SMART CORAL CLASSIFICATION FROM REEF IMAGERY USING DEEP CNN TECHNIQUES

Meerupelli Meghana[1], P. Shivakumar[2*], Korivi Sahitya[1], Basaraju Sriram[1], Nelakuditi Ranjith[1], Kinnera Sandeep[1]

[1]UG Student, [2]Assistant Professor, [1,2]Department of Computer Science and Engineering (AI&ML)

[1,2]Vaagdevi Engineering College, Bollikunta, Warangal, 506005, Telangana, India

*Correspondence: P. Shivakumar (shivapujarigoud2024@gmail.com)

To Cite this Article
Meerupelli Meghana, P. Shivakumar, Korivi Sahitya, Basaraju Sriram, Nelakuditi Ranjith, Kinnera Sandeep, "SMART CORAL CLASSIFICATION FROM REEF IMAGERY USING DEEP CNN TECHNIQUES", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 04, April 2026,pp: 346-356, DOI: http://doi.org/10.64771/jsetms.2026.v03.i04.pp346-356

Submitted: 28-02-2026 Accepted: 01-04-2026 Published: 09-04-2026

Abstract

Coral reefs are among the most biologically diverse ecosystems, supporting nearly 25% of marine life while providing vital ecological, economic, and coastal protection benefits. However, factors such as climate change, ocean acidification, and human activities have significantly accelerated reef degradation, creating an urgent need for accurate and efficient coral species identification. Conventional coral identification approaches utilize handcrafted features such as shape, texture, and color, but these methods struggle with scalability and generalization across diverse underwater environments and visually similar species. To overcome these limitations, this study proposes an intelligent and scalable framework for underwater coral species identification using deep feature extraction and machine learning techniques. A Vision Transformer (ViT) model is employed to extract robust and high-dimensional feature representations from coral images. These features are then used to train multiple classifiers, including Natural Gradient Boosting (NGB), Histogram Gradient Boosting (HGB), Extreme Gradient Boosting (XGB), and a proposed Scope Rules Classifier (SRC). The proposed system is evaluated using performance metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis. Results indicate that the SRC model outperforms baseline methods in classification performance. Additionally, an Explainable Artificial Intelligence (XAI) module enhances interpretability, while a Telegram bot interface enables real-time coral species identification. This framework offers a practical, scalable, and interpretable solution for supporting marine ecosystem monitoring and conservation efforts.

Keywords: classification task, coral reefs, deep learning, marine ecosystems, vision transformer, XAI

1. Introduction

In an era of rapid environmental change, reliable and precise ecological data is crucial for developing effective management strategies to prevent the decline of ecosystems. Although hypothesis-driven and adaptive management approaches play a vital role in conservation monitoring [1], limitations in accessing and processing ecological data remain a significant challenge. As a result, there is a growing need to minimize the time and cost associated with ecological surveys. Long-term monitoring of coral reef ecosystems is essential for implementing effective policies and management decisions. In addition, the remote locations of coral reefs and the requirement for scuba diving often lead to fragmented and spatially limited long-term datasets [2]. To reduce costs and expand usability, underwater digital photography has increasingly been adopted for monitoring at smaller spatial scales. Despite this advancement, extracting meaningful ecological information from these images such as RGB intensity and texture to determine benthic composition remains highly time intensive.

This process typically relies on experts, including ecologists and taxonomists, to analyse the data before it can be used for conservation planning. Consequently, this dependency creates a significant bottleneck, delaying the transfer of critical information from monitoring programs to conservation practitioners [3]. The classification and identification of marine organisms, including plankton and coral reefs, play an important role in managing marine ecosystems, preserving biodiversity, and understanding species variation. Analysing the distribution of marine organisms also helps in assessing the effects of global warming and human activities on marine life, thereby supporting sustainable resource utilization.

However, underwater imaging presents several challenges, such as reduced edge clarity, loss of detail, low contrast between objects and background, and noise caused by complex underwater conditions [4]. These factors make feature extraction from underwater images particularly difficult. Early approaches to underwater image classification primarily relied on traditional image processing and pattern recognition techniques. These methods involved preprocessing steps such as filtering and segmentation to improve image quality. For example, Spampinato utilized gray-level histograms and extracted features like contour shape and texture patterns of underwater objects for fish classification.

