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EXPLORING MACHINE LEARNING MODELS FOR CORAL REEF CLASSIFICATION FROM IMAGES

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Abstract: This research proposes a robust and automated approach to categories coral reefs according to their state of health, which significantly advances the cause of coral reef conservation. Researchers, environmentalists, and marine biologists can monitor and assess coral reef ecosystem health more effectively and comprehensively with the help of this suggested approach. Our study focuses on using deep learning methods to automatically identify healthy and bleached corals by extracting important features from images of coral reefs. We specifically employ the DenseNet-169 and VGG19 architectures, which have demonstrated effectiveness in image classification tasks, making them well-suited for our coral reef classification objective. Using a sizable dataset of annotated images of coral reefs, including both healthy and bleached species, we thoroughly train and fine-tune these models in order to achieve this. The trained models are then assessed using an independent test set, and performance measures including accuracy, precision, recall, and F1-score are computed to determine how effective the models are. In order to evaluate the relative effectiveness of the Dense Net 169 and VGG19 architectures in coral reef classification, we also run a comparative analysis.

Index Terms **- Visual Geometry Group (VGG-19), DenseNet-169**

I. INTRODUCTION

Tropical waters with high transparency are the habitat of coral reefs. These reefs thrive in seabed's nearly 150 feet below the surface, as they rely on sunlight for survival. Optimal water temperatures for coral reefs range between 20 and 28 degrees Celsius, making them commonly found near the Eastern coastlines and areas with vigorous wave action. The waves play a crucial role in supplying food and oxygen to coral reefs while also preventing debris buildup.

Unfortunately, coral bleaching, induced by climate change, has caused corals to lose their vibrant colors. This phenomenon, primarily caused by increased carbon dioxide levels from human activities, has led to a significant decline in coral populations. Figure 1 illustrates the three stages of coral—healthy, bleached, and dead—along with their impact on aquatic life. Coral reefs support millions of species and play a vital role in the economy and culture of coastal communities worldwide. However, recent degradation of coral reef ecosystems due to environmental changes and human activities necessitates monitoring and conservation efforts to mitigate further decline.

The paper begins by examining different methods for identifying coral features. It highlights how the categorization approach influences the features extracted from images. As mentioned earlier, classification can be based on factors such as the family, species, or color of corals. Additional characteristics like surface roughness, hole types, and branch length can further aid accurate coral classification. It emphasizes the need for effective automation of coral classification while minimizing computational complexity.

DenseNet169 has demonstrated high efficiency in various image classification tasks, particularly in classifying images like coral reefs. Its extensive connectivity and feature reuse capabilities enable it to effectively capture complex patterns and representations present in coral reef images, facilitating accurate classification and identification of different species or reef conditions. On the other hand, VGG19 is known for its simplicity and architectural consistency. Compared to earlier CNN models like Alex Net, VGG19's deeper structure allows for significantly improved performance in tasks such as coral reef classification. VGG19 can effectively capture both shallow and high-density features in reef images, leading to precise classification and identification of coral species or reef conditions through its multiple convolutional and pooling layers. Despite its computational complexity due to the large number of parameters, VGG19 remains a formidable model in image classification tasks.

The utilization of image data has become commonplace in underwater monitoring, yet traditional analysis of coral image data entails high time and labor costs. The aim is to analyze the spatial distribution of various coral populations in the surveyed area using image segmentation techniques to aid oceanographers in developing effective management and conservation strategies. Indeed, deep learning has demonstrated superior predictive performance compared to traditional image processing or conventional

AI algorithms in coral image segmentation tasks. This paper summarizes advanced segmentation techniques in deep learning applied to underwater images, ranging from the classification of irregular point annotations to the segmentation of sparsely labeled data and densely labeled data. The study is structured into several sections: Section 1 presents a literature review, Section 3 outlines the implementation, Section 2 discusses the methodology and research contributions, and Section 4 presents the results.

