Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

Reef Vista: Deep Learning-Powered Underwater Coral Reef Monitoring

Dr. Soma Prathibha[1*],Mr. Vivekanandan G[2],Mrs. Rupali S Kamathe[3],Dr. Hanchate Vandana Vijaykumar[4],Dr. G. Bhuvaneswari[5],Dr. G. Manikandan[6],Dr. G. Sabarinathan[7],Mr. Mustafa Nawaz S M[8]

[1]Professor, Department of Information Technology, Sri Sairam Engineering College Chennai, Tamil Nadu, India*

[2]assistant Professor, Department of Computer Science and Engineering Sri Sairam Institute Of Technology, Chennai, India

[3]professor, Pes' S Modern College of Engineering, Pune

[4]assistant Professor, Department of E & Tc, Pes's Modern College of Engineering, India

[5]professor / Cse, Department of Computer Science and Engineering, Saveetha Engineering College, Saveetha Nagar, Sriperumbadur Taluk, Chennai, Tamil Nadu 602105, India

[6]professor And Head of The Department, Department of Information Technology, Kings Engineering College, Sriperumbudur Taluk, Irungattukottai, Tamil Nadu 602117, India

[7]associate Professor, Department of Mathematics, Psna College of Engineering and Technology (Autonomous), Dindigul, Tamil Nadu, India

[8]assistant Professor, Department of Computer Science and Engineering, Sri Sai Ram Institute Of Technology, India.

Abstract- Coral reefs, vital ecosystems supporting biodiversity and providing economic benefits to millions, face threats that necessitate effective monitoring and conservation efforts. In this study, we present a deep learning-based approach for coral reef monitoring and underwater image enhancement. Leveraging advanced techniques, our model achieves high accuracy in classifying bleached and healthy corals from images captured in diverse underwater conditions. In this paper, we introduce a suite of advanced deep learning-based techniques tailored for coral reef monitoring and underwater image enhancement. These techniques not only augment image quality but also surpass earlier methodologies in terms of effectiveness and accuracy. Key innovations include leveraging Bright Channel Prior for image enhancement and employing state-of-the-art deep learning algorithms for superior results. Our model architecture comprises convolutional layers followed by dense layers with L2 regularization, offering robust performance in distinguishing between coral conditions. We employ data augmentation techniques to enhance model generalization and mitigate overfitting, contributing to reliable predictions on unseen data. Evaluation of the model with various optimizers demonstrates consistent performance across different configurations. Our findings highlight the efficacy of deep learning in coral reef monitoring and underline the importance of leveraging technological advancements for marine conservation efforts.

Keywords- Coral reef monitoring, image enhancement, Bright channel prior, deep learning

I. Introduction

Coral reefs, often hailed as the rainforests of the sea, stand as indispensable ecosystems nurturing a diverse tapestry of marine life. Yet, the fragility of these underwater realms is under siege from the relentless forces of climate change, overfishing, and pollution. Vigilant monitoring of coral reef health becomes imperative, transcending traditional approaches to forge a path toward resilience and timely conservation measures.

In recent years, a confluence of technological strides, notably in computer vision and deep learning, has ushered in a transformative era for effective coral reef monitoring. Conventional methods, tethered to manual interpretation of underwater imagery, grapple with sluggish processes and compromised accuracy. Recognizing the urgency of preserving coral reefs, this endeavor harnesses the prowess of Convolutional Neural Networks

(CNNs) to redefine the landscape of monitoring and evaluating these vital ecosystems. Motivated by the pivotal role coral reefs play in marine biodiversity and ecological equilibrium, this research confronts the limitations embedded in current methodologies, reminiscent of challenges encountered in thyroid disease detection with its associated low accuracy rates.

As climate change-induced coral bleaching events surge, the early identification of stress indicators and coral diseases becomes pivotal, necessitating targeted conservation strategies. This project charts a course to elevate the precision and efficiency of coral reef monitoring through the deployment of cutting-edge deep learning techniques, specifically CNNs. Unlike conventional machine learning algorithms, deep learning networks proffer a holistic approach to feature extraction and classification, underpinned by end-to-end problem-solving capabilities. The selection of CNNs is deliberate, grounded in their innate ability to capture intricate spatial features within images, a critical element in discerning the health nuances of complex coral structures. Drawing inspiration from the triumphs of deep learning architectures in medical image classification, this research introduces bespoke modifications tailored to the intricacies of coral reef monitoring. These adaptations facilitate meticulous feature extraction and guarantee continuous refinement through dual optimizers. Our methodology centers on early detection, embodying a proactive stance toward coral reef conservation.

The infusion of advanced technology into coral reef monitoring not only streamlines detection processes but also offers a solution that is both cost-effective and time-efficient. By mitigating reliance on manual interpretation and expediting the identification of potential threats to coral health, our aspiration is to endow conservationists and policymakers with actionable insights. Amidst escalating pressures on coral reefs, the early identification of anomalies stands as a linchpin in safeguarding these subaqueous ecosystems. This paper unfurls the narrative of deploying state-of-the-art technology to surmount the challenges in coral reef monitoring, underscoring the significance of early detection in the preservation of these biodiversity hotspots. The utilization of CNNs heralds a paradigm shift in coral reef monitoring, offering a robust and efficient solution that stands as a beacon in the realm of conservation efforts.

II. Literature survey

Underwater image enhancement techniques have evolved significantly to combat issues like color degradation, contrast diminishment, and detail blurring in marine environments. This literature survey delves into diverse methodologies proposed by researchers to elevate the quality of underwater imagery. Techniques such as Rayleigh-extension constrained contrast adaptive histogram equalization, holistic approaches incorporating image dehazing and bilateral filtering, and the application of particle swarm optimization showcase innovative strides in addressing the challenges posed by the underwater domain. The integration of deep learning, exemplified by Retinex-based methods and CNN models, demonstrates immense potential for enhancing image quality. Additionally, specialized systems like the conflation-based approach engineered by Zhou and the unique low-light blurring degradation simulation by Zhou further contribute to the arsenal of underwater image enhancement techniques. The survey also explores research endeavors focusing on marine environment management in the Persian Gulf, introducing convolutional neural networks (CNNs) to assess damage sustained by marine flora. The synthesis of these methodologies reflects substantial progress in the field, promising applications in ocean exploration, marine biology, and underwater archaeology.

