Deep Learning-Based Coral Reef Health Assessment Using Modified Inception V3

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***Abstract*— Marine biologists have accumulated extensive data on underwater environments, yet the analysis of this data is often challenging and labor-intensive. Deep learning has emerged as a powerful tool for interpreting complex data, including imagery. This study introduces a modified InceptionV3 deep learning model for classifying coral health conditions (healthy and bleached) using a dataset of 1,169 images. Transfer learning was applied to adapt the pre-trained InceptionV3 architecture, and hyperparameter tuning was employed to enhance performance. The model achieved an impressive accuracy of 99.14%, significantly improving upon the previous study's highest accuracy of 86%, marking a 13.14% increase. These findings highlight the potential of advanced deep learning techniques, particularly the InceptionV3 model, in accurately classifying coral health conditions. Future research is necessary to validate these results on larger, more diverse datasets and in real-world applications.**

Keywords*— *InceptionV3, CNN, deep learning, coral health, transfer learning.

I. INTRODUCTION

Coral reefs, as vital marine ecosystems, play a crucial role in maintaining biodiversity, supporting fisheries, and protecting coastlines. In the Philippines, coral reef fisheries support over a million small-scale fishermen, generating nearly USD 1 billion each year for the national economy. [3]. However, these fragile ecosystems face significant threats due to climate change, pollution, and human activities. Monitoring and assessing coral reef health are essential for conservation efforts and sustainable management.

Coral reef health is threatened by rising water pollution and the impacts of climate change. The destruction of these coral reefs becomes relevant as the Philippines has a huge coral reef presence making it the second largest in Southeast Asia.[1]

From 2015 to 2017, data from 166 stations across 31 provinces (108 in Luzon, 31 in Visayas, and 27 in Mindanao) showed that none were classified as excellent in live coral cover, with over 90% rated poor or fair and an average hard coral cover of 22% (95% CI: 19.4, 24.9). These findings highlight a significant decline in local reef conditions over the past four decades, underscoring the urgent need to revise and update conservation and management policies. [4].

Marine biologists have extensive data on the underwater environment, but analyzing it is challenging and tedious, making automation beneficial for efficient monitoring and preservation. Their research, focusing on coral reef classification, emphasizes image enhancement and recognition, with an interest in determining if a single enhancement technique is suitable for coral reefs due to the challenging conditions in which images are captured. [5].

In recent years, deep learning has emerged as a powerful tool for analyzing complex data, including imagery. Deep learning is driving innovation and transformation throughout various aspects of contemporary life. Many of the artificial intelligence advancements featured in the media are grounded in deep learning techniques. [6]. Leveraging deep neural networks, such as the InceptionV3 architecture, can enhance our ability to assess coral reef health.

The study addresses the lack of good data on economic well-being in developing countries. They propose a new method using high-resolution satellite images and machine learning to estimate how well-off people are. This method is accurate, cheap, and can be easily applied to many areas. With freely available data, this could be a game-changer for tracking poverty and designing policies to fight it. The success with limited data also suggests this method could be useful in other areas of science [7].

Deep learning (DL) is revolutionizing marine ecology by enabling faster, automated analysis of vast data from underwater sensors and cameras, allowing real-time species identification and pattern recognition. This research bridges the gap between marine ecologists and data scientists by explaining DL, showcasing applications like tracking marine life and monitoring pollution, and discussing future advancements and challenges in managing large datasets. [8].

To address these shortcomings, this study proposes modifications to Inception V3's top layers combined with transfer learning to achieve higher classification accuracy for coral health. The innovations include:

Global Average Pooling. Replacing traditional fully connected layers to reduce overfitting by minimizing the number of parameters.

Dense Layers. Adding dense layers with 512 and 1024 neurons using ReLU activation function, and incorporating dropout and L1 regularization to further combat overfitting.

Output Layer. Implementing a softmax activation function to classify images into two categories: healthy and bleached.

Fine-Tuning. Freezing the pre-trained layers of inceptionV3 to retain learned features and focusing training on the newly added top layers to enhance performance for the specific classification tasks.

These modifications were specifically designed to reduce overfitting and improve computational efficiency, thereby enhancing the model's performance for the classification of coral health.