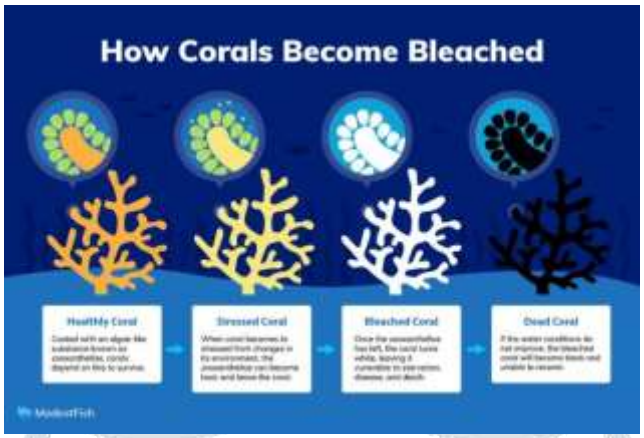

fig 1. different types of corals and their impact on aquatic life

II. Literature Survey

An extensive examination of existing literature was conducted to explore the application of affordable embedded systems and digital image processing techniques in maritime systems. One research endeavor focused on deploying a hybrid approach that combined Convolutional Neural Networks (CNN) with Support Vector Machines (SVM) to classify coral reefs. The study involved exploring different sets of hyperparameters for the CNN model, resulting in the achievement of notable accuracy levels. However, the learning duration varied based on the selected hyperparameter configurations.[1]

An alternative study introduced a methodology that integrates HSV color features, LBP texture features, and the Multi-Layer Perceptron Neural Network model. This fusion of features presents numerous benefits for marine researchers, facilitating the estimation of various benthic groups and supporting initiatives for marine conservation. The proposed methodology demonstrated favorable accuracy outcomes.[2]

The approach for automated coral reef annotation described in this study integrates completed local binary patterns (CLBP) and hue information. It demonstrates that employing multiple SVMs to aggregate various texture descriptors at the score level results in higher precision compared to using a single technique. The combined solution incorporates three texture representations: textons, activation weights derived from a deep convolutional neural network trained for object detection, and a blend of global descriptors (CLBP, hue, and opponent angle histograms).[3] The study employed a methodology that leveraged deep learning models relying on convolutional neural networks (CNN) to classify Acropora spp, a specific type of coral. The CNN models exhibited notable accuracy, with overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA) all achieving high percentages in the classification of Acropora spp. This suggests that the CNN models were successful in precisely identifying and categorizing various species of Acropora coral.

To tackle the task of coral reef categorization, the study integrated a convolutional neural network (CNN) with local-spatial pyramid pooling (SPP). Across three separate studies, the CNN+SPP approach demonstrated accuracy values situated within a higher range. These findings highlight the efficacy of the CNN+SPP methodology in precisely classifying and identifying various aspects or categories within the coral reef dataset.[5]

In another paper, a computer vision and deep learning-based framework were introduced for the automatic annotation of unlabeled coral images. This framework employs techniques from computer vision and deep learning to automatically annotate or classify coral images without manual labeling. The proposed framework explores the potential implications and advantages of achieving high annotation accuracy using automated techniques, emphasizing the benefits of utilizing computer vision and deep learning approaches for coral reef studies.[6]

Additionally, the method utilizes LIBSVM alongside a Convolutional Neural Network (CNN) to automatically annotate coral reef survey images. The proposed strategy is evaluated using the Moorea Labelled Corals dataset in the mentioned publication. The literature review encompasses discussions on the implementation and performance of the CNN and LIBSVM, comparisons with other relevant methods, and an exploration of the significance and potential applications of the automated annotation approach for coral reef survey images.[8]

From the literature studies, it's evident that AI tools employing various methodologies hold great promise for addressing complex challenges in fields such as ecology, particularly in coral classification.

In summary, the CNN method emerges as a prevalent choice. Unlike methods that solely rely on provided labels within datasets, CNN requires users to program the system regarding the features to extract and what additional features to seek.