2.1 Image Contrast Enhancement

Ghani et al. [1] proposed Rayleigh-extension constrained contrast adaptive histogram equalization method by Ghani and team significantly enhances low contrast in underwater images. The strategy not only ameliorates overall image quality but also improves visual appeal by equalizing both global and initial contrast-enhanced images. Li et al. [2] and colleagues introduce a holistic approach that combines various techniques, including dehazing algorithms and bilateral filtering, effectively addressing issues such as blurriness, color fading, low contrast, and noise in underwater imagery. Braik et al. [3] harnesses particle swarm optimization (PSO) in a flyspeck mass optimization method to mitigate light absorption and scattering in underwater images, showcasing an innovative approach to address these influences. Table 1.1 shows the Image Contrast Enhancement.

Table 1.1 Image Contrast Enhancement

Title	Data Augmentation	Key contribution
A retinex- grounded enhancing approach for single aquatic image [4]	Retinex-based method	❖ Deep learning techniques Introduced a method for enhancing underwater images, showcased potential in distinguishing between damaged and recovered images, valuable for image enhancement and restoration.
Lednet Joint low- light improvement and deblurring in the dark [5]	Conflation-based system	❖ Engineered a multifaceted system to augment the aesthetic appeal of underwater prints, highlighting the diverse methods available for enhancing underwater image quality.
KinD and Retinex-Net Image enhancement [7]	Restoration network	❖ Proposed a simultaneous input of deconstructed illumination map and reflectance map, synergistically enhancing both for a restored image aligned with the original image.

Additionally, research endeavors in marine environment management and conservation, as well as innovative approaches like conflation-based systems [6] and simulation of low-light blurring degradation, contribute to the advancement of underwater imaging technologies. The survey highlights the importance of simultaneous enhancement of illuminance and reflectance maps and explores the conceptualization of image pollution in the context of low-light conditions and scattering. The findings hold significant promise for applications in ocean exploration, marine biology, and underwater archaeology.

2.2 Coral reef monitoring

Deep learning and computer vision techniques have shown significant promise in revolutionizing underwater coral reef monitoring, offering faster, more efficient, and cost-effective alternatives to traditional manual survey methods. This literature survey synthesizes key inferences from multiple papers, providing insights into the application of convolutional neural networks (CNNs), data augmentation, and explainable AI in the context of automated coral reef monitoring. Table 1.2 shows the Coral reef monitoring.

Table 1.2 Coral reef monitoring

Title	Image Type	Data Augmentation	Algorithm	Key contribution
Automated image-based coral reef monitoring using deep learning [8]	RGB underwater video frames	Horizontal flipping	CNN classifier	❖ The paper successfully applies Convolutional Neural Networks (CNNs) to automate the classification of

				Stony corals, achieving an impressive accuracy of around 94.5%. ❖ The RGB image pre-processing approach proves superior, emphasizing the importance of incorporating color information for accurate coral feature extraction. ❖ The developed model holds practical value, serving as an efficient tool for marine scientists and coral annotators, offering a robust alternative to manual classification methods.
CoralNet: An integrated web-application for annotation and recognition of coral reefs[9] [10]	Underwater photos and manually extracted ROIs	-	CNN classifier	❖ CoralNet addresses the manual annotation bottleneck in coral reef image analysis by combining computer vision methods with human expertise, achieving 50-100% automation. It began as CoralNet Alpha, evolving to Beta with cloud hosting and improved deep learning-based algorithms. ❖ CoralNet 1.0, backed by NOAA funding, demonstrated automated annotations highly correlated with human annotators, effectively overcoming the manual annotation bottleneck. The development included an API for easy classifier deployment and enhanced core technology for superior performance.
Stony Coral Species Recognition System using Deep Learning [11]	RGB coral	Flipping, mirroring, rotating, zooming, color shifting	CNN classifier	❖ The paper presents a web application using Convolutional Neural Network (CNN) for stony coral species recognition, addressing challenges in

				manual identification. A dataset of 10 stony coral species was used, achieving high training accuracy (99%), validation accuracy (97%), and testing accuracy (91.9%). ❖ The system underwent functionality testing and received a high System Usability Scale (SUS) score of 94, indicating user acceptance. The proposed model can serve as a basis for developing a mobile application, offering efficient stony coral recognition and information retrieval for users.
Assessing the impact of data augmentation on classification of coral reef benthic communities [12]	Annotated orthomosaic photo surveys	Random cropping, rotations	Faster R-CNN object detector	❖ Specific data augmentation methods (e.g., Random Rotation, Brightness) are highly effective for improving taxonomic classification in marine benthic images, outperforming general policies. ❖ Augmentation policies optimized for marine datasets show a negative impact when applied to urban traffic images, indicating the need for domain-specific adaptation. ❖ The study underscores the significance of tailoring data augmentation to specific image domains, acknowledging that what works well in one domain may not generalize to others.

Applying deep learning to analyze underwater imagery can revolutionize coral reef monitoring by enabling faster and more efficient assessments. This approach has the potential to outperform traditional manual survey methods, supporting widespread and regular monitoring to enhance our understanding of reef health. While most existing work focuses on broad image classification using CNNs, opportunities exist to develop more granular classifiers, such as coral genera or health levels. Autonomous underwater vehicles equipped with cameras can further reduce time and cost barriers compared to human diver surveys, emphasizing the potential for advancing autonomous survey platforms.

Accurately labeling diverse coral reef image datasets for supervised learning remains challenging. The integration of advanced data augmentation techniques, such as generative adversarial networks, could alleviate the need for large labeled datasets. Additionally, the application of explainable AI techniques becomes crucial for validating and building trust in algorithmic predictions for reef health assessments. The integration of deep learning techniques in underwater coral reef monitoring presents a transformative approach, offering advantages in efficiency, cost-effectiveness, and accuracy. While challenges persist in data labeling and model explainability, ongoing research aims to address these issues and further refine automated monitoring systems for coral reefs.

2.3 Existing System

Upon an exhaustive examination of the current literature, it becomes evident that contemporary researchers often overlook the intricate web of interconnected challenges in their pursuits. Haze removal algorithms, for instance, frequently fall short in addressing noise-related concerns, leaving the dark channel prior (DCP) [13] relatively underexplored. Additionally, the critical aspect of uneven brightness tends to be neglected, introducing potential flaws in the efficacy of haze removal techniques. Prior strategies, including contrast enhancement and color saturation, have yielded inconsistent results, thereby injecting an element of variability into the final coloration of images.

