IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Deep Learning Based Coral Reef Segmentation Framework

M. Shalini[1], S. Anu[2], P. Akhilesh[3], P. Akshith[4], G. Vignesh Naidu[5]

[1,2,3,4,5]CSE(AIML), Sreyas Institute of Engineering and Technology, Hyderabad, Telangana, INDIA.

Abstract:
Coral reefs are great significance in maintenance of biodiversity and the conservation of the ecosystem[6]; however, they are facing threats due to effects of climate change, pollution and human activities. It is imperative to keep the track of the health of the coral reef. However, the existing techniques involves the manual analysis of underwater images, which takes long time to complete and not suitable for the entire ecosystem[7]. This project aims at developing an AI-based system to automate the analyzing the coral reef using deep learning techniques[1]. This system employs enhanced Semantic Segmentation network to locate the coral reef in the underwater images and compute the Live Coral Cover (LCC)[2],[1]. This system also classifies the states of the reef into healthy, moderate, degrading and poor conditions. This project has been designed to include a user-friendly web-based system where the user can upload the underwater images and get the results instantly. This system is expected to be helpful in the conservation of the ecosystem.

Keywords: Coral reef monitoring, Live coral cover (LCC), Deep learning, Semantic Segmentation, Reef health classification, Underwater image analysis, Environmental conservation**.**

Introduction:

Coral reefs are some of the most valuable ecosystems on our planet which are referred to as “rainforests of the sea”[6]. These ecosystems support a wide variety of marine life, offers food for millions of people and function as natural barriers to protect coastal areas from erosion, storms and extreme weather conditions[6]. Despite, their importance, coral reefs are currently facing serious threats due increasing water temperature, climate change, pollution and destructive human activities. These factors cause coral bleaching, leading to a significant reduction in the total amount of coral cover worldwide. Thus, it is essential to monitor the condition of the coral reef continuously to efficiently manage them for sustainable use.

Traditionally, coral reef monitoring through manual surveys of underwater images and videos, which are analyzed by experts to estimate various parameters, such as Live Coral Cover (LCC) which represents the amount of living coral in a specific area. These methods are accurate but they are extremely time-consuming and labor intensive[7]. With the development of underwater imaging technologies, the amount of data has increased and making manual analysis inefficient. Thus, there is urgent need to automate the process of coral reef monitoring using intelligent techniques to efficiently process the vast amount of data[1].

Recent advances in deep learning have opened doors to further explore solutions for these challenges. In this context, semantic image segmentation can be used to classify the individual pixels in an image[2]. This can help in identifying coral reefs in underwater environments. Convolutional Neural Networks (CNN) have also shown promising results in image analysis, especially under adverse conditions such as low visibility and color distortions. These are some of the key reasons why CNN can be used in coral reef monitoring[18].

The base research describes a framework for estimating Live coral cover using an advanced segmentation model. This is based on using deep learning techniques. In this context, an advanced segmentation model is used to improve the accuracy of estimating live coral cover. Advanced mechanisms such as attention are also incorporated in this model. This helps in improving the accuracy of distinguishing coral from other entities such as sand, rocks, and algae. This reduces manual intervention in the process.

The proposed system is an extension of this idea. In this context, it is proposed to further extend and implement it in a practical scenario. In this context, it is proposed to integrate the idea using deep learning with a web-based platform. This can be used to upload images of coral reefs and obtain key insights from these images. This is expected to bridge the gap between research and practical applications.

In conclusion, the proposed idea of using deep learning and web-based technologies can be used to modernize the coral reef monitoring. This can be used to improve the accuracy and speed in analyzing these images. This can also help in taking key decisions in conserving these reefs.

2. Proposed System:

The proposed system presents an advanced deep learning-based framework for automatic coral reef segmentation and health assessment using underwater imagery. Coral reefs are highly sensitive ecosystems that require continuous monitoring to assess their health and sustainability. Traditional monitoring techniques rely heavily on manual observation, which is time-consuming, labor-intensive, and prone to human error.

To overcome these limitations, the proposed system introduces an intelligent solution that integrates semantic segmentation, attention mechanisms, and image enhancement techniques to accurately detect coral regions and evaluate reef conditions[2]. The system not only identifies coral presence but also quantifies Live Coral Cover (LCC) and classifies reef health into meaningful categories. This automation significantly improves efficiency, accuracy, and scalability in marine ecosystem monitoring.