2. Literature Survey

Raphael A et al [5], introduced the methods used in each of the advances in the application of deep learning (DL) to coral research that took place between the years: 2016–2018. DL has the unique capability of streamlining the description, analysis, and monitoring of coral reefs, saving time, and obtaining higher reliability and accuracy compared with error-prone human performance. Piñeros VJ et al [6]. covered the development of unmanned underwater vehicles based on their technical capabilities, particularly those designed for research exploration in underwater ecosystems and for assessing coral reef vulnerability. The study emphasized the collection of in situ data supported by molecular biomarkers and marine ecology indicators. It described the geographic distribution of coral reefs and biological approaches used to evaluate reef vulnerability.

Tao J et al [7] proposed Coral-YOLO, a novel framework for detection and forecasting. They introduce the Holistic Attention Block Head (HAB-Head), which enables deep cross-scale reasoning through explicit feature interaction, and MCAttention, a randomized training mechanism that enables the network to learn scale-invariant features with inherent robustness. Trudeau GA et al [8] introduced a novel mathematically based nonlinear spectral unmixing method for benthic habitat classification, which provides sub-pixel estimates of benthic composition, capturing the mixed benthic composition within individual pixels. They compared its performance against two machine learning approaches: semi-supervised K- Means clustering and AdaBoost decision trees.

Rahman LF et al [9] aimed to develop a machine learning–based prediction model for marine fish and aquaculture production. Based on feature importance scores, a group of climatic variables was selected for three different ML models, namely linear regression, gradient boosting, and random forest regression. Alonso, I et al. [10] proposed a workflow to leverage underwater hyperspectral image transects and two machine learning algorithms to produce dense habitat maps of 1150 m 2 of reefs across the Curaçao coastline. Their multi-method workflow labelled all 500+ million pixels with one of 43 classes at taxonomic family, genus or species level for corals, algae, sponges, or to substrate labels such as sediment, turf algae and cyanobacterial mats.

Hieu NTD et al [11] examined two decades of changes in coral spatial distribution within the Nha Trang Bay Marine Protected Area (MPA) using remote sensing and machine learning (ML) approaches. Identified various factors contributing to coral reef loss and analyzed the effectiveness of management policies over the past 20 years. Li Z et al [12] introduced an innovative deep learning–based approach that utilized semantic segmentation to automatically interpret LCC from underwater videos. Specifically, they enhanced PSPNet for live coral segmentation by incorporating channel and spatial attention mechanisms, along with pixel shuffle modules.

Sterling Tebbett et al [13] considered how different factors shaped turf productivity and turnover rates. Among the factors examined, depth was the primary driver of turf productivity rates, while turnover was predominantly related to turf biomass. Sreenivas Pratapagiri et al. [14] proposed a plant leaf disease detection system using Convolutional Neural Network (CNN). The model extracted visual features from leaf images. The system classified diseases accurately for early agricultural intervention. Nathaphon Boonnam et al [15] predicted coral reef bleaching under climate change by using machine learning techniques to provide the data to support coral reefs protection. Supervised machine learning was used to predict the level of coral damage based on previous information, while unsupervised machine learning was applied to model the coral reef bleaching area and discovery knowledge of the relationship among bleaching factors.

Rekha Gangula et al. [16] proposed a methodology for early Alzheimer’s disease detection using Brain Magnetic Resonance Imaging (MRI). The system performed image preprocessing and feature extraction. The classification model improved early-stage disease identification. Rekha Gangula et al. [17] proposed a diabetes prediction model using Logistic Regression. The framework analyzed clinical datasets for risk prediction. The model improved prediction accuracy and disease prognosis. Pavankumar Nagapuri et al. [18] proposed a deep learning hybrid model for lung disease detection using Chest X-Ray (CXR) images. The model combined feature extraction and classification stages. The approach improved diagnostic accuracy in medical imaging. Rekha Gangula et al. [19] proposed an ensemble machine learning approach for dengue disease prediction. The framework utilized multiple classifiers for improved performance. The model enhanced prediction accuracy and reliability.