In the domain of computer vision, the ability to discern objects holds paramount importance across various visual tasks such as scene comprehension, image search, object tracking, and print bus-reflection. While considerable progress has been made in the development of single-object tracking systems, the challenges escalate in the presence of multiple objects. Object tracking becomes especially formidable when objects are partially or entirely occluded, rendering them imperceptible due to variations in viewing angles and illumination conditions.

The current object shadowing system [14-16], rooted in Multi-Layer Perceptrons (MLPs), exhibits remarkable robustness. This resilience is achieved through the strategic implementation of the Adaboost strong bracket fashion, coupled with a meticulous selection of distinguishing attributes. Aligning with the DSSD on ResNet fashion for optimal network model training [17-18], the primary objective is to enhance sensitivity. The initial enhancement involves replacing the VGG network, originally utilized in SSD, with ResNet. Additionally, a series of complexity point layers are integrated into the final subcaste of the underlying network for added sophistication.

In the realm of object detection, methods like R-CNN have shown notable performance improvements by reducing the number of candidate regions requiring classification. This strategic approach focuses the detector on the most promising regions, conserving computational resources that might be wasted on irrelevant image areas. Despite its merits, R-CNN [19] faces limitations, particularly in terms of computational efficiency during both training and testing phases. The time-intensive selective search algorithm for region proposal generation, coupled with a substantial volume of proposals, poses challenges. Moreover, the absence of an end-to-end training framework within R-CNN may lead to suboptimal region proposals, thereby diminishing overall system accuracy.

To elevate the existing system to a professional and sophisticated level, there is a need for a nuanced approach in addressing the identified challenges. Leveraging advanced noise reduction techniques, exploring innovative strategies for handling uneven brightness, and optimizing object tracking algorithms for occluded scenarios can enhance the system's robustness. Additionally, adopting state-of-the-art methodologies in object detection, such as more efficient region proposal techniques and end-to-end training frameworks, can contribute to overcoming existing limitations and ensuring real-time applicability. The pursuit of these enhancements positions the system at the forefront of current research in computer vision and object detection.

III. Methodology

In our cutting-edge system, we combat underwater image challenges by introducing a pioneering brightness enhancement algorithm—built on the Bright Channel Prior (BCP)—that particularly targets gray areas affected by poor illumination. Our preprocessing involves gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) to counter atmospheric haze. Utilizing Convolutional Neural Networks (CNNs), we focus on the identification and mapping of diverse coral reef types: atoll, barrier, and fringing reefs. Beyond classification, our study extends to detailed coral reef mapping, offering crucial insights for monitoring and conservation. Effective communication of our findings aims to heighten awareness and empower stakeholders, especially in the fishing sector, fostering sustainable management of these essential marine ecosystems.

3.1 Dataset Collection for Coral Classification:

Curating a robust coral image dataset was pivotal for this classification task. The dataset draws from diverse sources, like Kaggle, offering a comprehensive array of coral species. This meticulous collection ensures representation from various geographic locations and environmental conditions, enriching the dataset with diverse coral types. Table 2 shows the Dataset Collection. The number of images gathered for each coral type is tabulated below:

Table 2 Dataset Collection

TYPE OF CORAL	NO. OF IMAGES
Brain Coral	1420
Staghorn Coral	2198
Fire Coral	1285
Pillar Coral	1212
Finger Coral	1176
Elkhorn Coral	1293

This strategic dataset compilation aims to enhance the effectiveness and generalization of the coral classification model.

3.2 Data Augmentation:

To address the scarcity of datasets and enhance model robustness, we integrate advanced data augmentation techniques. Employing the Image Data Generator class from Keras, which is seamlessly integrated into Tensor Flow's high-level API (tensorflow. keras), our strategy encompasses various operations. Table 3 shows the Data Augmentation

Table 3: Data Augmentation

Augmentation	Operations
Rotation	Images undergo rotation by specified angles, enriching dataset variability.
Shearing	Transformations in image orientation are achieved through the shearing process.
Zooming	Augmentation involves zooming in and out, contributing to diverse image perspectives.
Cropping	Images are subject to cropping or selective area extraction, introducing variability.
Flipping	Both horizontal and vertical flipping are applied, diversifying image orientations.

Brightness Adjustment	Illumination changes are combated by adjusting brightness levels.

This approach ensures the generation of augmented data, mitigating overfitting risks and bolstering the model's adaptability to diverse scenarios. Leveraging these techniques in tandem with your code fosters a more resilient and versatile model for improved performance in image classification tasks.

3.3 Preprocessing:

In the pursuit of refining image datasets for optimal performance in coral reef classification, our proposed system employs a sophisticated preprocessing pipeline. This pipeline encompasses several advanced techniques aimed at enhancing image quality and standardizing dataset characteristics. Ensuring uniformity in image dimensions is paramount for effective model training. Through robust resizing techniques, images are standardized to a predetermined size, such as 300x300 pixels. This not only streamlines computational processes but also promotes consistency in feature extraction across all images. Grayscale conversion plays a pivotal role in mitigating variations in color and illumination, thereby enhancing the model's ability to generalize. By converting images to grayscale, the influence of color disparities is minimized, enabling the model to focus solely on relevant features crucial for classification. Addressing illumination inconsistencies is imperative for accurate image analysis. Advanced white balance techniques, such as LAB color space transformations, dynamically adjust pixel values to achieve optimal balance across the image. This ensures uniform illumination levels and enhances the overall visual quality of the dataset. By integrating these advanced preprocessing techniques, our research aims to provide the CNN model with a refined and standardized dataset, conducive to robust learning. Each preprocessing step contributes to the enhancement of image quality and consistency, laying a solid foundation for accurate coral reef classification. This sophisticated approach aligns with the rigorous standards of modern image processing methodologies, promising significant advancements in coral reef conservation and research.

3.4 Image Enhancement Techniques:

In the pursuit of refining the visual quality of images afflicted by poor illumination, our research introduces sophisticated image enhancement methodologies centered around the Bright Channel Prior (BCP). Leveraging the inherent characteristics of BCP, our proposed algorithm focuses on mitigating grayness, thereby significantly improving image clarity and detail.

