Coral Reef Health Assessment Using Deep Learning

Ainara Yu Elio San Martin, Chihab El-Menyari, Mihai-Robert Bogdan,
Nikola Savić, Prity Chowdhury, Rian Chakraborty
Faculty of Electrical Engineering and Computing
University of Zagreb
Zagreb, Croatia
{ainara.martin, chihab.el-menyari, mihai-robert.bogdan,
nikola.savic, prity.chowdhury, rian.chakraborty}@fer.hr

***Abstract*—Coral reefs face critical threats from climate change requiring scalable monitoring solutions. We developed an automated coral health classification system using deep learning architectures including ResNet18, EfficientNetV2-B2, and TResNet-M trained on underwater coral imagery. Four models were evaluated to classify coral health into six categories: healthy, compromised, dead, rubble, physical issues, and disease. EfficientNetV2-B2 achieved the highest accuracy of 80.68% on the test set. Weighted loss functions improved detection of minority health classes despite minimal impact on overall performance. This approach demonstrates the feasibility of automated coral health assessment for large-scale reef monitoring applications.**

***Index Terms*—Coral Reef Health Assessment, ResNet, EfficientNet, TResNet, Deep Learning**

I. Introduction

Coral reefs support 25% of marine species while occupying less than 1% of the ocean floor area [1], [2]. Climate change represents the primary threat, with temperature increases of just 1°C for four weeks triggering coral bleaching [3]. Recent monitoring indicates 84% of global reefs experienced the most severe bleaching event on record [4].

Traditional monitoring relies on diver-based visual surveys that are labour-intensive, time-consuming, and error-prone [5], [6]. Manual image analysis creates processing bottlenecks as survey techniques requiring human presence remain limited in scope for economic reasons [7]. These constraints necessitate automated approaches for scalable reef assessment.

Image processing becomes particularly relevant since coral health assessment fundamentally depends on visual characteristics. Healthy corals exhibit vibrant coloration from symbiotic algae, while unhealthy specimens show bleaching (color loss) and tissue damage. These visual differences provide the foundation for automated classification using deep learning architectures that can learn complex patterns directly from raw image data.

This project develops a multiclass coral health classifier using pre-trained deep learning architectures. The approach demonstrates practical application of contemporary computer vision techniques in biological image analysis, leveraging the ability of deep neural networks to automatically extract relevant features from underwater imagery without extensive manual preprocessing.

Recent advances in deep learning for coral reef classification have shown promising results [8], [9], providing the foundation for educational exploration of modern computer vision techniques applied to environmental monitoring challenges.

II. Brief Literature Review

Monitoring coral reef health evolved from diver-based transect surveys in the 1990s, where practitioners recorded live and bleached coral cover using belt transects or quick visual scores, to coordinated global networks like GCRMN and CoralWatch in the 2000s, which standardized protocols and harnessed citizen science color cards for broader geographic coverage. In the 2010s, high-resolution underwater photography and 3D photogrammetry enabled detailed mapping of bleaching extent, while satellite-derived sea surface temperature indices (e.g., NOAA's Degree Heating Weeks) provided large-scale early warnings, albeit needing in situ calibration. More recently, drone-based multispectral imaging and AI-driven CNN classifiers (e.g., CoralNet) have automated image analysis, achieving a precision of over 90 % in curated datasets, but are still struggling with geographic bias and variable lighting. Despite these advances, most global observations still rely on a few traditional methods and there is a persistent lack of interoperable, FAIR-compliant datasets that integrate in-water, photogrammetric and remote-sensing data. Our study addresses these gaps by comparing state-of-the-art CNNs (EfficientNetV2, TResNet, etc.) on a balanced, metadata rich global image repository, laying the groundwork for a unified coral health monitoring framework [10].

