Coral Health Assessment Using Modified Inception V3 and DenseNet 121

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***Abstract*— This study compares the training performance of modified InceptionV3 and DenseNet121 models for coral health assessment. DenseNet121 exhibits a gradual improvement in accuracy and a significant reduction in validation loss towards the end of training. Despite these improvements, the model faces considerable fluctuations in validation loss and accuracy early in the process, with a peak validation accuracy of 88.37%. In contrast, the modified InceptionV3 model demonstrates a more stable and consistently high performance throughout its training. It achieves a peak validation accuracy of 99.14%, with validation loss steadily decreasing and maintaining minimal fluctuation. This stability suggests that InceptionV3 converges more quickly and effectively. Overall, modified InceptionV3 outperforms DenseNet121 in terms of peak validation accuracy and consistency, proving to be a more robust and reliable choice for coral reef health assessment tasks.**

Keywords— InceptionV3, DenseNet121, CNN, deep learning, coral health, transfer learning.

I. Introduction

Coral reefs, often referred to as the “rainforests of the sea,” harbor immense biodiversity and play a crucial role in maintaining marine ecosystems [21]. However, these delicate habitats face unprecedented threats due to climate change, ocean acidification, and human activities [20].

Monitoring their health is essential for conservation efforts and sustainable management [18]. Deep learning models have emerged as powerful tools for ecological research, including coral reef assessment. In this study, we investigate the performance of a modified Inception V3 model alongside other state-of-the-art deep learning architecture [19].

Convolutional networks (ConvNets) are crucial for computer vision tasks. Since 2014, deep ConvNets have gained popularity, leading to significant improvements. While larger models improve performance, computational efficiency and low parameter count matter for mobile vision and big-data scenarios [1].

Our evaluation focuses on key metrics—accuracy, precision, and recall—to determine which model excels in assessing coral reef health. By understanding the strengths and limitations of these models, we can enhance monitoring strategies, inform policy decisions, and contribute to the preservation of these invaluable ecosystems.

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].

II. Related Works

A. Coral Heath

Marine biologists have collected a vast amount of data about underwater environments, but analyzing this data is both labor-intensive and complex. Automation presents a promising solution for more efficient monitoring and conservation. Studies on coral reef classification have concentrated on image enhancement and recognition to assess whether a single enhancement method is effective under the challenging conditions of coral reef imagery [22].

Recently, deep learning has proven to be a powerful tool for analyzing complex datasets, including images. This technology is fueling innovation across various fields, with many notable advancements in artificial intelligence covered by the media being based on deep learning techniques [23]. Employing deep neural networks like the InceptionV3 architecture can greatly enhance our capacity to assess the health of coral reefs [1].

A study has proposed an innovative method to tackle the lack of reliable economic data in developing countries by utilizing high-resolution satellite imagery and machine learning to estimate economic well-being. This method is accurate, cost-effective, and applicable across diverse regions. The use of free data could transform poverty tracking and policy-making, and its effectiveness with limited data hints at potential uses in other scientific field [24].

Deep learning (DL) is transforming marine ecology by enabling the rapid, automated analysis of large datasets from underwater sensors and cameras, facilitating real-time species identification and pattern recognition. This research serves as a bridge between marine ecologists and data scientists, providing a clear explanation of DL, showcasing its applications in tracking marine life and monitoring pollution, and discussing future advancements and challenges in managing large datasets [25].

B. *Deep learning for Coral Reef Image Assessment*

VGGNet, introduced in 2014, is renowned for its simplicity and depth, employing a uniform architecture with multiple convolutional layers. While VGGNet achieves high accuracy, it has a significantly higher number of parameters compared to InceptionV3, leading to increased computational cost and training time. Studies have shown that InceptionV3 outperforms VGGNet in various image classification tasks, achieving higher accuracy rates due to its efficient layer design and deeper feature extraction capabilities [1] [2].

Recent advancements in deep learning have significantly enhanced various applications in computer vision and pattern recognition. For instance, explored deep learning techniques for coral classification, illustrating the potential of neural networks in marine biology [11]. Convolutional Neural Networks (CNNs) have been widely studied for their effectiveness in image analysis, as detailed by Prabhu, who provided an in-depth understanding of CNNs and their applications in deep learning [12].