3.4.1. Bright Channel Prior (BCP) Model:

The cornerstone of our image enhancement strategy lies in the utilization of the Bright Channel Prior (BCP) model. This model capitalizes on the observation that well-lit images often contain local patches with pixels exhibiting high brightness values. By harnessing this insight, our algorithm effectively targets and enhances these bright regions, thereby enhancing overall image quality.

3.4.2. Gamma Correction for Intensity Enhancement:

To further elevate the visual intensity and contrast of the images, we employ gamma correction—a powerful technique widely used in image processing. Gamma correction operates by amplifying darker tones more than lighter ones, thereby linearizing the non-linear output of display devices. This ensures that the output intensity (Vout) accurately reflects the input intensity (Vin), resulting in enhanced visual fidelity.

3.4.3. Contrast Limited Adaptive Histogram Equalization (CLAHE):

Addressing visibility challenges posed by hazy or foggy images, we incorporate Contrast Limited Adaptive Histogram Equalization (CLAHE). A variant of traditional Adaptive Histogram Equalization (AHE), CLAHE mitigates the risk of over-amplification of contrast. By operating on discrete tiles within the image and seamlessly blending boundaries using bilinear interpolation, CLAHE effectively redistributes brightness values. This tailored approach enhances local contrast and edge definition, ensuring optimal image clarity.

Our image enhancement pipeline is a testament to our commitment to achieving unparalleled visual quality through the fusion of BCP-based enhancement, gamma correction, and CLAHE techniques. By strategically addressing issues related to poor illumination and contrast, our methodology not only enhances image fidelity but also lays the groundwork for more robust and accurate visual analysis in various applications, including coral reef monitoring and classification.

3.5 Coral Reef Detection Model

Coral reefs, as crucial marine ecosystems, face ongoing threats, including coral bleaching. To address these challenges, this research introduces a refined approach to coral health classification through the development of a specialized Deep Convolutional Neural Network (DCNN). This sophisticated model aims to provide accurate and robust predictions for improved coral monitoring and conservation efforts.

3.5.1. Model Architecture:

The proposed DCNN architecture consists of foundational layers that employ a series of convolutional operations. Let I represent the input image, and f be the convolutional filter. The output feature map O_c of a convolutional layer can be represented as:

Oc= $\sigma(I * f + b)$

where sigma denotes the rectified linear unit (ReLU) activation function, and b is the bias term. Following the convolutional layers, down-sampling layers, facilitated by max-pooling operations, play a crucial role in spatial reduction while retaining essential features. Let P represent the max-pooling operation. The output of the max-pooling layer Op can be computed as:

Op = P(Oc)

Global Average Pooling serves as a pivotal stage in consolidating spatial information, denoted by *G*. By summarizing the output of previous layers, it facilitates higher-level reasoning and prepares the data for further processing in dense layers. Let *Og* represent the output of the global average pooling layer. Then:

Og = G(Op)

The dense layers form the latter part of the DCNN, orchestrating the final classification. Let Wd represent the weights of the dense layer, and b_d be the bias term. The output of the dense layer O_d can be calculated as:

$O_d = \sigma(Og \,.\, Wd + b_d)$

The inclusion of dropout layers mitigates overfitting, contributing to the model's generalization ability. Let D denote the dropout operation. The output of the dropout layer $O_d$drop can be represented as:

$O_d$drop= D(O_d)

The final layer, utilizing a softmax activation function, yields class probabilities, enabling effective coral health categorization. Let S denote the softmax function. The output probabilities P can be computed as:

P = S($O_d$drop)

This architecture emphasizes feature extraction, spatial hierarchical representation, and robust classification, contributing to the model's accuracy and efficacy in coral health classification. Fig 1 shows the Model architecture.

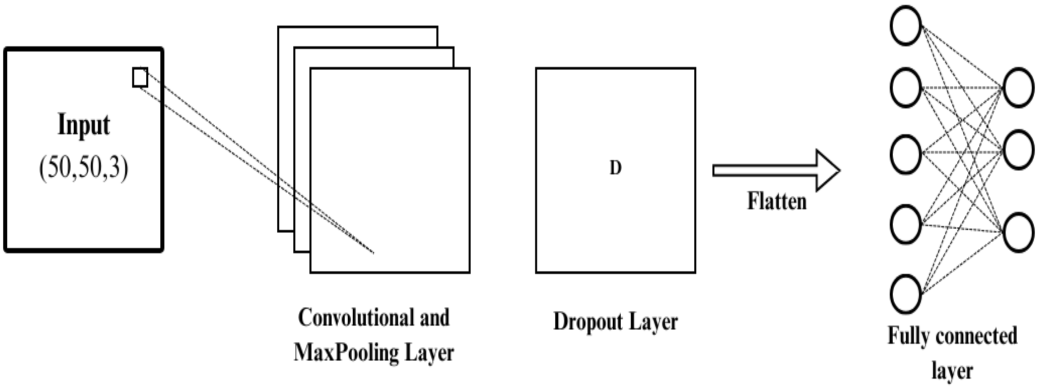

Fig 1: Model architecture

3.5.2. Feature Extraction Layers:

The foundational layer of the proposed DCNN consists of a convolutional layer with 32 filters, each of size 3 \times 3 . The layer acts as a feature extractor, initiating the hierarchical process of identifying patterns crucial for coral health classification. In pursuit of a richer feature hierarchy, subsequent convolutional layers are introduced. A convolutional layer with 64 filters and another with 128 filters follow the initial layer, each maintaining a 3 \times 3 filter size. This progressive increase in filters enables the model to capture intricate details and foster a nuanced understanding of the input images.

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 3 (2024)

3.5.3. Spatial Hierarchical Representation:

Strategically placed max pooling layers with a 2x2 pool size follow each convolutional layer. These layers serve a dual purpose – firstly, downsampling the spatial dimensions, aiding in the extraction of dominant features, and secondly, introducing a degree of translational invariance to enhance the model's generalization capability. The transition from traditional pooling to global average pooling before the dense layers is a deliberate choice. This layer computes the average of each feature map, condensing the spatial information into a single value per feature. This contributes to a more compact and informative representation before the fully connected layers.