3. Proposed System

The proposed framework represents a sophisticated, hybrid architecture for Transformers-Driven Multi-Class Coral Reef Classification. The system integrates high-dimensional feature extraction via ViT, a robust ensemble of machine learning classifiers including the proposed SRC, and a cloud-based External XAI Service layer. As shown as Figure 1. The architecture is designed with a dual-interface approach, allowing users to interact via a local Tkinter GUI or a remote Telegram Bot, both of which are secured through a TinyDB-based authentication system. The workflow is divided into two primary pipelines: a training pipeline that serializes ViT features and model weights, and a real-time inference pipeline that aggregates deep learning predictions with descriptive XAI analysis.

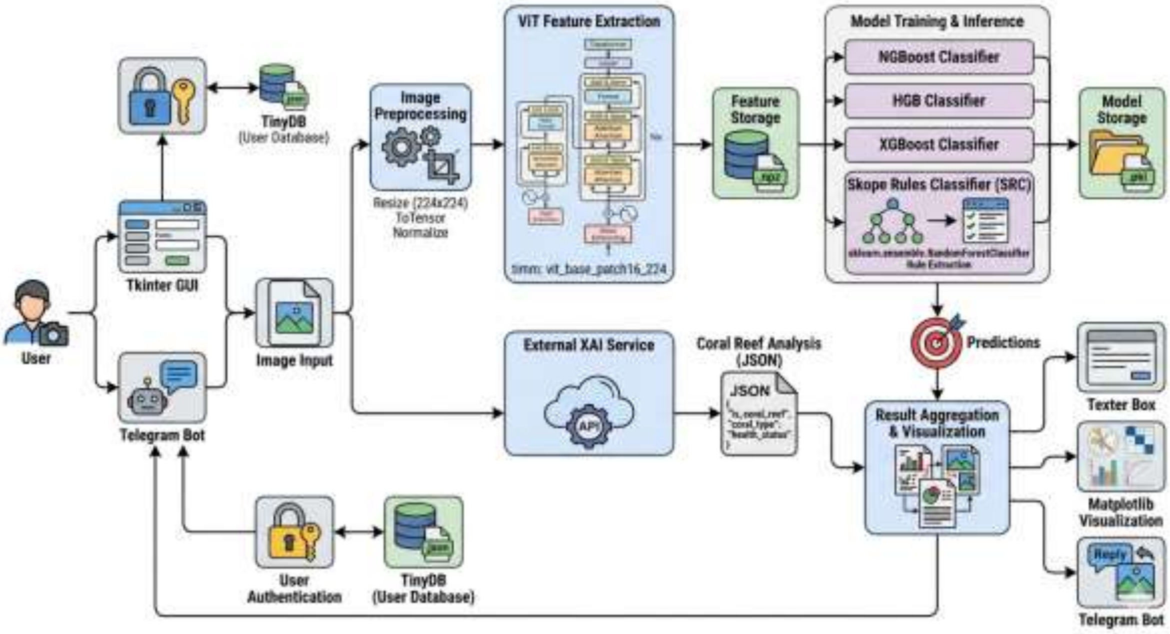

Figure. 1: Proposed system architecture

User Authentication and Data Initialization: The process begins with a secure entry point where users (Admin or Standard) are authenticated against a TinyDB user database. Once verified, the system initializes the environment. For training, the admin selects the coral dataset directory via a Tkinter dialog. The system scans sub-directories to identify and categorize the various coral species, preparing the raw imagery for the preprocessing stage.

Image Preprocessing: To ensure compatibility with the transformer backbone, all input images undergo a standardized preprocessing sequence. This involves resizing the images to a fixed 224x224 resolution, converting them to numerical tensors, and applying normalization (centering the mean and standard deviation). This step ensures that regardless of the source—be it the dataset or a live Telegram upload—the input data is consistent for the ViT model.

ViT-Based Feature Extraction: The core of the system's "vision" relies on the timm library's vit_base_patch16_224 architecture. Rather than using the model for direct classification, the framework utilizes it as a deep feature extractor. By bypassing the final head, the system generates a rich, 768-dimensional feature embedding for each image. These discriminative vectors are stored in a compressed .npz file to optimize subsequent training phases and reduce redundant computations.

Model Training and Inference Suite: The framework evaluates the extracted features across a diverse suite of ensemble classifiers. While the system supports NGB, HGB, and XGB, it prioritizes the Proposed SRC. The SRC is built upon enhanced for interpretability through rule extraction. Once trained on an 80:20 stratified split, the final model weights are serialized into a .pkl file within the model storage.