Further developments in automated image annotation have been demonstrated and implemented Mask RCNN for object detection, showcasing its utility in annotating complex datasets [13]. Additionally, applied vision-based techniques to measure canopy areas, highlighting the versatility of image processing methods discussed the use of transfer learning for classifying conidial fungi, emphasizing how pre-trained models can be adapted for specific classification tasks [14, 15].

Investigated macroscopic classification of Aspergillus fungi species using CNNs, demonstrating the practical applications of deep learning in microbiology [16]. Visual percepts quality recognition, further underscoring the advancements in convolutional neural networks and their impact on visual quality assessment [17].

ResNet, or Residual Network, is designed to combat the degradation problem in deep networks by incorporating skip connections, which allow gradients to flow through the network more effectively. Although ResNet models (such as ResNet50 and ResNet101) achieve competitive results, InceptionV3 often surpasses them in terms of precision and recall due to its parallel convolutional approach that captures more diverse feature representations [3]. Moreover, InceptionV3 performs exceptionally well in transfer learning scenarios, making it a preferred choice in applications where labeled data is limited [4].

III. Materials and Methods

A. *Data Set*

The dataset, comprising 1,169 images uniformly sized at 224x224 pixels, includes 684 images captured by Vivian O. Ecunar and Jason Artates, and 485 images sourced from Kaggle by Marionette. These images are categorized into two classes: healthy coral and bleached coral. Importantly, the dataset is free from any bias that could introduce systematic errors into the models.

B. *Machine Learning Software*

Python serves as the primary programming language due to its user-friendly nature and rich ecosystem of machine learning libraries. Google Colab is selected for its web-based Python execution environment and powerful hardware resources. For deep learning tasks, we rely on TensorFlow and Keras. NumPy is essential for efficient array manipulation, while Matplotlib and Seaborn handle data visualization.

C. *Image Classification Process for modified InceptionV3*

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.

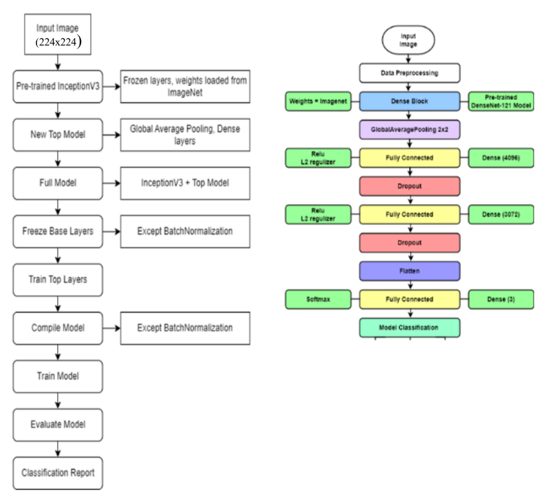

Fig. 1. Conceptual framework of the study

D. *InceptionV3 modification 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 and DenseNet-121 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.

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

Precision is the ratio of true positive predictions (correctly predicted positive samples) to the total number of positive predictions (which includes both true positives and false positives).

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

Recall measures the proportion of true positive predictions out of all actual positive samples (true positives and false negative Recall quantifies the ability of a classification model to correctly identify positive instances (true positives) out of all actual positive samples (which includes both true positives and false negatives).

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

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

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

In multi-class classification, the macro-AUC (Area Under the Curve) represents the average AUC across all classes. Each class has its own ROC curve, and the macro-AUC provides an overall assessment of the model's performance by considering all classes equally.

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

IV. Experimental Results and Discussion

The modified InceptionV3 model achieved a high level of performance as shown in table 1, with an accuracy of 99.14%, precision of 99.00%, recall of 99.00%, and an F1-score of 99.00%. These metrics indicate that the model is both highly accurate in its predictions and balanced in handling the classification of both bleached and healthy coral reef images, despite the slight class imbalance in the dataset. The consistency between precision and recall suggests that the model is effective at minimizing both false positives and false negatives, indicating strong generalization to the target task.

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%

In comparing the performance of the InceptionV3 and DenseNet-121 models, InceptionV3 significantly outperformed DenseNet-121 as presented in table 2. InceptionV3 achieved an accuracy of 99.14% and an AUC of 100, indicating near-perfect classification and excellent separability between classes. In contrast, DenseNet-121 yielded an accuracy of 88.36% and an AUC of 96.31%, suggesting lower classification accuracy and less effective class discrimination. These results highlight the superior performance of InceptionV3 for this specific task, particularly in distinguishing between bleached and healthy coral reef images.