3.5.4. Dense Layers and Classifier:

The dense layers play a pivotal role in high-level reasoning, amalgamating the hierarchical features extracted by previous layers. The incorporation of L2 regularization with a coefficient of 0.001 in the dense layers contributes to the model's robustness, preventing overfitting and enhancing generalization.

3.5.5 Output Layer:

The final layer, a densely connected softmax layer, outputs the classification probabilities for the two coral health classes. The choice of softmax activation ensures that the model's predictions align with the principles of multiclass classification, providing a clear and interpretable output. Fig 2 shows the Coral reef detection model.

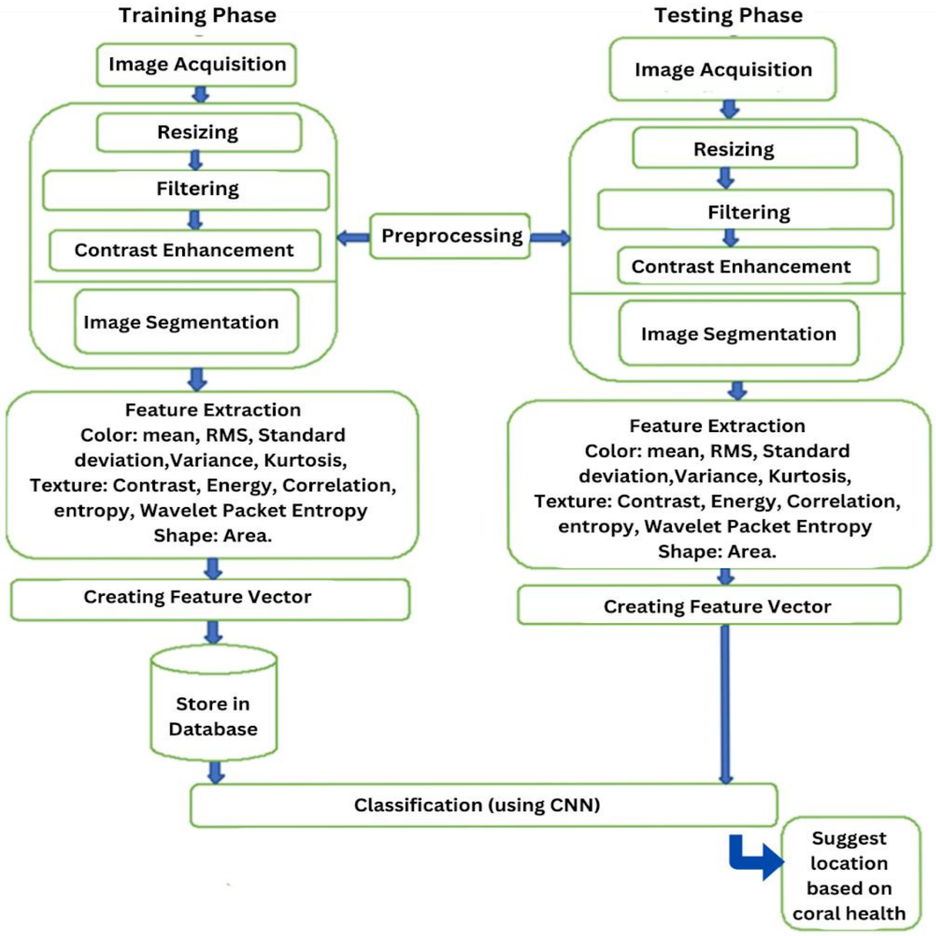

Fig 2: Coral reef detection model

3.6 Coral Location Analysis:

Additionally, a geographical analysis of coral locations is performed using XML data. The coordinates extracted from XML files are visualized on an interactive map, and the density of unhealthy corals within a specified radius is calculated. This geographical insight can aid in monitoring and decision-making for coral reef conservation.

3.6.1. Geographical Analysis of Coral Locations:

The study employs the Folium library to develop an interactive map, denoted as coral map, enabling the visualization of coral reef locations. This map is dynamic, allowing for customization of the center coordinates and zoom level, ensuring adaptability to specific research requirements. Fig 3 shows the Geographical Locations of Coral reefs

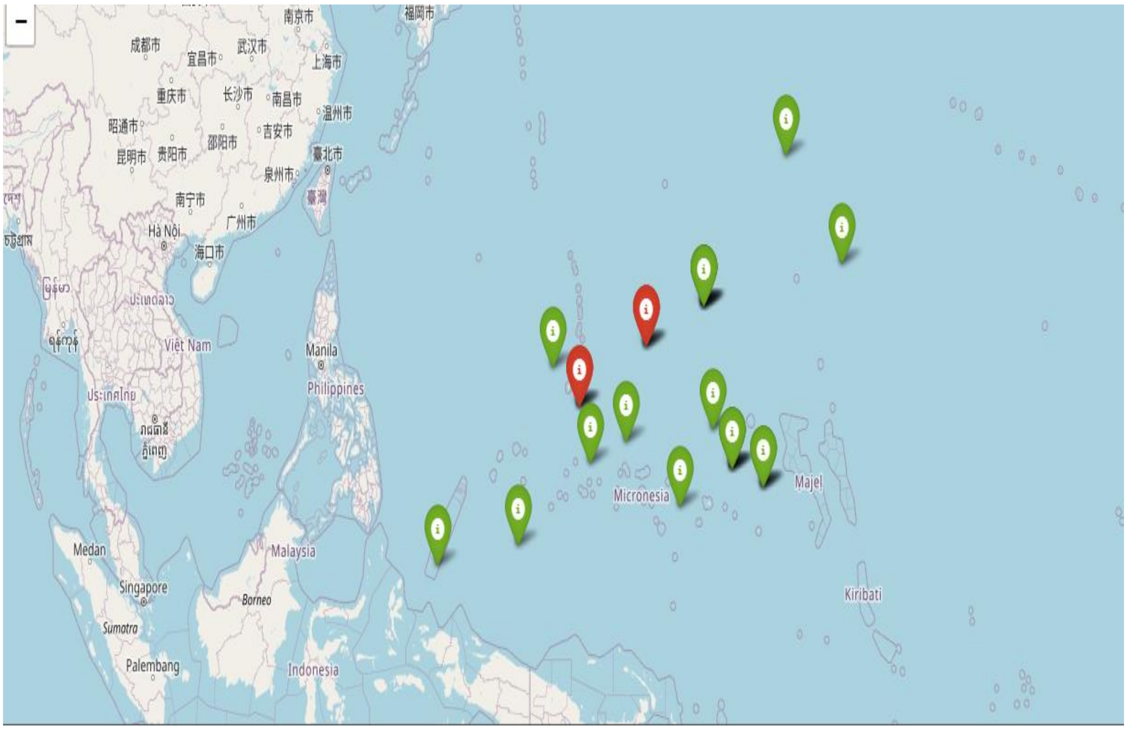

Fig 3: Geographical Locations of Coral reefs

3.6.2. XML Data Extraction:

XML files containing crucial information about coral locations and types are processed using a structured methodology. The extract location type from xml function systematically parses XML data, extracting latitude, longitude, and coral type details. The results are organized into lists of all types and all locations for further analysis.