External XAI Service Integration: During the inference phase, the system triggers a parallel "Explainable AI" workflow. The input image is sent to an External XAI Service via a secure Application Programming Interface (API) request. This component performs a high-level qualitative analysis, returning a Java Script Object Notation (JSON) object that verifies if the scene is a coral reef and provides metadata on coral type, health status, visibility, and dominant color. This provides a "common sense" validation layer that complements the raw classification.

Result Aggregation and Visualization: In the final stage, the system aggregates the outputs from both the SRC Prediction and the External XAI Analysis. The results are processed through a visualization engine that generates:

- **Matplotlib Visualizations:** Including Confusion Matrices and ROC Curves for performance tracking.
- **Tkinter Output:** Displaying class predictions and XAI metadata in a dedicated Text Box.
- **Telegram Bot Reply:** Sending a formatted response back to the mobile user with the classified image and analysis summary.

This integrated approach ensures that the identification of coral species is not only accurate but also contextually explained through the XAI component.

3.1 ViT Feature extraction

Patch Embedding is the foundational step within the ViT architecture. It transforms the pre-processed image into a sequence of fixed-length vector representations, allowing the transformer to process visual data in the same way it handles text tokens in natural language processing. Instead of scanning the image using convolutional kernels, ViT divides the image into smaller patches and embeds each patch into a high-dimensional feature space. This enables the model to capture long-range spatial relationships and global structural patterns that are essential for identifying coral shapes, textures, and morphology shown in Figure 2.

1. Image Patching and Embedding The first and most critical step in the ViT pipeline is to convert the image into a sequence of patches, like the tokens in an NLP model.

- **Patch Splitting:** The input image, usually of size $H \times W \times C$(height, width, and channels), is divided into fixed-size patches. For example, an image of size 224x224 can be split into non-overlapping 16x16 patches, resulting in $\frac{224}{16} \times \frac{224}{16} = 14 \times 14 = 196$patches.
- **Patch Flattening:** Each patch is then flattened into a 1D vector. A patch of size $P \times P \times C$(e.g., 16x16x3) is reshaped into a vector of size $P^2 \times C$, creating 196 patch vectors for an image.
- **Patch Embedding:** Each flattened patch is researched into a higher-dimensional space (embedding dimension D) through a learnable linear researchion. This linear transformation enables the model to learn richer feature representations for each patch. The result is a sequence of patch embeddings, each representing a part of the image. The total number of patches in the sequence is $N = \frac{H}{P} \times \frac{W}{P}$, where $N$is the number of patches. For instance, with a 224x224 image and 16x16 patches, we have 196 patches.