For example, if the task involves detecting a giraffe in an image, specific characteristics of a giraffe must be programmed into the algorithm for it to successfully identify a giraffe in an image.

III. Methodology

The following steps explains the data processing architecture selection, training and hyperparameter optimization, performance and comparative analysis

1. Dataset Collection and Preprocessing:

· Collect a diverse and representative dataset of coral reef images.

· Preprocess the images by resizing, normalizing, and removing noise.

2. CNN Architecture Selection and Transfer Learning:
· Evaluate different CNN models (VGG19, DenseNet) for coral reef classification.
· Utilize pre-trained weights from large-scale image datasets.
· Modify the models by replacing the final fully connected layers.

3. Training, Evaluation, and Hyperparameter Optimization:
· Split the dataset into training, validation, and testing sets.
· Use the training set to train the models, and keep an eye on validation accuracy.
· Optimize hyperparameters using appropriate techniques.

4. Performance Analysis and Iterative Refinement:
· Analyse performance through confusion matrix, class-wise accuracy, and misclassified samples.
· Refine models using techniques such as ensemble learning or class balancing.

5. Comparative Analysis:
· Perform comparative analysis of CNN models (VGG19, DenseNet).
· Consider accuracy, computational efficiency, and memory requirements.

VI. Implementation

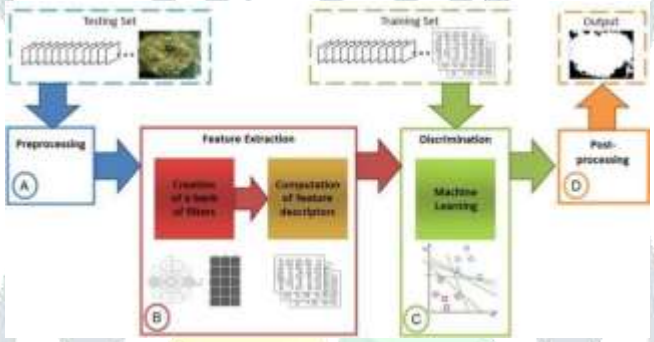

fig.2 flow chart for data-pre-processing of images

The above-mentioned diagram illustrates the process of image data undergoing several steps. To implement this, we utilize two types of CNN architectures: DenseNet-169 and VGG-19.

4.1. DenseNet-169

DenseNet architecture revolutionizes traditional convolutional neural networks (CNNs) by introducing dense connections among layers. Unlike conventional CNNs, where each layer is connected only to the subsequent layer, DenseNet forms direct connections between all layers in a forward-flowing fashion. Consequently, every layer in DenseNet receives feature maps from all preceding layers, leading to the formation of densely connected blocks.DenseNet-169 is a specific variant of the DenseNet architecture, characterized by its 169 layers. It comprises four dense blocks, each housing multiple convolutional layers. Furthermore, DenseNet-169 incorporates transition layers positioned between each dense block. These transition layers serve to regulate the sizes of the feature maps as information flows through the network.

To succinctly summarize the architecture of DenseNet-169:

1. Initial Convolutional Layer: This layer conducts an initial convolution operation on the input image to extract fundamental features.

2. Dense Blocks: DenseNet-169 comprises four dense blocks, where each layer within a block is densely connected to all preceding and subsequent layers. This dense connectivity fosters feature reuse and enables efficient information flow across the network.

3. Transition Layers: These layers are employed to reduce the spatial dimensions of the feature maps and compress information before forwarding it to the next dense block. Typically, a transition layer includes batch normalization, a 1x1 convolutional layer for dimensionality reduction, and a downsampling operation (e.g., average pooling) to diminish the feature map size.

4. Global Average Pooling: Following the final dense block, a global average pooling layer consolidates spatial information into a fixed-length feature vector by computing the average value for each feature map across its spatial dimensions.