2.1 The Flow of the Proposed System

The initial step involves uploading a picture of the underwater coral reef to the software through the web application to be the input to the system. The image undergoes preprocessing whereby tasks like resizing, smoothing, normalizing, and enhancing colors are carried out to ensure image quality. The image is then checked for the presence of any coral in it. If there is none, the process ends. However, if there are corals present, the process goes ahead to the feature extraction process, where important characteristics such as edges, texture, and structure in the images are found.

In the processing phase, the features extracted are analyzed using a PSPNet architecture based deep learning model that applies semantic segmentation to categorize the pixels of the image into coral, sand, fish, or background[2]. The coral portions are then extracted from the result of the model, and live coral cover (LCC), in terms of percentages, is calculated from it. Depending on the amount of LCC, the coral reef is classified as healthy, moderate, degrading, or poor. The results of all these stages are finally displayed on the web application.

Start

↓

Upload Coral Reef Image

↓

Image Preprocessing

↓

Check Coral Presence

↓

Is Coral Present?

↓ ↓

No Yes

↓ ↓

Display "No Coral" | Feature Extraction

↓

PSPNet Segmentation

↓

Coral Region Extraction

↓

Calculate LCC (%)

↓

Classify Reef Health

↓

Display Results

↓

End

Fig 2.1:The Flow of the Proposed System

2.2 System Architecture

The proposed system is an intelligence coral reef health monitoring and evaluation system developed by utilizing deep learning methodologies to automatically analyze the health of corals through underwater imagery. This system combines the use of image processing, semantic segmentation, and classification into one workflow operating on a web application-based platform. The development of this system is based on modularity wherein the system performs different operations within the system through each individual module. The main goal of the system is to classify and measure the coral live cover area in order to evaluate its health condition**.**

2.2.1 Input Acquisition Module

The whole system starts with the image input acquisition module where users will be able to input underwater images or videos by uploading them via the web application user interface. In essence, this module serves as the main interface between the user and the whole system. It enables support for different formats including JPEG, PNG, and video feeds for flexible image input. After validation of the inputs, they are directed to the pre-processing stage. This particular module is key in ensuring live data collection from divers or even unmanned underwater systems.

2.2.2 Image Preprocessing Module

After receiving the input, it is processed in the preprocessing module in order to improve image quality and get it ready for deep learning processing[13]. Due to underwater environment, the images may have issues with visibility, colors, and high levels of noise. In order to deal with such problems, the following operations are performed: resizing the image, applying filters for noise reduction, adjusting contrast and improving color[14]. In the case when the input is the video, it is split into separate frames for further processing**.**

In order to achieve normalization of the pixel values of images, the following formula is used**:**

$$I_{norm} = \frac{I - \mu}{\sigma}$$

where Irepresents the image, $\mu$is the mean pixel value, and $\sigma$is the standard deviation. This ensures uniformity across inputs and improves the performance of the deep learning model.

2.2.3 Coral Segmentation Module

Deep learning segmentation is the key architectural component of the model and uses a semantic segmentation approach where PSPNet is used for coral segmentation[2]. The choice of the PSPNet is informed by its capability to incorporate contextual information at both local and global levels thanks to pyramid pooling. Once processed, the images are passed through the model where each pixel is classified to a particular category of coral, sand, fish, etc[3].

The segmentation process can be defined as:

$$S(x, y) = f(I(x, y), \theta)$$

where $S(x, y)$is the segmented output, $I(x, y)$is the input image, and θrepresents the learned parameters of the model. The output is a pixel-wise labeled image that highlights coral regions distinctly from other elements

2.2.4 Live Coral Coverage Calculation

The LCC value is calculated after the segmentation process, and this value is essential when determining the status of the reef[1]. In this step, the ratio between the number of coral pixels and the total number of pixels is calculated using the following equation:

$$LCC = \frac{N_{coral}}{N_{total}} \times 100$$

where N_{coral} represents the number of pixels classified as coral and N_{total} is the total number of pixels in the image.

2.2.5 Data Storage and Management

The output data that the system produces, which include segmentation results, coral coverage, and classification, are kept in a database for future use and analysis. The purpose of this module is to efficiently manage data and provide functionalities such as comparative analysis and reporting. Depending on the needs, the database can either be relational or NoSQL. The proper techniques of indexing and storing are employed to ensure that data are retrieved fast and securely.