III. Methodology

A. Dataset

The dataset consists of underwater coral reef images collected from two environmental conditions: wet (underwater) and dry (above water) surveys. Images were annotated using metadata files containing patch identifiers and corresponding health classifications. The dataset includes multiple coral health categories: Healthy coral, Compromised coral, Dead coral, Rubble, Physical Issues, and Disease. Class distribution analysis revealed a significant imbalance, with some categories containing as few as 3 samples. Classes with single images were excluded from training to enable stratified splitting. The filtered dataset was partitioned into 80% training, 10% validation, and 10% test sets using stratified sampling to maintain class proportions across splits. All images were resized to 256×256 pixels using Lanczos interpolation to ensure consistent input dimensions. Data preprocessing included normalization with mean [0.5, 0.5, 0.5] and standard deviation [0.5, 0.5, 0.5] across RGB channels.

B. Architecture

Four deep learning architectures were evaluated: ResNet18, EfficientNetV2-B2 with and without weighted loss, and TResNet-M. All models used transfer learning with ImageNet pre-trained weights, replacing the final classification layer to match the number of coral health classes. ResNet18 served as the baseline architecture due to its proven effectiveness in image classification tasks. EfficientNetV2-B2 was selected for its efficiency and strong performance on visual recognition benchmarks. TResNet-M was included to evaluate modern architectural improvements over traditional ResNet designs. To address class imbalance, weighted cross-entropy loss was implemented using sklearn's balanced class weights. The weighted version assigns higher penalties to misclassified minority classes during training. All models were trained using AdamW optimizer with 3×10^{-4} learning rate and StepLR scheduler (step size 5, gamma 0.5). Training was conducted for 10-15 epochs with a batch size of 32. Models were evaluated using accuracy, precision, recall, and F1-score metrics calculated on the held-out test set.

IV. Results

Four deep learning architectures were evaluated for coral reef health classification: ResNet18 as a baseline, EfficientNetV2-B2 with and without weighted loss functions, and TResNet. All models were trained for 10-15 epochs using the same preprocessing pipeline with images resized to 256×256 pixels.

Table I summarizes the performance metrics across all tested models. EfficientNetV2-B2 without weighted loss achieved the highest test accuracy of 80.68%, outperforming the baseline ResNet18 by 3.36 percentage points. The weighted F1-scores ranged from 0.76 to 0.80, indicating reasonable overall performance across the imbalanced dataset.

TABLE I: Performance comparison of deep learning models for coral health classification

Model	Test Accuracy	Macro Avg F1	Weighted Avg F1
ResNet18	77.32%	0.64	0.77
EfficientNetV2-B2	80.68%	0.63	0.80
EfficientNetV2-B2 (weighted)	79.49%	0.64	0.79
TResNet	75.52%	0.55	0.76

Figures 1 through 4 present the confusion matrices for each tested model, revealing detailed classification patterns and systematic misclassification errors across coral health categories.