5. Fully Connected Layer: The global average pooled feature vector is fed into a fully connected layer, which serves as the output layer of the network. This layer establishes connections between every neuron and each neuron in the preceding layer, facilitating the learning of complex relationships and patterns. Subsequently, the fully connected layer maps the features to the desired number of classes and generates the final classification probabilities using an appropriate activation function, such as SoftMax, which normalizes the output into a probability distribution over the classes.

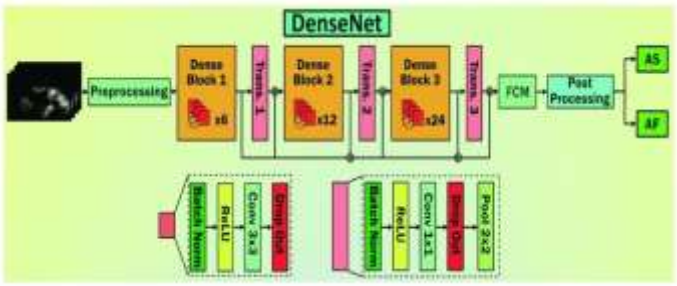

fig.3 densenet-169 architecture

4.2.VGG-19

VGG-19 is a renowned deep convolutional neural network (CNN) widely utilized for image classification purposes. Created by the Visual Geometry Group (VGG) at the University of Oxford, it serves as an extension of the initial VGGNet architecture. VGG-19 is characterized by its depth, comprising a total of 19 layers encompassing convolutional, pooling, and fully connected layers. Here is a breakdown of the VGG19 architecture:

1. Input Layer: VGG19 takes input images of fixed dimensions, usually 224x224 pixels, and three RGB color channels.

2. Convolutional Layers: VGG19 is composed of multiple convolutional layers that apply convolutions to the input image. These layers utilize 3x3 filters with a stride of 1 and padding of 1 to preserve spatial information, focusing on learning hierarchical features from the input.

3. Max Pooling Layers: Following some convolutional layers, VGG19 includes max pooling layers to downsample the feature maps, reducing spatial dimensions while retaining essential information. VGG19 typically employs 2x2 pooling windows with a stride of 2.

4. Fully Connected Layers: After convolutional and pooling layers, VGG19 incorporates three fully connected layers responsible for learning high-level representations and making predictions. These layers contain numerous parameters, allowing the model to capture intricate patterns and relationships.

5. SoftMax Activation Layer: The final layer in VGG19 is a SoftMax activation layer, which generates class probabilities for image classification. It assigns probabilities to each class, indicating the likelihood of the input image belonging to a particular class.

VGG19 is esteemed for its uniformity and simplicity in architecture. Compared to earlier CNN models like AlexNet, it boasts a deeper structure and excels in image classification tasks, including the categorization of coral reefs. VGG19 effectively identifies and classifies coral reef images by leveraging multiple convolutional and pooling layers to capture both low-level and high-level features. However, it's worth noting that VGG19 is computationally intensive due to its numerous parameters. DenseNet-169 and VGG-19 are popular deep learning models utilized for coral reef categorization applications.

V. RESULTS

Comparing the outcomes of analyzing bleached and healthy coral images using DenseNet169 and VGG19, two widely-used deep learning models, offers valuable insights into how coral bleaching impacts their visual representation and overall condition.

DenseNet169, renowned for its dense connections between layers, excels in capturing intricate details and fine patterns present in coral imagery. When applied to bleached coral images, the model demonstrates a remarkable ability to detect subtle alterations in color, texture, and morphology. It effectively identifies areas with reduced pigmentation, loss of vibrant colors, and changes in structural integrity, thus providing a comprehensive assessment of the bleaching phenomenon. Moreover, DenseNet169 can highlight stress-induced adaptations, such as enhanced polyp expansion and modifications in skeletal structure, aiding in understanding coral resilience.In contrast, VGG19, characterized by its deep architecture comprising multiple convolutional layers, is adept at capturing broader features and global context. When employed on healthy coral images, VGG19 accurately recognizes the vibrant spectrum of colors, intricate patterns, and diverse textures that signify a thriving reef ecosystem.