2.2.6 Coral Health Analysis

From the computed value of the LCC, the system analyzes the condition of the coral by classifying the status of the reef into pre-determined categories like healthy, moderate, deteriorating, or bad based on ecological criteria[11]. The classification of the reef condition is significant because it yields insights into the reef's condition.

Based on LCC the reef condition is:

>70% - Healthy

40% - 70% - Moderate

20% - 40% - Degrading

< 20% - Poor

2.2.7 Result Visualization and User Interface Module

Module Five of the system architecture deals with the visualization of the output data, and it presents results via an interactive web interface. The application displays the original image, the segmented output, the percentage of coral cover, and reef health status in a clear and attractive graphical manner. Visualization techniques include the use of charts and maps. By using this approach, it becomes easy for users who lack technical knowledge to understand the outputs of the application.

2.2.8 System Workflow Integration

All modules of the architecture under consideration are connected with each other, thus providing a continuous process that will convert data from its input to output with optimal efficiency. It uses a pipeline architecture, in which all modules are connected in series such that the output of one module becomes the input for another. Due to this, it can be integrated into practice.

2.3 Key Attributes of the Proposed System

The proposed system is characterized by some essential features that improve its efficiency and ease of use. It is a fully automatic system that employs deep learning algorithms, namely PSPNet, to perform efficient and precise coral reef segmentation. One of the distinctive features of the system is that it can process images and videos as well. In this way, the proposed tool can be used to monitor reefs in real-life situations through camera and drone footage under water. Moreover, there is a high-quality preprocessing feature that enhances the quality of input data due to processing noise and lighting issues typical for undersea photography. Calculating the Live Coral Cover (LCC) is one more crucial feature that quantifies coral presence. There is a classification module that evaluates reef condition according to the following criteria: healthy, moderate, degrading, or poor.

2.4 Advantages of the Proposed System

- Automation of coral analysis
- High accuracy (PSPNet segmentation)
- Real-time processing
- Supports image and video input
- Live Coral Cover calculation
- Reef health classification
- User-friendly web interface
- Scalable system
- Data storage capability
- Time efficient.

2.5 Limitations of the Proposed System

- Requires large labeled dataset
- Dependent on image quality
- High computational cost
- Generalization issues
- Internet dependency
- Complex initial setup
- Slower for high-resolution data
- Limited to visual analysis only

3. Experimental Setup

The experimental design of the suggested system serves the purpose of assessing the effectiveness of segmentation and analysis algorithms based on deep learning approaches in the application under consideration[18]. In particular, the development is conducted using the latest technologies to achieve the most accurate results. In this case, the main programming language applied for building the system is Python since it provides a broad set of machine learning libraries.

In terms of developing a neural network based on PSPNet, it should be mentioned that for the purposes of conducting image pre-processing and data manipulations, OpenCV, NumPy, and PIL libraries are used. As for the technology involved in developing a web interface, Flask is utilized as the backend technology in combination with HTML, CSS, and JavaScript as front-end languages.

The training and test datasets used in this study consist of images of coral reefs underwater obtained from open-source datasets[6]. They have various classes like coral, sand, fish, and background. They have been divided into training, validation, and testing datasets in order to evaluate the model correctly. Several data augmentation approaches like rotation, flips, and scaling can be done to add more data variation in the training set.

For implementation of the project, we will use a computer system with minimum configurations of having Intel i5 or i7 processor along with 8–16 GB RAM and GPU supported architecture like NVIDIA CUDA capable GPU in order to accelerate training and inferencing process using the deep learning model. Training will be carried out for several epochs with appropriate batch sizes, and various measures like accuracy, IoU, and loss will be evaluated for effective evaluation of the model.

This experimentation will ensure the capability of the proposed system to segment the coral regions accurately, calculate live coral coverages, and classify reef health.