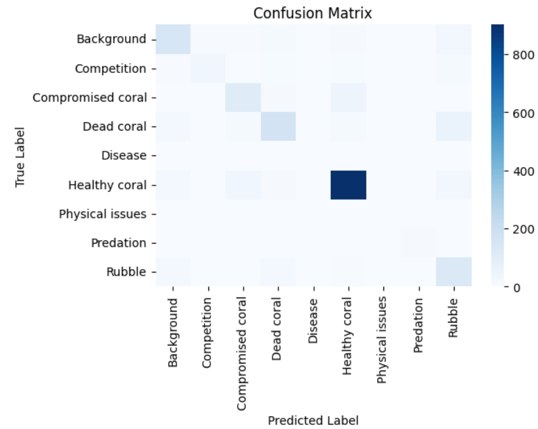


Fig. 1: Confusion matrix for ResNet18 baseline model

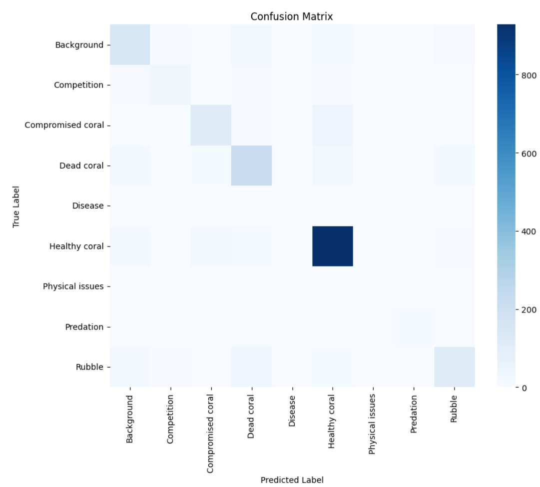


Fig. 2: Confusion matrix for EfficientNetV2-B2

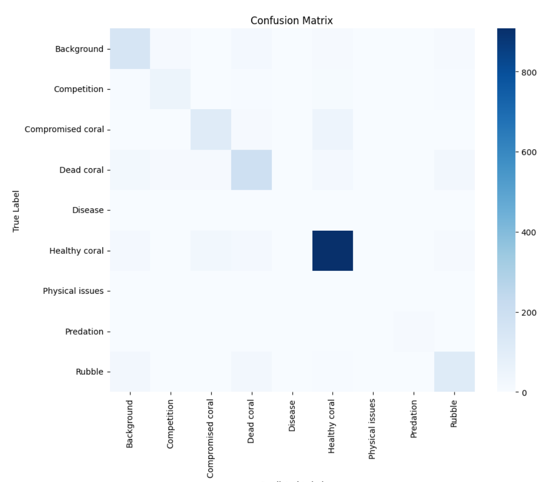


Fig. 3: Confusion matrix for EfficientNetV2-B2 with weighted loss

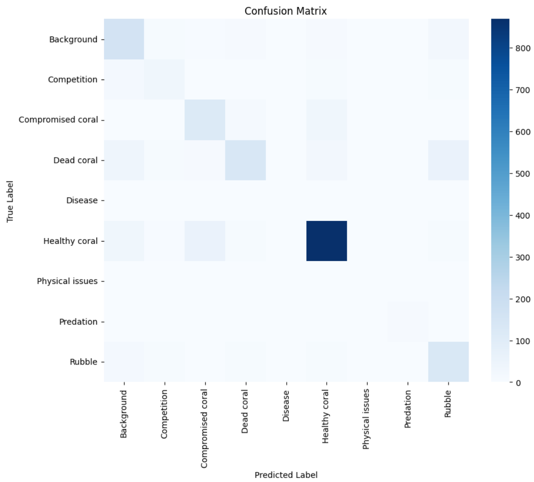
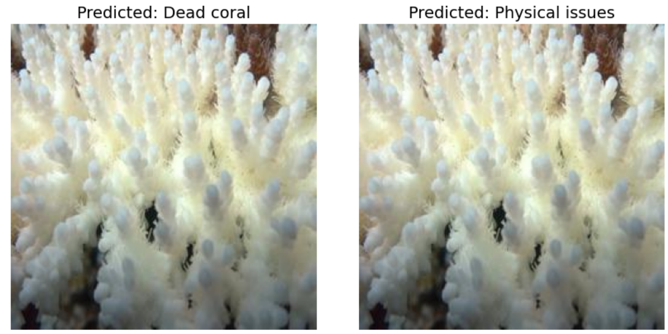


Fig. 4: Confusion matrix for TResNet

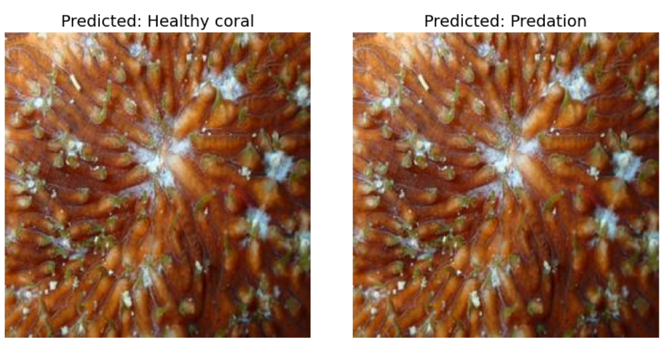


(a) Original EfficientNetV2-B2: Dead coral

(b) Weighted EfficientNetV2-B2: Physical Issues

Fig. 6: Example 2: Weighted loss correctly identifies Physical Issues class, demonstrating improved sensitivity to rare coral health conditions

The confusion matrices demonstrate that all models achieved the highest accuracy on the Healthy coral class while exhibiting systematic confusion between visually similar degraded states, particularly Dead coral and Rubble categories.