II. Related works

A. *Coral Heath*

Coral reefs, as vital marine ecosystems, play a crucial role in maintaining biodiversity, supporting fisheries, and protecting coastlines. In the Philippines, coral reef fisheries provide livelihood for more than a million small-scale fishers who contribute almost US$ 1 billion annually to the country's economy [3]. However, these fragile ecosystems face significant threats due to climate change, pollution, and human activities. Monitoring and assessing coral reef health are essential for conservation efforts and sustainable management.

The health of the coral reefs is at risk due to the increase in water pollution and climate change. The destruction of these coral reefs becomes relevant as the Philippines has a huge coral reef presence making it the second largest in Southeast Asia.[1]

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B. *Deep learning for Coral Reef Image Assessment*

Classifying underwater images of coral reefs is crucial for marine scientists, but the traditional method of manual analysis by experts in a lab is slow and laborious. This is because the first step, classifying the coral species, is highly intensive and difficult to automate due to the sheer volume of images and the similar appearance of many coral species. This paper focuses specifically on the challenging task of classifying Scleractinian (stony) corals, which are particularly difficult to differentiate. The study proposes a deep learning technique using Convolutional Neural Networks (CNNs) as a potential solution for automating coral classification. The approach aims to find a faster, more efficient way to analyze these images, especially for branching corals where structure plays a key role in identification. Initial results show promise, with the model learning and predicting coral types accurately when trained and tested on similar datasets [23].

A powerful machine learning technique, is being used to tackle challenging computer vision problems like image classification. This study focuses on using Convolutional Neural Networks (CNNs) to classify coral reef images into healthy and stressed states, achieving up to 90% accuracy with models like ResNet50 and Inception V3. Early detection of stress in coral reefs can help prevent further damage and aid in their restoration, crucial for maintaining marine ecosystem balance [24].

Recognizing coral species from underwater texture images is challenging due to the lack of global structure information, similar characteristics among species, and difficulty in defining spatial borders. This paper aims to develop an accurate classification model for coral texture images using Convolutional Neural Networks (CNNs), data augmentation, and transfer learning. By applying variations of ResNet to small datasets like EILAT and RSMAS, state-of-the-art accuracies were achieved despite class imbalances and inter-class variation. [25].

Deep learning (DL) has become the Gold Standard in machine learning (ML), achieving outstanding results on complex cognitive tasks and often surpassing human performance. This review provides a comprehensive survey of DL, including its importance, types of techniques and networks, and the development of Convolutional Neural Networks (CNNs) from AlexNet to High-Resolution Network (HR.Net). It also addresses challenges, solutions, major applications, and the impact of computational tools like FPGA, GPU, and CPU on DL, concluding with an evolution matrix, benchmark datasets, and a summary [26]. Traditional methods for monitoring coral reefs, like underwater surveys and satellite imagery, have limitations. In-person surveys are costly and inconsistent, while satellites can be expensive and affected by weather. Drone imagery offers a high-resolution alternative at a lower cost, but processing the data is typically complex and time-consuming. This study addresses this by proposing a new, semi-automatic workflow for processing drone images. The method utilizes Google Earth Engine (GEE) and free open-source software (FOSS). Using this workflow, researchers successfully processed drone images of Australia's Heron Reef and classified the coral, sand, and dead coral coverage with high accuracy. This approach offers a more efficient and potentially cost-effective way to analyze coral reefs using drone imagery [27].

C. *Inception V3 for coral health image classification*

Due to the rising number of lung diseases, radiologists are struggling to keep up with the demand for chest X-ray analysis. This can lead to missed or incorrect diagnoses. This study proposes a deep learning approach to address this challenge. They developed a computer-aided diagnostic model using a pre-trained Inception-v3 model (transfer learning) to automatically extract features from lung X-rays. This model then classifies the images as healthy, diseased, or needing further investigation. Compared to traditional methods, their approach achieved high accuracy (over 95%) and offers a faster and potentially more reliable way to diagnose lung diseases [9].