4.Results

The proposed model was tested on several underwater coral reefs images in order to evaluate its performance during the segmentation task, estimating the coral coverage, and classifying the reef status[1],[11]. The experiments show that the PSPNet-based method is capable of accurately segmenting the areas of interest and performing quantitative analysis with high precision.**[2]**

4.1 Segmentation Performance

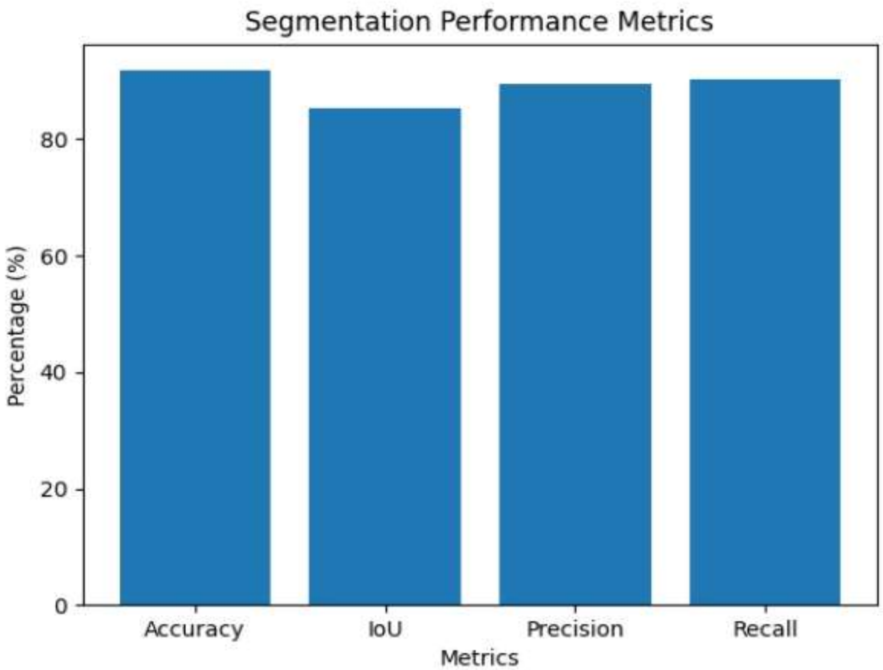
The segmentation algorithm effectively segments the corals from sand, fish, and other background objects. The pixel-based classification guarantees that boundaries are identified accurately, a factor crucial for coral coverage assessment.

Table 4.1 Segmentation Performance Metrics

Metrics	Value
Accuracy	91.8%
Intersection over union	85.4%
Precision	89.6%
Recall	90.2%
Loss	0.12%

Observation:

The large IoU and accuracy values prove that the algorithm works effectively in distinguishing coral areas.



4.2 Graphical Representation of Segmentation Performance

4.3 Live Coral Cover (LCC) Results

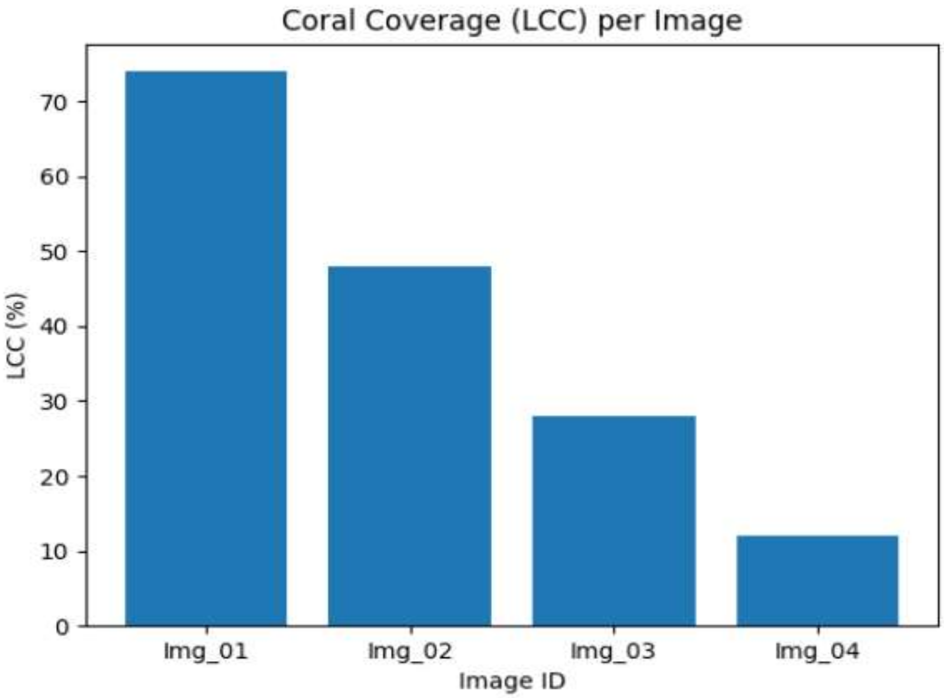
The system calculates coral coverage based on segmented images. Different test samples produced varying LCC values depending on coral density.