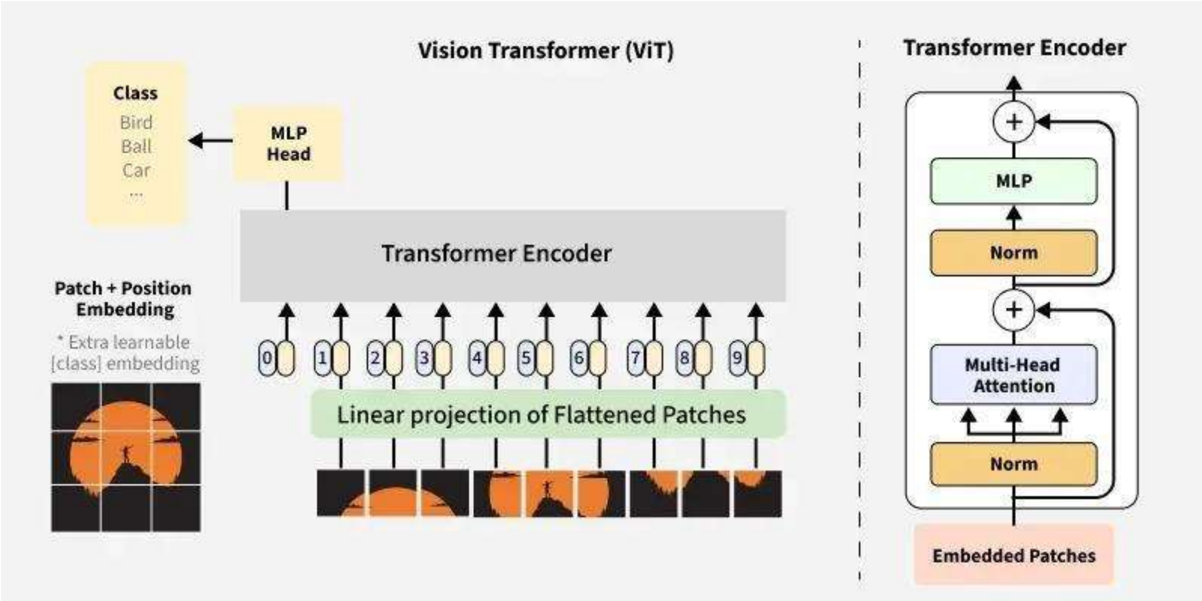

Figure 2: Architecture and Working of ViT

2. Positional Encoding Transformers do not inherently capture the spatial order of input sequences. Since the patches are processed as independent tokens, it's essential to introduce positional encodings to retain the spatial structure of the original image.

- **Positional Embedding:** Positional encodings are added to each patch embedding to encode information about the location of patches within the image. These embeddings help the model understand the spatial relationships between patches.

- **Learned vs. Fixed Positional Encoding:** In ViTs, positional encodings can either be learned during training or predefined (fixed). Most implementations of s use learnable positional encodings.

3. Transformer Encoder Layers Once the patches are embedded and augmented with positional information, they are passed through a stack of transformer encoder layers. These layers consist of two primary components: Multi-Head Self-Attention (MSA) and a Feed-Forward Neural Network (FFN).

- **Multi-Head Self-Attention (MSA):**
  - **Self-Attention:** The self-attention mechanism allows each patch to attend to every other patch in the sequence. This means that the transformer can model long-range dependencies and relationships between different parts of the image. Each patch computes a weighted sum of the values of all other patches based on its similarity to them, known as the attention score.
  - Where Q(query), K(key), and V(value) are learned linear researchions of the input patch embeddings. The dot product between queries and keys determines the attention score, and softmax normalizes it. The weighted sum of values determines the output.
  - **Multi-Head Attention:** The attention mechanism is computed in parallel across multiple attention heads, allowing the model to focus on different parts of the image simultaneously.

- **Feed-Forward Network (FFN):** After self-attention, the patches are passed through a feed-forward network (FFN). The FFN consists of two fully connected layers with a non-linear activation function (typically GELU) in between.

Each transformer encoder layer includes residual (skip) connections and layer normalization to stabilize training and improve convergence. These techniques ensure that the deeper layers do not lose important information from the earlier layers.

4. Classification Token (CLS Token) In ViT, a special classification token (CLS token) is introduced at the beginning of the input sequence. This token serves a critical role: it gathers information from all the patches throughout the transformer layers. The CLS token learns to represent the entire image by attending to the different patches through the self-attention mechanism. At the output of the transformer layers, the CLS token is extracted and passed to a classifier for the final prediction.

5. MLP Head (Classification Head) After the transformer encoders process the sequence of patches and the CLS token, the output corresponding to the CLS token is used for classification. The output of the CLS token is fed into an MLP, typically consisting of one or two fully connected layers. A soft max layer is applied at the end of the MLP for classification tasks, predicting the image’s label.

4. Results and Discussion

Figure 3 depicts the confusion matrix of the Proposed SRC for coral reef classification, clearly demonstrating its high prediction accuracy across all six coral categories. The strong diagonal dominance indicates that the SRC model correctly classifies almost all test samples, with several classes such as Boulder Coral, Plate Coral, and Soft Coral achieving near-perfect classification. Only minimal misclassifications are observed, primarily between visually similar coral types, which are negligible compared to the overall correct predictions. This confusion matrix highlights the effectiveness and reliability of the proposed SRC model when combined with ViT features, confirming its superior performance and improved class separability compared to existing baseline classifiers.

Figure 4 illustrates the One-vs-Rest ROC curves for the Proposed SRC applied to the multi-class coral reef classification task. All coral categories Bleached, Boulder, Branched, Healthy, Plate, and Soft Coral achieve an AUC value of 1.00, indicating perfect class separability and exceptional discriminative performance. The ROC curves closely follow the top-left boundary of the plot, reflecting a very high true positive rate with near-zero false positive rate across all classes. The micro-average ROC curve further confirms the overall robustness and reliability of the proposed SRC model, clearly demonstrating its superiority over existing baseline classifiers when combined with ViT features.