With the growing volume of online data, content-based image classification has become crucial for efficient retrieval, particularly in sports where correct posture and environment are vital to prevent injuries. This paper presents a robust framework for classifying sports images using Inception V3 for feature extraction and neural networks for categorization. Tested across six sports—rugby, tennis, cricket, basketball, volleyball, and badminton—the framework achieved a notable 96.64% average accuracy, outperforming other classifiers like Random Forest, KNN, and SVM, demonstrating its effectiveness for accurate sports activity detection and classification. [10].

A new approach that combines Inception v3, a deep learning model, with manually extracted features. This combination effectively captures both general image patterns and specific cell characteristics, leading to a highly accurate classification system. To address limitations caused by small datasets, the researchers employed transfer learning, a technique that leverages knowledge from a pre-trained model. This approach achieved an accuracy of over 98% on the Herlev dataset, demonstrating its potential for computer-aided diagnosis of cervical cancer. The proposed method offers advantages like good generalizability, low complexity, and high accuracy, making it a promising tool for classifying other cancer cells as well [11].

Deep learning (DL) is a new tool being used in controlled environment agriculture (CEA) facilities like greenhouses and vertical farms. This review examined 72 studies to see how DL is being applied. The majority of studies (82%) focused on greenhouses, and the most common applications were yield estimation (31%) and monitoring plant growth (21%). Convolutional Neural Networks (CNNs) were the most popular DL model (79%), and accuracy was the most frequent way to measure success (21%). Interestingly, for studies focused on microclimate control, a different metric, Root Mean Squared Error (RMSE), was always used [12].

III. Materials and Methods

A. *Data Set*

The dataset comprises 1,169 images, including 684 images obtained by Vivian Ecunar and Jason Artates, and 485 images from Kaggle, uploaded by Marionette. The images are uniformly sized at 224x224 pixels and are categorized into two classes: healthy and bleached coral.

B. *Machine Learning Software*

Python is the primary programming language for its ease of use and robust machine learning libraries; Google Colaboratory is chosen for its web-based Python execution and powerful hardware; TensorFlow and Keras are used for their deep learning capabilities; NumPy for array manipulation; and Matplotlib and Seaborn for data visualization.

C. *Image Classification Process*

Step 1 Data Splitting The study utilizes a 70-15-15 train-validation-test split for InceptionV3 training on healthy and bleached coral images. This mitigates overfitting by evaluating on a held-out training and validation set as well as assesses generalizability using a separate test set.

Step 2 Pre-processing The pre-processing stage resizes images (224x224) for InceptionV3 and employs Keras' ImageDataGenerator for data augmentation. Augmentation techniques (rotations, shifts, shears, zooms, and flips) with defined ranges are applied to enrich the dataset and improve model robustness.

Step 3 Validation The validation help assesses the model's performance on unseen data and ensures that the model generalizes well beyond the training set. During training, the model learns from the training data.

Step 4 Testing The testing serving as a key factor in confirming their dependability, precision, and strength. In contrast to conventional software systems that operate based on clearly defined commands, model derive their functionality from patterns and inferences learned through data. The complete workflow is detailed in Fig. 1.

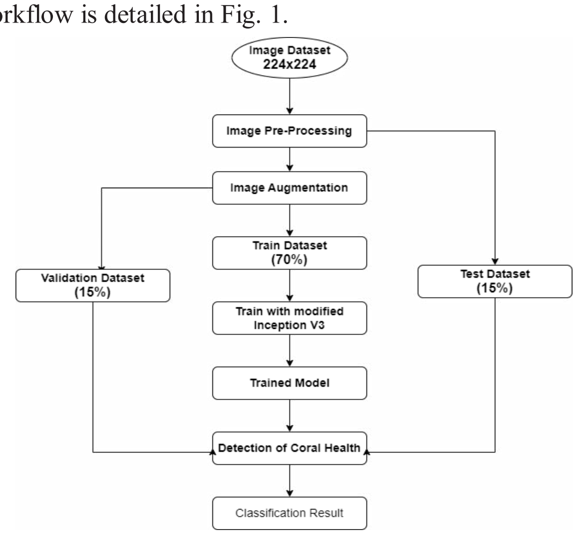

Fig. 1. Conceptual framework of the study

D. *InceptionV3 adaptation for classification*

The top pre-trained layers of InceptionV3 were removed and a new Softmax classifier with two dense ReLU layers (512, 1024 neurons) is added for class probability prediction. Also, a L1 regularization with weight penalty of (0.001) and dropout (0.5) applied to dense layers to prevent overfitting. Moreover, a Learning rate (0.001, adjusted), epochs (20), and batch size (32) optimized for training efficiency and performance.