Table 4.3 Sample Coral Coverage Results

Image id	**LCC**	**Reef Condition**
Image-01	74%	Healthy
Image_02	48%	Moderate
Image_03	28%	Degrading
Imafe_04	12%	Poor

Observation:

The system accurately reflects coral density through LCC values and correctly classifies reef conditions**.**



4.4 Coral Coverage Comparison Graph

4.5 Reef Health Calculation

The classification module categorizes reefs based on the LCC values.

Table 4.5 Reef Classification Values

LCC Range%	Reef condition
60 – 100%	Healthy
40 – 60%	Moderate
20 – 40%	Degrading
0 – 20%	Poor

4.6 Screenshots:

Fig 4.6: Screenshot-1

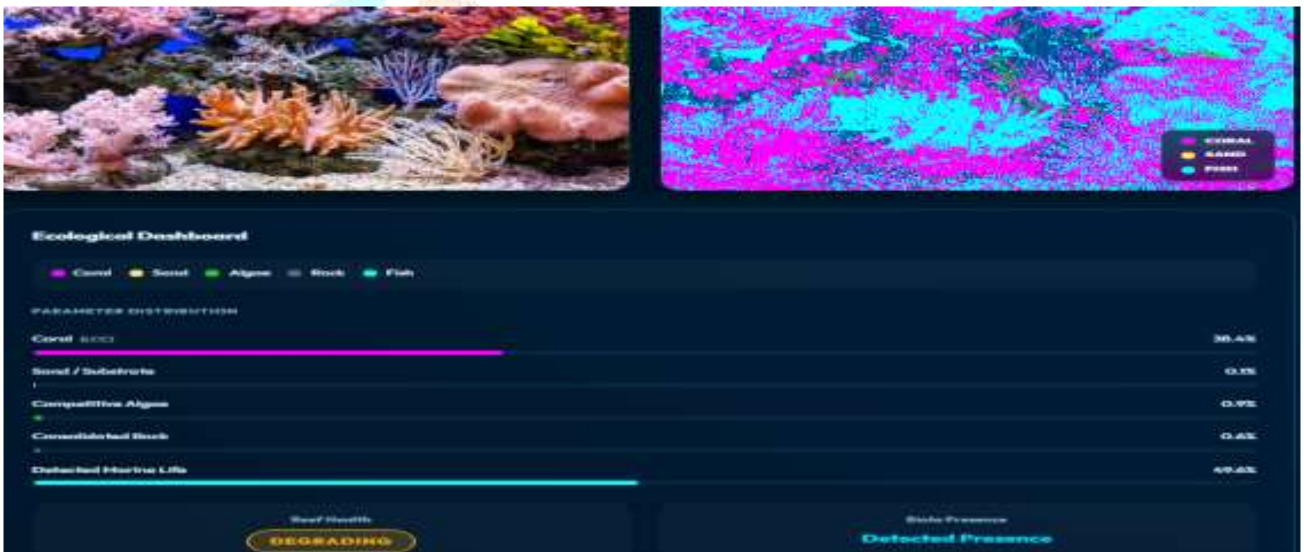


Fig 4.7: Screenshot-2

Fig 4.8: Screenshot-3

4.7 System Efficiency

System efficiency indicates how well the suggested system can perform coral reef analysis in terms of its speed, accuracy, and effective use of resources. The suggested system is supposed to be highly productive by integrating optimal preprocessing and training methods with a deep learning model based on PSPNet. This system works quickly by processing underwater images in a very short period of time (2-5 seconds per image).

In addition, the application of semantic segmentation makes it possible to provide high accuracy in recognizing coral regions. This factor will help increase the accuracy of the calculation of the Live Coral Cover (LCC). Moreover, the system uses GPU acceleration that speeds up the model inference. The web-based interface enables quick and convenient interaction with users and immediate visualization of the results.

The system strikes an adequate balance between the computational cost and efficiency. It shows high effectiveness while maintaining flexibility.