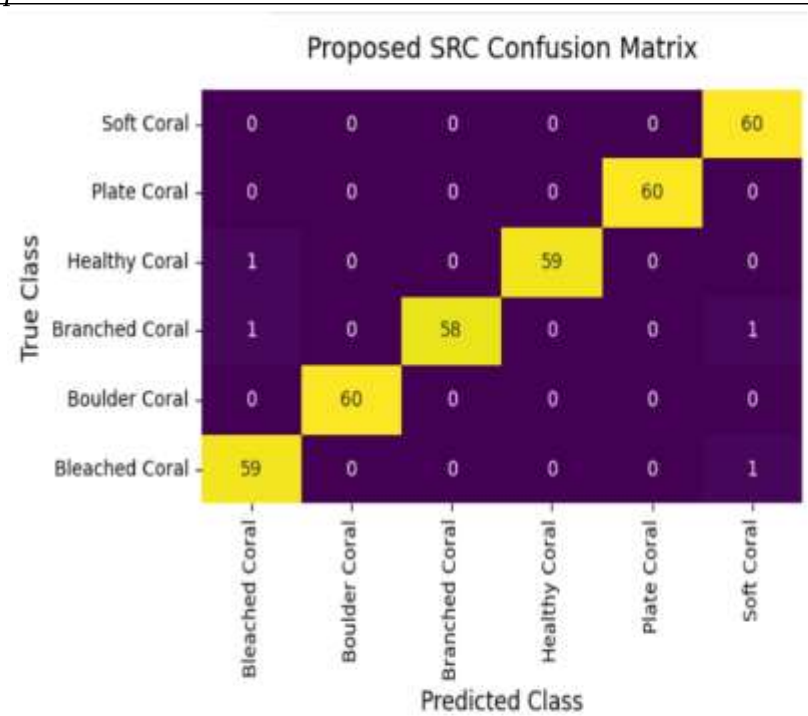

Figure 3: Confusion matrix obtained using SRC.

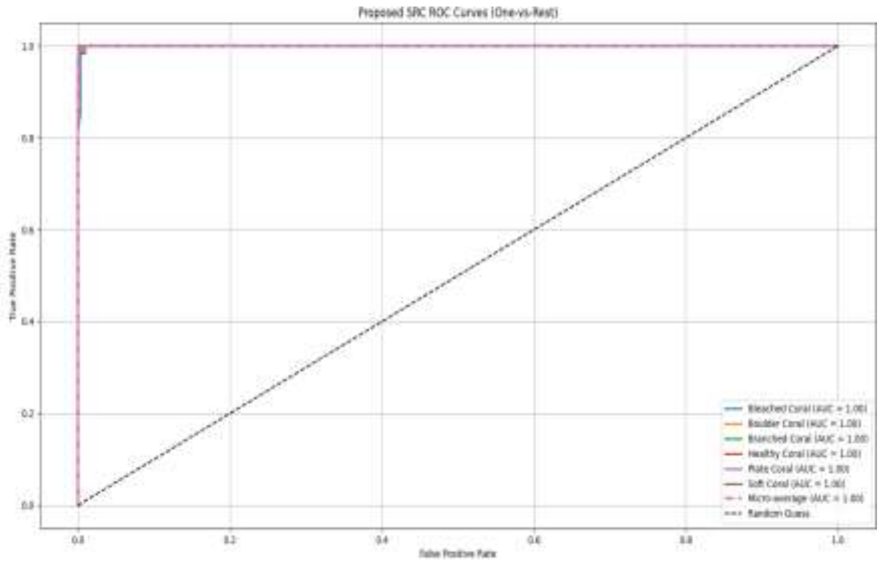

Figure 4: ROC Curve obtained using SRC.

Table 1 presents a comparative performance analysis of the NGB, HGB, XGB, and the Proposed SRC model for multi-class coral reef classification. Among the existing models, XGB achieves the best baseline performance with an accuracy of 82.5%, demonstrating improved precision, recall, and F-score compared to NGB and HGB. However, the proposed SRC model significantly outperforms all baseline classifiers, achieving an accuracy of 98.88% along with consistently high precision, recall, and F-score values close to 99%. This substantial improvement highlights the effectiveness of combining ViT feature representations with the SRC classifier, resulting in superior class discrimination, reduced misclassification, and enhanced overall reliability for coral species identification.