(a) Original EfficientNetV2-B2: Healthy

(b) Weighted EfficientNetV2-B2: Predated

Fig. 5: Example 1: Weighted loss enables correct classification of minority class samples

Figures 5 and 6 demonstrate how weighted loss corrects majority class bias in EfficientNetV2-B2. The standard model misclassified minority class samples as Healthy coral and Dead coral, while the weighted variant correctly identified the actual health states. Although weighted loss showed minimal impact on overall accuracy, it significantly improved detection of rare coral health conditions that require distinct management responses. TResNet showed the lowest performance with 75.52% accuracy and a macro F1-score of 0.55, indicating potential underfitting or sensitivity to the class imbalance present in the dataset. The baseline ResNet18 demonstrated stable performance, proving effective for this classification task despite its simpler architecture compared to the more complex models tested.

V. Discussion

EfficientNetV2-B2 achieved the highest accuracy (80.68%) among tested architectures, validating the effectiveness of compound scaling for underwater coral classification. The 3.36 percentage point improvement over the ResNet18 baseline demonstrates architectural advances beyond simple depth increases.

Weighted loss implementation showed limited benefit for overall performance, with macro F1-scores remaining nearly identical (0.63-0.64) across variants. However, qualitative analysis reveals that weighted loss improved detection of ecologically critical minority classes, correctly identifying Physical Issues and Disease conditions that the standard model misclassified as common categories like Healthy or Dead coral. The persistent challenges with minority classes confirms that data scarcity rather than algorithmic limitations represents one of the primary constraints for automated coral health monitoring systems.

The dataset originates from the Koh Tao Coral Condition Survey Project [9], where expert annotations followed standardized coral reef conservation protocols. The original study employed an ensemble combining Swin-Transformer-Small, Swin-Transformer-Base, and EfficientNet-B7 for multi-label classification, achieving superior performance through model diversity. Our single-model approach using EfficientNetV2-B2 represents a computationally efficient alternative for resource-constrained deployment scenarios.

TResNet's underperformance despite architectural innovations suggests sensitivity to the specific visual characteristics of underwater coral imagery. The frequent confusion between Rubble, Dead coral, and Compromised coral classes indicates these categories share similar visual features that challenge current deep learning approaches, consistent with documented difficulties in coral health assessment [5].

The 256×256 pixel resolution represents a practical compromise between computational efficiency and feature preservation. Higher resolutions might improve minority class recognition, but would increase computational requirements for real-time monitoring applications.

Results demonstrate the feasibility of automated coral health classification using standard CNN architectures, providing the foundation for scalable reef monitoring systems. However, addressing severe class imbalance through data augmentation or synthetic generation remains essential for robust deployment in conservation applications.

VI. Conclusion

This study evaluated deep learning architectures for automated coral health classification. EfficientNetV2-B2 achieved the best performance at 80.68% accuracy, demonstrating that compound scaling architectures outperform traditional CNN designs for underwater imagery classification.

Class imbalance remains the primary limitation, with minority classes consistently misclassified regardless of loss weighting strategies. While weighted loss showed promise for detecting ecologically critical conditions like physical issues and disease, the scarcity of training samples limits its effectiveness. This indicates that algorithmic solutions alone are insufficient without adequate training data.

The approach proves viable for automated coral monitoring systems but requires expanded datasets for minority health categories before reliable field deployment. Future work should prioritize data collection for underrepresented classes and evaluate cross-site generalization for global reef monitoring applications.

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