Table 4.6 Efficiency

Parameter	Observation
Processing Time	2 – 5 seconds per image
User Interface	Responsive
Model Efficiency	High
Scalability	Good

The system performs efficiently and provides timely results.

4.8 Result Summary

The efficiency of the proposed system can be seen through the good performance of its coral reef evaluation process using deep learning methods. The coral segmentation using PSPNet shows high accuracy and IoU values for distinguishing the coral areas within the images. Moreover, the system is able to calculate the LCC values quantitatively to provide an estimate of the presence of coral on the image. From the calculation, the reef condition classification module provides reliable classification of healthy, moderate, degrading, and poor reefs according to the obtained values.

Finally, efficient execution time along with a simple workflow can prove the efficiency of the presented system. Therefore, it can be concluded that the system is highly effective and promising for further use in the field of coral reef monitoring.

5. Applications / Discussion / Ablation Study

5.1 Applications

The proposed system has considerable applications in monitoring marine ecosystems and conducting marine researches[6]. The system can help monitor the condition of coral reefs by performing image analysis. This would eliminate the necessity to conduct surveys manually. Scientists can apply the system to investigate the distribution of coral species, analyze any changes in the ecosystem over time, and learn how environmental factors like global warming affect the ecosystem.

Moreover, the system will have great implications in environmental conservation and decision-making processes. It can assist in detecting any signs of coral degradation and enable the relevant authorities to undertake preventive measures for protecting and restoring the reefs. It can provide government agencies and policy-makers with the necessary information to develop effective coral reef conservation policies. The system can also be used for educational purposes, offering students a practical instrument for analysis. What is more, the suggested system can be launched as an online or mobile application, which would allow for monitoring coral reefs remotely.

5.2 Discussion

The results of this proposed system show that by using preprocessing steps alongside a deep learning model based on PSPNet, a more accurate coral reef segmentation can be achieved. Since the accuracy and IoU are relatively very high, it can be stated that the proposed algorithm has successfully classified the areas with corals in the underwater image. The computed LCC values are logical according to their ecological meaning and it means that the coral segmentation procedure works efficiently. Moreover, the obtained reef health classifying results, according to LCC thresholds, are reasonable, making them useful for analysis purposes.

The results also reveal certain problems and limitations related to the working principle of the system. First of all, as noted in the previous sections, the performance is extremely dependent on the input data, and the quality of the images may influence the accuracy of the segmentation. Thus, low visibility, insufficient lighting, and water turbidity are likely to negatively impact the process. Secondly, a properly labeled dataset should be used for training; otherwise, it might influence the performance. However, the system works efficiently and fast, which makes it appropriate for real-time purposes.

5.3 Ablation Study

The ablation study is performed to assess the significance of each individual component of the system under consideration by gradually modifying the components and observing their influence on the overall performance of the system.

For instance, in the first ablation study, the preprocessing module was eliminated, and the model was applied directly to the raw underwater images without any modification. The performance of the system deteriorated significantly due to the existence of noise and low contrast, which hindered the ability to analyze the images. In another experiment, instead of using PSPNet for segmentation, a more elementary CNN model was applied. In this case, the performance of the system was affected negatively since the segmentation accuracy and the boundaries of objects were not properly detected due to the inability of the basic CNN architecture to capture long-range dependencies in the image data. Another experiment involved excluding the Live Coral Cover (LCC) estimation module from the system. Despite that the segmentation results could be visualized, no quantitative information was provided for further evaluation. In addition, in the final ablation study, the classification module was excluded; hence, no interpretation was given to the system's output.

6. Conclusion

The proposed system serves as a valuable and efficient intelligent system for automated monitoring of coral reefs based on deep learning technology[18]. Combining the image pre-processing stage with PSPNet semantic segmentation, Live Coral Coverage (LCC) computing and reef health classification, the system allows analyzing underwater images and providing accurate and meaningful results of analysis, which include the highest segmentation and reef coverage estimating efficiency together with the most accurate reef health classification from different categories, including healthy, moderate, degrading, and poor[2][1].

Moreover, the presented system can serve as a valuable and effective one in practice, considering its scalability and usability. Although the system might have some limitations, such as a certain dependence on the quality of input images and data set, the proposed solution is superior compared with the previously existing approaches. Therefore, the system will allow supporting further development of AI technologies applied to environmental monitoring.