3.6.3. Marker Placement on the Map:

The extracted coral type and location information is utilized to position markers on the interactive map. The map employs a color-coded system, with healthy coral reefs marked in green and unhealthy ones in red. This visual representation aids in the immediate identification of coral health status.

3.6.4. Visualization of Coral Locations:

The resulting map is visualized using the display function from IPython. This dynamic presentation facilitates an intuitive exploration of coral locations, enhancing the understanding of their spatial distribution and health conditions.

3.6.5. Density Calculation and Alerts:

To quantify the density of unhealthy corals in proximity to a specified location, the Haversine formula is employed for precise distance calculations. The calculated density function assesses the density within a defined radius. Alert thresholds low-density thresholds and high-density thresholds are established to categorize coral reef conditions. Fig 4 shows the Density calculation.

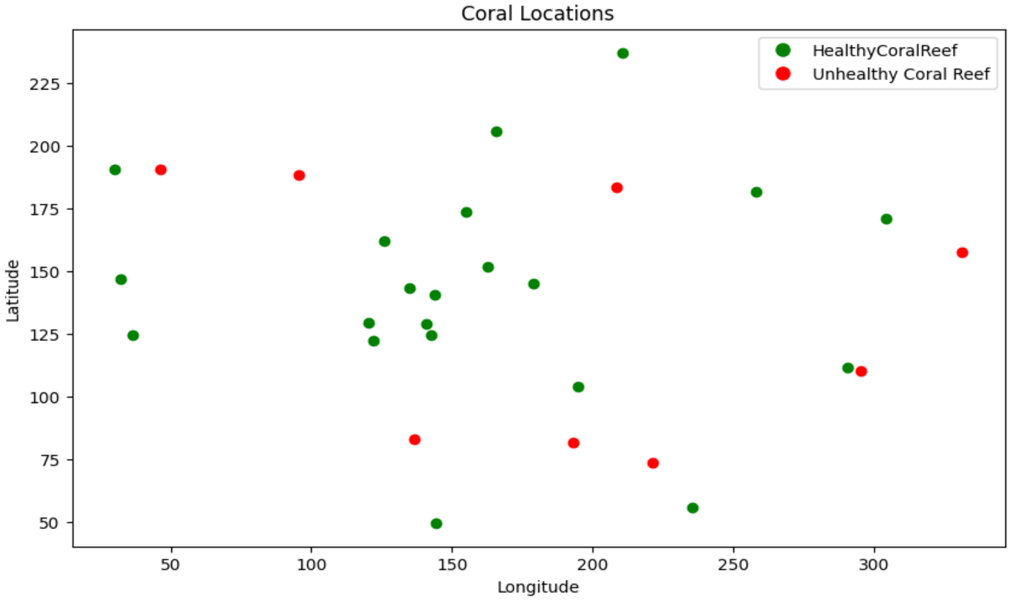

Fig 4: Density calculation

3.6.6. Thresholds for Alerts:

The study introduces alert thresholds to categorize the health status of coral reefs:

- Safe Zone : Indicates a low density of unhealthy corals, suggesting a relatively healthy reef environment.
- Caution : Highlights a moderate density of unhealthy corals, signaling a potential area of concern.
- Alert : Identifies a high density of unhealthy corals, prompting an immediate call to action for conservation efforts.

IV. Enhancement in Training

Each layer of the DCNN is equipped with batch normalization, a technique essential for mitigating internal covariate shifts during training. This ensures a more stable and accelerated convergence of the model. A key innovation in training involves optimizing Conv2D operations during the residual module. By adjusting the feature extraction process through the use of (3, 3) matrices, the model gains a more nuanced understanding of the input data, contributing to improved accuracy. Stochastic Gradient Descent (SGD) and Adam optimization techniques are employed to enhance the training dynamics. SGD, with momentum considerations, minimizes parameter variance, resulting in a more stable and accurate training process. Adam optimization, a combination of AdaGrad and RMSProp, further refines the model's weight updates, contributing to increased accuracy.

The model's performance is rigorously evaluated using standard metrics, including accuracy, precision, recall, and F1-score. The validation accuracy is consistently monitored across various optimization techniques, providing a comprehensive understanding of the model's efficacy. The proposed DCNN architecture, coupled with refined training strategies, demonstrates a significant advancement in coral health classification. This research contributes to the field of marine biology by providing a nuanced and accurate tool for monitoring coral reefs. The detailed insights into the model's architecture and training enhancements offer a valuable resource for researchers and practitioners involved in coral conservation efforts.

4.1 Optimizer Selection and Learning Rate Schedule:

The pivotal role of optimizers in model convergence is accentuated by the intricate interplay between the learning rate and training epochs. The adoption of the Exponential Decay learning rate schedule, tailored for each optimizer, offers an adaptive mechanism. It enables swift learning in the initial phases while gradually reducing the rate to fine-tune the model.

a. Stochastic Gradient Descent (SGD): SGD with momentum considerations minimizes parameter variance by updating the model's weights based on the gradient of the loss function with respect to the parameters. The update rule for SGD with momentum can be represented as:

$$\Delta w = -\eta \Delta L(w) + \alpha \Delta w_{prev}$$

where eta is the learning rate, alpha is the momentum parameter, Δ L(w) is the gradient of the loss function, and Δ w_{prev} is the previous update.

b. Adam Optimization: Adam optimization combines AdaGrad and RMSProp to further refine the model's weight updates. It calculates adaptive learning rates for each parameter based on estimates of first and second moments of the gradients. The update rule for Adam optimization can be represented as:

$m_t = \beta 1\ m_{t-1} + (1 - \beta 1)\ g_t$

$vt = \beta 2\ v_{t-1} + (1 - \beta_2)\ g_t$^2

$\hat{m}t = \frac{mt}{1-\beta 1^\wedge t1}$

$\hat{n}_t = \frac{vt}{1-\beta 1^\wedge t2}$

$w_{t+1} = w_t - \eta \frac{\hat{m}t}{\sqrt{\hat{v}t+\varepsilon}}$

where mt and vt are the first and second moments of the gradients, gt is the gradient at time t , $\beta 1$ and $\beta 2$ are decay rates, and epsilon is a small constant to prevent division by zero.

