, which shows a true positive for coral. The correct classification of the coral class confirms the model's accuracy in terms of precision and recall for the coral class.

Fig. 6 Sample Predictions in Test Images

According to the results, the Dual-Branch CNN-Transformer Hybrid Model is highly efficient in distinguishing between coral and non-coral images. It is exact and recalls the coral class with a high level of accuracy, probably because coral images constitute a larger percentage of the training set. Such class imbalance has enabled the model to exhibit greater capacity to reduce false negatives and enhance the classification capacity of coral in general. The relative performance compared to the non-coral class is relatively worse, a typical problem associated with imbalanced datasets. The popular model in this situation is to give more weight to the majority category —in this case, coral.

The misclassifications, where images of non-coral are incorrectly classified as coral, indicate that the model may be susceptible to the characteristics of coral, a phenomenon also observed in the greater precision of coral classification. The F1-score for non-coral pictures is 86.07%, which is a good score but indicates that there is still scope to improve performance in identifying non-coral pictures perfectly. This challenge can be exacerbated by environmental factors such as varying water conditions, light scattering, and non-coral structures that resemble coral.

These findings are supported by the AUC-ROC curve (fig 7), which measures the model's performance at various classification thresholds. The larger C would indicate that the model is stable and does not become inaccurate when the decision thresholds change, allowing it to operate confidently in different scenarios, as images can vary.

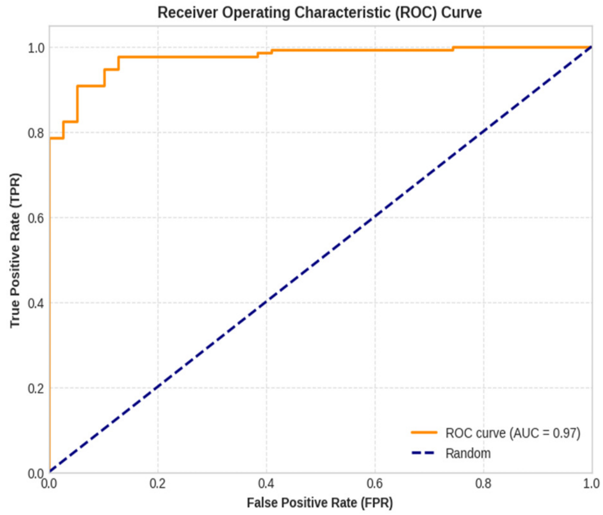

Fig. 7 Receiver Operating Characteristics (ROC) Curve

V. CONCLUSSION

This research successfully developed and validated a dual-branch CNN-Transformer hybrid model for classifying images of coral and non-coral species. The model effectively addresses key challenges in underwater image analysis by combining the detailed feature extraction of a CNN with the global contextual understanding of a Transformer.

The results are highly promising. The model achieved an overall accuracy of 93.49%. This proves its strong capability to distinguish between the two classes. Its outstanding performance on coral images highlights its precision. While performance on the minority non-coral class was slightly lower, it remained robust. Crucially, the model maintained high accuracy across a range of synthetic color-shift tests, demonstrating its resilience to common underwater environmental variations, such as changes in light and water clarity.

The primary issue identified is a minor bias in the majority class, specifically coral, which is common with skewed data. There may be some non-coral images that are misclassified due to this bias. This imbalance should be corrected in future work using methods such as data resampling or loss-function correction.

Overall, a CNN-Transformer hybrid model is an effective and flexible architecture that can be applied to monitor the coral reef. It provides a useful automated identification system applicable in a wide variety of underwater environments, adding value to conservation and marine ecology, protecting biodiversity, and assisting in the protection of the most important coral reef ecosystems.

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