The model discerns well-defined structures, the rich palette of coral species, and the complex symbiotic relationships contributing to overall coral health and biodiversity.

Comparing the outcomes from both models provides a holistic understanding of the contrasting attributes between bleached and healthy corals. While DenseNet169 emphasizes the specific effects of bleaching on individual corals, VGG19 reveals the overall health and diversity of a reef ecosystem. By integrating insights from both models, researchers and conservationists can gain a deeper understanding of coral bleaching's extent and severity, formulate effective mitigation strategies, and safeguard these delicate marine ecosystems for future generations.

For the neural network experiment, a series of images underwent preprocessing before being fed into the network. The experiment involved iterating the dataset through the neural network 15 times for training. A total of 923 images were used in this study. The results for each epoch, including training loss, accuracy, and validation loss, are depicted in Fig. 4 and 5, with further details presented in Fig. 6 and 7 for the 15 epochs. The accuracy values show an increasing trend, while the loss values decrease, indicating effective *training.*

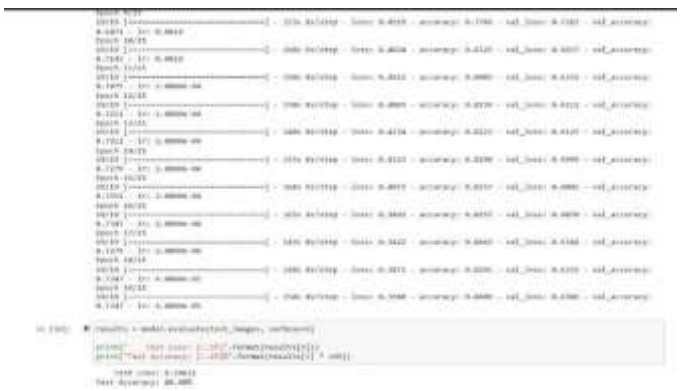

fig.4 epoch (densenet-169)

fig.5 epoch (vgg-19)

fig.6 training and validation metrics (densenet-169)

fig.7 training and validation metrics (vgg-19)

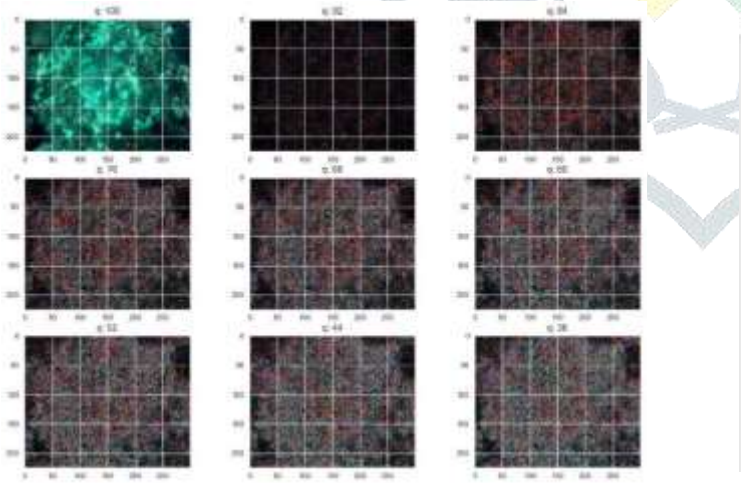

fig 8 visualization using ela (densenet-169)