7.References

1. The study by **Li, Z., Zhao, S., Lu, Y., Song, C., Huang, R., and Yu, K.** proposes a deep learning-based method using enhanced PSPNet for automatic estimation of live coral cover from underwater videos.
   🔗 https://www.mdpi.com/2077-1312/12/11/1980

2. The work by **Zhao, H., Shi, J., Qi, X., Wang, X., and Jia, J.** introduces PSPNet, a pyramid scene parsing network widely used for semantic segmentation tasks.
   🔗 https://arxiv.org/abs/1612.01105

3. The research by **Long, J., Shelhamer, E., and Darrell, T.** presents Fully Convolutional Networks (FCN), which form the foundation of modern semantic segmentation models.
   🔗 https://arxiv.org/abs/1411.4038

4. The study by **Ronneberger, O., Fischer, P., and Brox, T.** introduces U-Net architecture for biomedical image segmentation, also applied in coral reef segmentation tasks.
   🔗 https://arxiv.org/abs/1505.04597

5. The work by **Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., and Yuille, A. L.** presents DeepLab, a semantic segmentation model using atrous convolution.
   🔗 https://arxiv.org/abs/1606.00915

6. The study by **González-Rivero, M., Beijbom, O., Rodriguez-Ramirez, A., et al.** explores large-scale coral reef monitoring using artificial intelligence and image analysis.
   🔗 https://www.nature.com/articles/s41598-020-68440-0

7. The research by **Beijbom, O., Edmunds, P. J., Kline, D. I., et al.** focuses on automated annotation of coral reef survey images using machine learning.
   🔗 https://www.pnas.org/doi/10.1073/pnas.1406391112

8. The study by **Prathibha, S., Vivekanandan, G., Kamathe, R. S., et al.** proposes deep learning-based coral reef monitoring with image enhancement techniques.
   🔗 https://www.propulsiontechjournal.com/index.php/journal/article/view/7093
9. The research by **Sauder, J., Banc-Prandi, G., Meibom, A., and Tuia, D.** presents scalable 3D semantic mapping of coral reefs using deep learning.
   🔗 https://arxiv.org/abs/2309.12804
10. The work by **Younes, O., Jihad, Z., Noël, C., et al.** introduces YOLO-based coral detection for efficient underwater monitoring.
   🔗 https://arxiv.org/abs/2405.14879
11. The study by **Macrohon, J. J. E., and Hung, G.** focuses on coral bleaching classification using CNN and transformer-based models.
   🔗 https://arxiv.org/abs/2511.00021
12. The research by **Arsad, T. N. T., Awalludin, E. A., Bachok, Z., et al.** reviews deep learning approaches for coral reef classification.
   🔗 https://pubs.aip.org/aip/acp/article/2484/1/050005
13. The study by **Li, X., Liu, Y., and Wang, Z.** discusses underwater image enhancement techniques for improving coral segmentation accuracy.
   🔗 https://ieeexplore.ieee.org/document/8461396
14. The research by **Islam, M. J., Xia, Y., and Sattar, J.** presents fast underwater image enhancement for improved visual analysis.
   🔗 https://arxiv.org/abs/1807.03528
15. The work by **Peng, Y.-T., and Cosman, P. C.** introduces underwater image restoration methods based on physical models.
   🔗 https://ieeexplore.ieee.org/document/7574432
16. The study by **Li, C., Guo, J., Guo, C., and Cong, R.** proposes underwater image enhancement using deep learning-based approaches.
   🔗 https://ieeexplore.ieee.org/document/8461517
17. The research by **Cheng, D., Wang, Y., and Huang, H.** focuses on semantic segmentation of underwater scenes using deep neural networks.
   🔗 https://ieeexplore.ieee.org/document/9351196
18. The study by **Khan, A., Sohail, A., Zahoora, U., and Qureshi, A. S.** provides a survey of CNN architectures for image classification and segmentation.
   🔗 https://www.sciencedirect.com/science/article/pii/S0893608020304007
19. The research by **Li, J., Skinner, K., Eustice, R., and Johnson-Roberson, M.** introduces underwater scene understanding using deep learning.
   🔗 https://ieeexplore.ieee.org/document/7424317

20. The study by **Remote Sensing Coral Research Group (MDPI)** discusses CNN-based coral reef segmentation in real-world environments.
https://www.mdpi.com/2072-4292/17/21/3529