Figure 5 demonstrates the prediction result on a test coral reef image using the proposed SRC model integrated with XAI. The original underwater image is shown on the left, while the central panel presents the XAI-based coral reef analysis, confirming that the image corresponds to a coral reef scene and providing semantic attributes such as coral type (Branched), health status (Healthy), visibility (High), and dominant color (Blue). On the right, the final classification output produced by the SRC model is overlaid directly on the image, identifying the coral species as Branched Coral. This combined visualization effectively illustrates how the proposed system not only achieves accurate coral species classification but also enhances transparency and interpretability by correlating model predictions with explainable semantic insights.

Table 1: Performance comparison for the, NGB, HGB, XGB and Proposed SRC Model

Algorithms Name	**Accuracy**	**Precision**	**Recall**	**F-score**
NGBClassifier	89.16%	89.47%	89.16%	89.11%
HGB Classifier	50.27%	55.80%	50.27%	49.53%
XGB Classifier	82.5%	82.61%	82.49%	82.34%
SRC Model	98.88%	98.91%	98.88%	98.89%

Figure 5: Prediction on test image using SRC model with XAI

5. Conclusion

The research successfully presents an advanced and reliable framework for underwater coral reef species identification by integrating ViT–based deep feature extraction with both existing machine learning classifiers and a proposed SRC. The use of ViTs enables robust representation learning from complex underwater imagery, effectively capturing discriminative coral structures under varying environmental conditions. Comparative experimental analysis demonstrates that while baseline models such as NGB, HGB, and XGB achieve reasonable classification performance, the proposed SRC model significantly outperforms them with superior accuracy, precision, recall, and F-score. The inclusion of XAI using the Gemini Vision API further enhances the system by providing semantic insights such as coral type, health status, visibility, and dominant color, thereby increasing transparency and trust in model predictions. A user-friendly Tkinter-based GUI with role-based authentication ensures ease of operation for both administrators and end users. Efficient model storage, reusable feature extraction, and comprehensive performance visualization contribute to system scalability and reliability and integrated with telegram bot for real time accurate predictions. The proposed approach offers an effective, interpretable, and practical solution for automated coral reef monitoring, supporting marine conservation efforts and enabling data-driven environmental assessment.

References

[1]. Explainable AI Framework for Policy-Compliant Anomaly Detection in Data Pipelines. (2025). Inaternational Journal of Communication Networks and Information Security, 16(4). https://doi.org/10.48047/ijcnis.16.4.2111

[2]. Chowdhury A, Jahan M, Kaisar S, Khoda ME, Rajin SMAK, Naha R. Coral Reef Surveillance with Machine Learning: A Review of Datasets, Techniques, and Challenges. Electronics. 2024; 13(24):5027. https://doi.org/10.3390/electronics13245027

[3]. Gaddam, S. Integrating Analytics into the Development Process: Bridging the Gap between Data Insights and Design Execution.

[4]. González-Rivero M, Beijbom O, Rodriguez-Ramirez A, Bryant DEP, Ganase A, Gonzalez-Marrero Y, Herrera-Reveles A, Kennedy EV, Kim CJS, Lopez-Marcano S, et al. Monitoring of Coral Reefs Using Artificial Intelligence: A Feasible and Cost-Effective Approach. Remote Sensing. 2020; 12(3):489. https://doi.org/10.3390/rs12030489

[5]. Raphael A, Dubinsky Z, Iluz D, Netanyahu NS. Neural Network Recognition of Marine Benthos and Corals. Diversity. 2020; 12(1):29. https://doi.org/10.3390/d12010029

[6]. Prodduturi, S. M. K. To Secure Your Paper as Per UGC Guidelines We Are Providing A ElectronicBar code.

[7]. Tao J, Tian H, Huang S, Ye Y, Xiong Y, Huang S, Qin J, Yin Y, Zhang J, Tang Y, et al. Coral-YOLO: An Intelligent Optical Vision Sensing Framework for High-Fidelity Marine Habitat Monitoring and Forecasting. Sensors. 2025; 25(23):7284. https://doi.org/10.3390/s25237284

[8]. Reddy, S. K. R. (2025). Tailoring Loyalty Rewards Systems across Industries: Cloud vs On-Prem Solutions. International Journal of All Research Education and Scientific Methods (IJARESM).