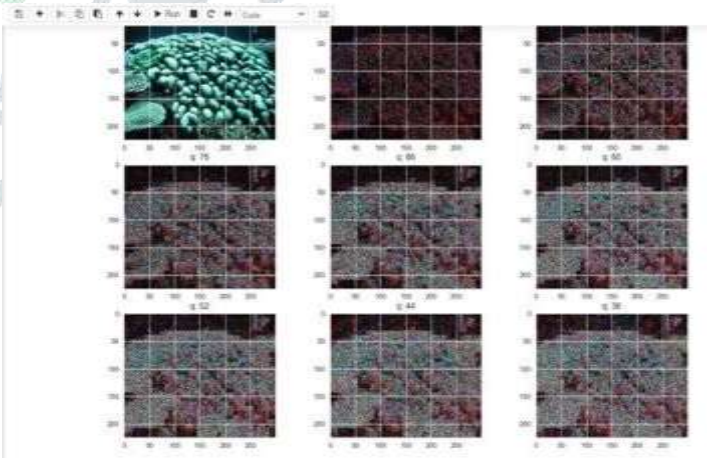

fig 9 visualization using ela (vgg-19)

In the process of creating the training dataset, multiple images were segmented from larger images, and subsequent rotations and zooming by a factor of 0.2 were applied. This diverse dataset encompassed various coral images aggregated together. Employing Error Level Analysis (ELA) enables the comparison of error levels across different parts of the image, thereby revealing areas that might have undergone digital modifications or enhancements. This capability proves invaluable for assessing the authenticity and integrity of coral reef images, as depicted in Fig. 8 and Fig. 9. ELA contributes significantly to coral reef research by shedding light on potential image manipulation or modifications, thereby ensuring the accuracy and credibility of scientific findings. Moreover, it supports conservation efforts by promoting transparency and accountability in image-based research.

Leveraging a Convolutional Neural Network (CNN)-based image classification model for distinguishing between healthy and bleached corals offers several advantages. The automated process delivers efficiency by swiftly and accurately classifying coral images, thereby saving time and effort compared to manual identification methods. Furthermore, the model's scalability allows for large-scale coral reef monitoring, covering extensive areas with ease. Its consistent and objective performance helps eliminate human errors or biases that may arise during manual assessments. Integration with underwater camera systems or aerial imagery

facilitates real-time monitoring of coral reef health, enabling prompt intervention when necessary. The insights derived from the model play a crucial role in informing decision.

fig 10. result (densenet-169)

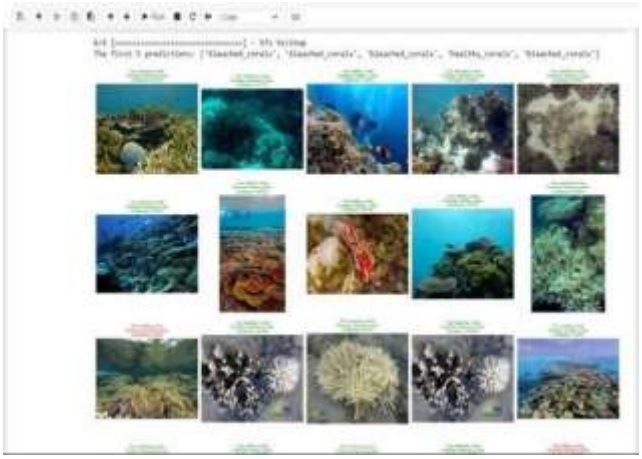

fig 11. result (vgg-19)

Comparison of two architectures:

Architecture	Epochs	Accuracy
DenseNet-169	25	80.00%
VGG-19	15	78.92%

VI. Conclusion

This study aimed to develop a specialized image classification model tailored for coral reef images, comprising steps like preprocessing, model design, training, and evaluation. Various data augmentation techniques were applied during preprocessing to enhance adaptability, including flipping, rotation, zooming, and contrast adjustment. DenseNet169 and VGG19 pre-trained models were considered, augmented with additional layers like batch normalization and dropout layers for regularization. Evaluation metrics such as loss and accuracy were used, with DenseNet169 achieving 80% accuracy, slightly higher than VGG19's 78.92%. These findings highlight the critical role of thoughtful model selection and effective data augmentation in achieving accurate coral reef image classification. Further research exploring different architectures and hyperparameter adjustments could enhance performance in this field.

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