Table 2. Comparison of modified InceptionV3 to DenseNet-121 model

Deep Learning Model	Accuracy Result
Modified Inception V3	99.14 %
DenseNet-121	88.36%

The Wilcoxon signed-rank test shows a statistically significant difference between the accuracy results of the InceptionV3 and DenseNet-121 models as detailed in Table 3, with a p-value of 0.00009. This indicates that the performance of the two models is significantly different, with InceptionV3 generally outperforming DenseNet-121.

Table 3. Wilcoxon signed-rank test of modified InceptionV3 and DenseNet-121 model

Wilcoxon Values	Result
Test Statistics (W)	2.0
p-Value	0.00009155

Over 20 epochs, the modified Inception V3 model demonstrates effective learning, with notable reductions in both training and validation losses, as depicted in Fig 2.

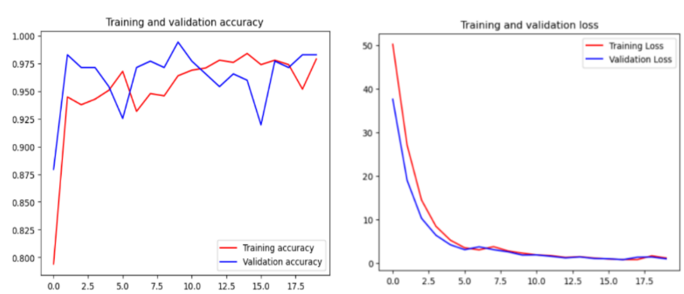

Fig. 2. Training/Validation Accuracy and Training/Validation Loss Graphs of the modified Inception V3 Model

Throughout the training and validation process, the loss curves demonstrate a consistent reduction in error rate, despite minor fluctuations. This indicates that the neural network is learning effectively. After 20 epochs, accuracy rates have notably improved, and loss values have decreased, as depicted in Fig. 2. These findings contribute to the overall high accuracy of the modified Inception V3 model

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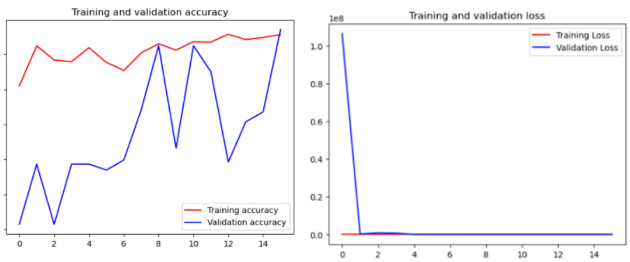
Fig. 3. Training/Validation Accuracy and Training/Validation Loss Graphs of the DenseNet121 model.



As shown in Fig. 3, the DenseNet121 model was trained over 20 epochs, during which the loss decreased gradually and accuracy improved. Early stopping was employed to prevent overfitting. In terms of validation metrics, the validation loss initially spiked but later stabilized, while validation accuracy fluctuated yet generally improved. On the test dataset, the model achieved a loss of 0.4705 and an accuracy of 88.37%. The significant fluctuations in validation loss and accuracy, particularly early in the training process, suggest potential overfitting issues. However, the use of early stopping and the eventual stabilization of validation metrics indicate that these issues were effectively managed.

V. CONCLUSIONS

Comparing the training logs of modified InceptionV3 and DenseNet121 reveals some notable differences in their performance. DenseNet121 shows gradual improvement in accuracy and a significant drop in validation loss towards the end of training. However, it experiences considerable fluctuations in validation loss and accuracy earlier on, with validation accuracy peaking at 88.37%. This indicates that DenseNet121 requires more time to stabilize and reach optimal performance.

In contrast, modified InceptionV3 demonstrates a more consistent and higher level of performance throughout its training. The model achieves a peak validation accuracy of 99.14%, with validation loss steadily decreasing and maintaining high performance with minimal fluctuation. This stability suggests that InceptionV3 converges more quickly and effectively, providing robust and reliable performance throughout the training process.

Overall, modified InceptionV3 appears to outperform DenseNet121 in terms of both peak validation accuracy and consistency, making it a more effective choice for achieving high and stable performance in coral reef health assessment tasks.

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