[9]. Rahman LF, Marufuzzaman M, Alam L, Bari MA, Sumaila UR, Sidek LM. Developing an Ensembled Machine Learning Prediction Model for Marine Fish and Aquaculture Production. Sustainability. 2021; 13(16):9124. https://doi.org/10.3390/su13169124

[10]. Poojari, R. (2025). A Comparative Analysis of Fine-Tuning Versus Retrieval-Augmented Approaches for Enhancing Healthcare-Centric Large Language Models.

[11]. Hieu NTD, Quang NH, Dien TD, Ha VT, Tran NDH, Son TPH, Nguyen-Quang T, Hang TTT, Thang HN. Trends in Coral Reef Habitats over Two Decades: Lessons Learned from Nha Trang Bay Marine Protected Area, Vietnam. Water. 2025; 17(8):1224. https://doi.org/10.3390/w17081224

[12]. Kalae, U. K. (2021). Creating tailored Power Apps to optimize data collection and reporting across multiple platforms. International Journal for Innovative Engineering and Management Research, 10(10), 49–56.

[13]. Tebbett, Sterling & Bellwood, David. (2021). Algal turf productivity on coral reefs: A meta-analysis. Marine Environmental Research. 168. 105311. 10.1016/j.marenvres.2021.105311

[14]. Sreenivas Pratapagiri; Rekha Gangula; Ravi G; B Srinivasulu; B Sowjanya; Lingala Thirupathi, "Early Detection of Plant Leaf Disease Using Convolutional Neural Networks,"

2021 3rd International Conference on Electronics Representation and Algorithm (ICERA), Yogyakarta, Indonesia, 2021, pp. 77-82, doi: 10.1109/ICERA53111.2021.9538659.

[15]. Boonnam N, Udomchaipitak T, Puttinaovarat S, Chaichana T, Boonjing V, Muangprathub J. Coral Reef Bleaching under Climate Change: Prediction Modeling and Machine Learning. Sustainability. 2022; 14(10):6161. https://doi.org/10.3390/su14106161

[16]. Rekha Gangula,A.Manjula, , R Bhukya, R Saturi, N Gayatri, R Rajesh "Innovative Approaches for Early Alzheimer's Disease Detection through Novel Analysis of Brain MRI Images" Vol. 1 No. 1 (2024): Special Issue: International Conference of Advance Research and Innovation,https://doi.org/10.5750/ijme.v1i1.1402.

[17]. Rekha Gangula, Chinnakka Sudha, K Sreeveda, Rajitha Bonagiri, C Bhagyashree, Swapna Saturi," "Prediction and Prognosis of Diabetes Using Logistic Regression," 2022 IEEE North Karnataka Subsection Flagship International Conference (NKCon), Vijaypur, India, 2022, pp. 1-7, doi: 10.1109/NKCon56289.2022.10126692.

[18]. Pavankumar Nagapuri, Swapna Saturi, K Vinay Kumar, G Rekha, Tejaswi Kalva, Amith Reddy Maada," "Deep learning hybrid for X-ray lung disease detection," 2022 Second International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE), Bangalore, India, 2022, pp. 1-7, doi: 10.1109/ICATIECE56365.2022.10047575.

[19]. Rekha Gangula, Lingala Thirupathi, Rajashekar Parupati, K. Sreeveda, Saritha Gattoju,Ensemble machine learning based prediction of dengue disease with performance and accuracy elevation patterns,Materials Today: Proceedings,Volume 80, Part 3,2023,Pages3458-3463,ISSN2214-7853,https://doi.org/10.1016/j.matpr.2021.07.270

[20]. Vasagam, M., Kumar, A., & Garg, A. (2026). Learning Execution Plan Embeddings for Multi-Dimensional Query Resource Prediction. IEEE Access.

[21]. Patyrykin, K. (2025). CANCEL CULTURE PROBLEM. Lex Localis: Journal of Local Self-Government, 23.

[22]. Purmani, S. S. R. (2025). Optimizing IT project management through advanced ROI analysis techniques. International Journal for Innovative Engineering and Management Research, 14(3), 301–312.