4.2 Strategic Dropout Placement:

The infusion of dropout layers after convolutional and dense layers serves as a regularization strategy. The judicious choice of dropout rates – 0.2 for convolutional layers and 0.3 for dense layers – strikes a delicate balance. It prevents overfitting by randomly dropping a proportion of neurons during training, fostering a more resilient and generalized model.

4.3 Computational Efficiency and Batch Normalization:

The application of batch normalization after convolutional and dense layers contributes to the stable and expedited training of the DCNN. It normalizes the input of each layer, mitigating internal covariate shift and fostering a more consistent gradient flow. Let x_i represent the input to a batch normalization layer. The normalized output y_i can be calculated as:

$y_i = \frac{Xi-\mu}{\sqrt{\sigma 2+\epsilon}}$

where π is the mean and σ^2 is the variance of the batch, and epsilon is a small constant to prevent division by zero. This ensures a more stable and accelerated convergence of the model by maintaining consistent activation distributions across layers.

The optimization of training time becomes imperative for large-scale datasets. The judicious selection of batch size, coupled with the efficiencies introduced by batch normalization, contributes to a streamlined training process. This focus on computational efficiency positions the proposed DCNN as a practical solution for real-world applications. The adjustment of feature extraction processes during the residual module using (3, 3) matrices enhances the model's understanding of the input data. By adjusting the parameters of the convolutional filters, the model gains a more nuanced understanding of the input data, leading to improved accuracy. Let I be the input image, F be the convolutional filter, and B be the bias term. The output feature map O of a Conv2D operation can be represented as:

$O = \sigma\ (I * F + B)$

V. Result and conclusion

This study presents a sophisticated methodology for automated coral reef health assessment using advanced image processing techniques and Convolutional Neural Networks (CNNs). The objective was to develop a robust system capable of accurately detecting and categorizing coral reef conditions to aid in monitoring and conservation efforts.

5.1. Performance Metrics

The performance of the developed models was meticulously evaluated using key classification metrics including Accuracy, Precision, Recall, and F1-score. These metrics provide insights into the effectiveness of the models in accurately classifying coral reef images.

Accuracy, serving as a primary performance metric, measures the overall percentage of correctly classified instances by the models. It is calculated as the ratio of true positives (TP) and true negatives (TN) to the total number of instances, including true positives, true negatives, false positives (FP), and false negatives (FN).

$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$

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ISSN: 1001-4055
Vol. 45 No. 3 (2024)

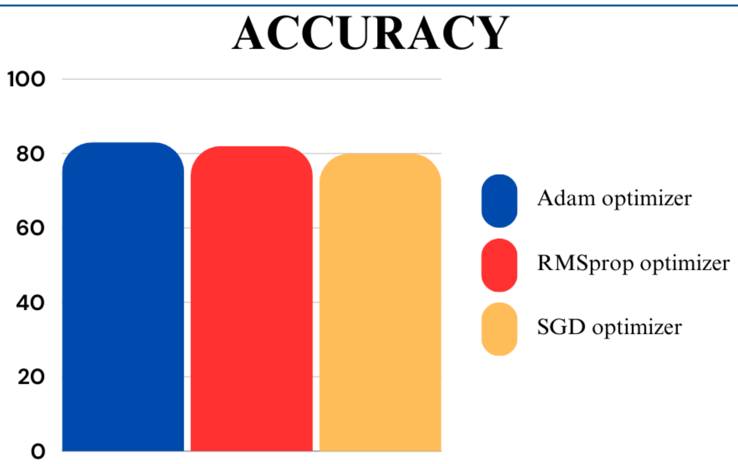

Fig 5: Accuracy analysis

Fig 5 shows the Accuracy analysis Recall, also known as sensitivity, quantifies the model's ability to correctly identify positive instances from all actual positive instances. It is calculated as the ratio of true positives to the sum of true positives and false negatives.

Recall = $\frac{TP}{TP + FN}$

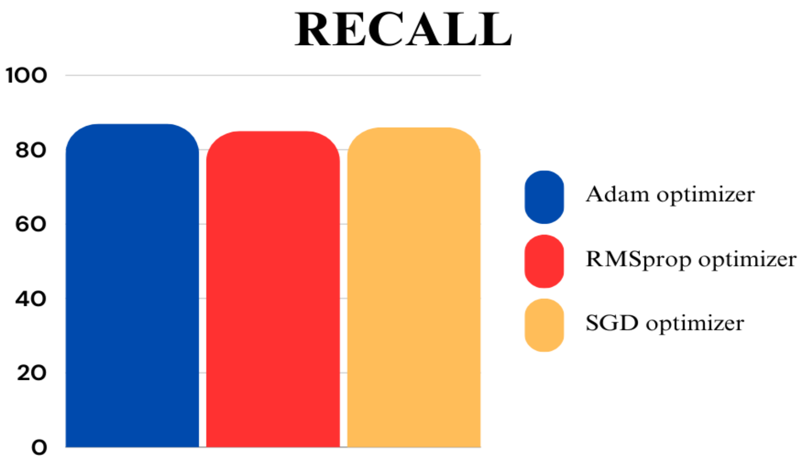

Fig 6: Recall analysis

Fig 6 shows the Recall analysis Precision measures the model's confidence in correctly identifying positive instances. It is computed as the ratio of true positives to the sum of true positives and false positives.