E. Evaluation Metrics

To assess the performance of the modified InceptionV3 model, various efficiency metrics were used with the calculations outlined accordingly.

Accuracy measures the proportion of correct predictions made by the model over the total number of predictions.

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{FN} + \text{TN} + \text{FP}) \quad (1)$$

Precision represents the proportion of true positive predictions (correctly predicted positive samples) out of all positive predictions (both true positives and false positives).

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (2)$$

Recall measures the proportion of true positive predictions out of all actual positive samples (true positives and false negatives).

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (3)$$

The F1 score balances precision and recall. It's the harmonic mean of precision and recall, providing a single metric that considers both.

$$\text{F1 Score} = \frac{\text{2x Precision x Recall}}{\text{Precision+ Recall}} \quad (4)$$

Macro AUC is used in multi-class classification. It is the average of the area under the receiver operating characteristic curve (AUC) for each class.

$$\text{Macro\_AUC} = (1 / C) * \Sigma (\text{AUC\_i}) \text{ (for i = 1 to C)} \quad (5)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The model demonstrates exceptional performance with an accuracy of 99.00%, correctly classifying nearly all samples. It maintains a high precision of 99.00%, indicating a very low rate of false positives. With a recall of 99.00%, it effectively identifies almost all true positives. The F1 score is also 99.00%, showing a strong balance between precision and recall. Additionally, the model achieves a perfect AUC of 100, highlighting its excellent ability to distinguish between classes.

Table 1. Performance results of modified InceptionV3 model

Metrics	**Result**
Accuracy	99.00
Precision	99.00
Recall	99.00
F1 Score	99.00
AUC	100

The modified Inception V3 model demonstrates outstanding performance in classifying coral health conditions. For the "Healthy" class, it achieves a precision of 99, a recall of 98, and an F1 score of 99. For the "Bleached" class, the model attains perfect precision and recall of 1.00, with an F1 score of 99. These results highlight the model's exceptional accuracy and reliability in distinguishing between healthy and bleached coral conditions.

Table 2. Performance result of InceptionV3 on each class

Coral Health	**Precision**	**Recall**	**F1-Score**
Healthy	99.00	98.00	99.00
Bleached	100	100	99.00

The modified Inception V3 model shows effective learning over 20 epochs, with both training and validation losses decreasing significantly as shown in Fig. 2, indicating effective learning on the training data.

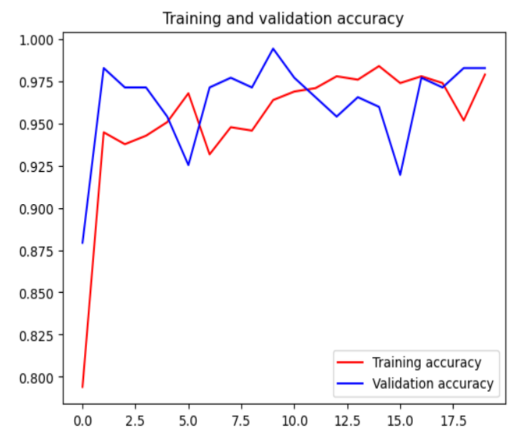

Fig. 2. Graph of Training/Validation Accuracy

Meanwhile, the training and validation loss curves exhibit a notable reduction in error rate, despite some fluctuations. This suggests that the network is learning at an appropriate pace during the training process. By the end of the 20 epochs, the accuracy rates have significantly improved, and the loss values have decreased as shown in Fig. 3, confirming successful model generalization and optimization.