Precision = $\frac{TP}{TP + FP}$

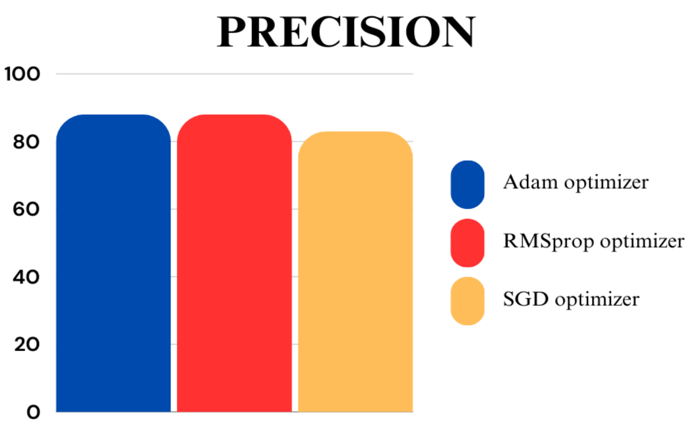

Fig 7: Precision analysis

Fig 7 shows the Precision analysis F1-score, representing the harmonic mean of precision and recall, provides a balanced assessment of the model's performance. A higher F1 score indicates better precision and recall balance, reflecting superior model performance.

F1-score = 2 X $\frac{Precision\ X\ \ Recall}{Precision + Recall}$

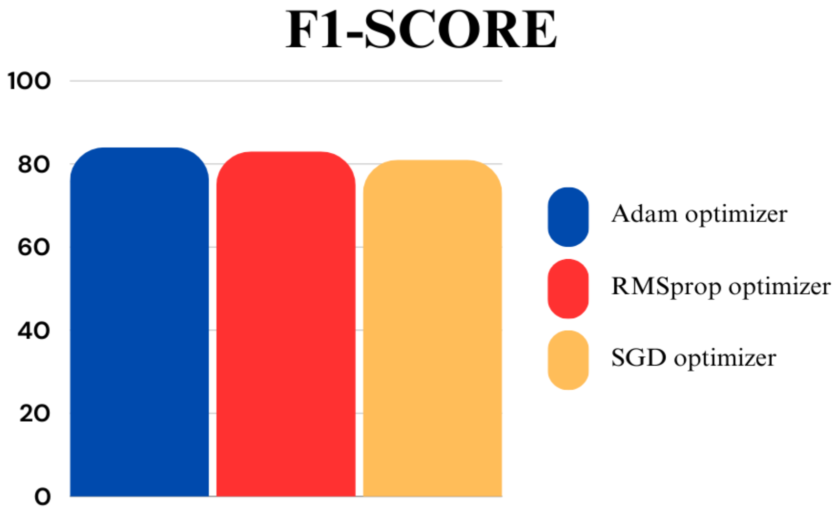

Fig 8: F1-Score analysis

Fig 8 shows the F1-Score analysis These performance metrics serve as crucial indicators of our models' efficacy in accurately classifying coral reef health conditions. By comprehensively evaluating these metrics, we gain valuable insights into the models' classification capabilities and their suitability for coral reef monitoring and conservation efforts.

The results obtained from the experiments demonstrate the efficacy of the proposed methodology. The models achieved impressive validation accuracies ranging from 80.54% to 83.78%, indicative of their ability to discern between bleached and healthy corals with high precision. Detailed performance metrics such as Precision, Recall, and F1-score were calculated for each model configuration. These metrics provide a comprehensive understanding of the models' classification capabilities and their ability to minimize errors in coral reef health assessment.

5.2. Comparative Analysis

In comparing the performance across different optimizers, it was observed that the Adam optimizer yielded a validation accuracy of 83.78%, while RMSprop and SGD achieved accuracies of 82.70% and 80.54% respectively. This suggests that the Adam optimizer slightly outperformed the other optimizers in terms of accuracy. Further analysis revealed that the modified ResNet architecture consistently outperformed the naive ResNet architecture across all optimizer configurations. The modified architecture achieved higher overall accuracies, demonstrating the effectiveness of the architectural modifications in enhancing model performance.

5.3. Graphical Representation

Graphical representations of precision, recall, and F1-score variations across different optimizer and architecture configurations were plotted for a visual understanding of the performance trends. These graphs provide insights into how changes in optimizer and architecture configurations impact classification metrics.

5.4. Conclusion

In conclusion, the developed models exhibit promising performance in automated coral reef health assessment. The high validation accuracies and robust classification metrics validate the effectiveness of the proposed methodology in accurately identifying and categorizing coral reef conditions. The findings of this study hold significant implications for coral reef monitoring and conservation efforts. By automating the detection and classification process, the developed models streamline monitoring efforts and facilitate timely interventions to mitigate threats to coral reef health. Moving forward, the methodology presented in this study can be further refined and extended to address additional challenges in coral reef conservation. Continued research in this area holds the potential to significantly contribute to the preservation and sustainable management of coral reef ecosystems. Fig 9 shows the Detected image

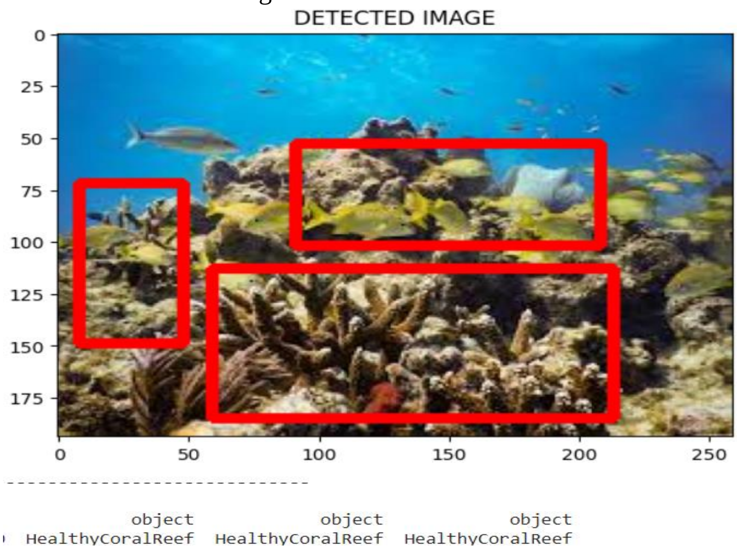

Fig 9: Detected image

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