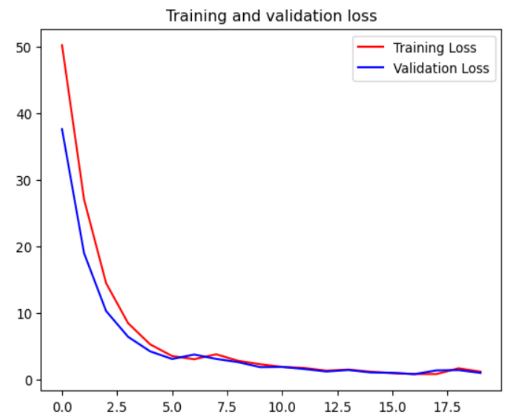

Fig. 3. Graph of Training/Validation Loss

The result from the examination of the confusion matrix in Fig. 4 reveals a representation of accurate and mistaken image classifications across classes. 'Bleached' appeared with a noteworthy 10 misclassifications, while 'Healthy' followed with 0 inaccuracies. This comprehensive outcome seamlessly integrates into the computation of the modified Inception V3 model's high accuracy, elevating the significance of its overall performance.

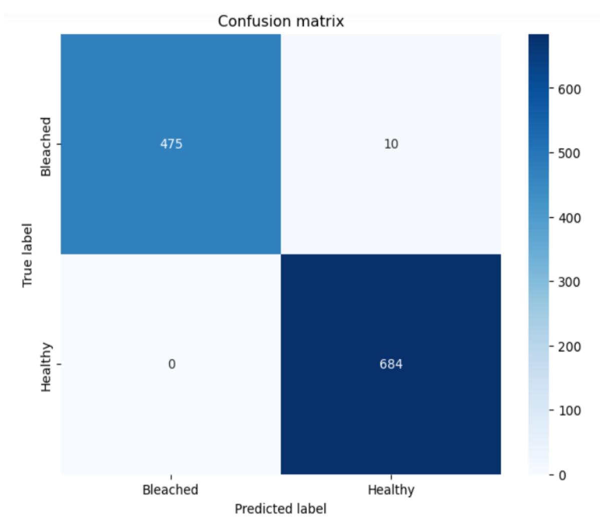

Fig. 4. Confusion Matrix

The modified Inception V3 model shown in table 3 significantly outperformed earlier studies that utilized various machine learning models for coral health and reef mapping. These studies employed different approaches, such as VGG, ResNet, Random Forest Classifier, and SVM, but the presented model demonstrated notably superior performance. Specifically, it achieved an impressive accuracy of 99.14%, which is a substantial improvement compared to the highest accuracy of 86% achieved by [1], using a Random Forest Classifier. This highlights the advancements in deep learning techniques and the effectiveness of the Inception V3 model in accurately classifying coral health.

Table 3. Performance Comparison of this study with other studies using CNN Models

Study	Year	Method	Accuracy (%)
Zhang et al.,	2024	VGG and ResNet	81.83
Bennett et.al	2020	Random Forest Classifier	86.00
Gapper et al.,	2019	SVM	78.80
This study	**2024**	**InceptionV3**	**99.14**

V. CONCLUSIONS

The class-wise performance metrics further validate the model's effectiveness. For the "Healthy" class, it achieved a precision of 99, recall of 98, and an F1 score of 99. For the "Bleached" class, it attained perfect precision and recall of 1.00, with an F1 score of 99. This indicates the model's reliability and precision in differentiating coral health conditions.

The training and validation metrics across 20 epochs demonstrate clear improvements in accuracy and reductions in loss, confirming the model's effective learning and optimization. The confusion matrix analysis shows minimal misclassifications, reinforcing the high accuracy and reliability of the model.

The modified InceptionV3 model exhibits exceptional performance in classifying coral health conditions, significantly outperforming previous studies. The model's ability to achieve an accuracy of 99.14% highlights the effectiveness of deep learning techniques, particularly the InceptionV3 architecture, in coral health classification tasks. This study underscores the potential of advanced CNN models in enhancing coral reef monitoring and conservation efforts.

Overall, this study highlights the potential of advanced CNN models, particularly the modified Inception V3, in enhancing the accuracy and reliability of coral health monitoring. The significant improvements over previous methodologies pave the way for more precise and effective coral reef conservation efforts, leveraging state-of-the-art deep learning techniques.

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ACKNOWLEDGMENT

The researchers would like to acknowledge the President Ramon Magsaysay State University for the Scholarship Grant.

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