Coral Reef Species Detection with a Modified Xception based Model

*Neeraj Kumar Gautam[0009-0002-7419-8219], Mayank Mishra[0000-0003-2047-3457],

Umesh C. Pati[0000-0001-9805-2543]

Department of Electronics and Communication Engineering, National Institute of Technology Rourkela, Rourkela 769008
*gautamneeraj1012@gmail.com, mmishra1208@gmail.com, ucpati@nitrkl.ac.in

Abstract. The Coral reef has been playing a vital role in the development of medicines required in various serious diseases such as HIV infections, heart disease etc. The role of coral reef has been found to be very significant towards providing the shelter to numerous species of marine life such as fishes, turtles, crabs etc. The automatic classification of coral reef species have been considered essential for monitoring the health of marine ecosystems, identifying the patterns in biodiversity, and implementing the conservation strategies to protect these vulnerable and diverse marine ecosystem. The classification of coral reef species can help the expert to identify the threatened as well as vulnerable coral species. This work has proposed an approach to detect coral reef species with deep learning techniques. This work has proposed an Xception based approach with some additional modification to detect the species of coral reef. In this work, the structureRSMAS dataset which comprises the underwater images of fourteen different species have been used. The proposed work performance has been compared with the other CNN models such as VGG16, VGG19, ResNet 101 and also with the state-of-the-art work. The classification performance of the proposed approach has exhibited the superior performance compared to the mentioned CNN models as well as the state-of-the-art works with highest accuracy of 88.46% achieved with the early stopping criterion and 86.54% accuracy has been achieved without the early stopping criterion.

Keywords: Classification, Coral reef species, Deep CNN Network, StructureRSMAS, Xception Network

1 Introduction

The coral reef is a crucial part of the marine ecosystem and also represents a closely coupled social-ecological system. The coral reef has often been misinterpreted as a plant, although it is, in fact, an animal. Coral reefs have a diverse range of species of various sizes, shapes, and colours. Three types of coral reefs are generally found which are fringing, barrier, and atoll. Corals can be categorized into hard coral and soft coral. The reef-building hard corals (also called Scleractinia or hermatypic corals) generally have limestone skeletons that persist after their death. Soft corals (also known as Alyconacea or ahermatypic corals) have a flexible structure that provides habitats for numerous marine species but only a few contribute to reef formation over time. Soft corals have a flexible structure that often leads to them being mistaken as plants. The health of any coral reefs can be assessed by examining the condition of hard corals [1, 2].

Coral reefs have crucial ecological and economic importance. They contribute to marine biodiversity by developing the structural habitats that give a home for numerous species. Moreover, it contributes significantly to local economies through fisheries and tourism, with an estimated annual value ranging from 30 to 375 billion US dollars [3]. In terms of ecological significance, coral reefs have been playing a vital role in coastal protection, and they also contribute to the biogeological cycles of carbon and sulfur. Sulfur-based molecules such as dimethylsulphoniopropionate (DMSP) and dimethylsulfide (DMS) have been generated by symbiotic algae associated with the local cloud formation. These molecules influence climate regulation over oceans and can affect the rainy season in reef areas [4, 5]. The structure of coral reef has been formed by the process of calcification, which is significantly affected by climate change. [6, 7]. In recent decades, coral reefs have been used in biomedical research for medicine development. Azidothymidine (AZT) drug had been developed for the treatment of Human Immunodeficiency Virus (HIV) infection and has been found in a coral reef sponge in the Caribbean reef [3]. Austrasulfone has been found in a type of soft coral species called Cladiella australis, which has the potential to protect our nerves and alleviate neuropathic pain associated with certain nerve-related conditions [8]. It has been observed in the research works that the AI based system to detect the species of coral reef can help the experts in tracking and detecting threatened and vulnerable coral species [1]. This work has proposed a deep learning based approach with the utilization of modified Xception network for the detection of coral reef species using structureRSMAS dataset.

The remaining part of the paper has an organised section such as section 2 present a detailed overview of relevant work, and section 3 explain the methodology used for coral reef species classification. Section 4 shows the classification result and discussion and section 5 provides a conclusion as well as suggestions for future work.

2 Related Work

Mahmood et al. [1] have presented the survey on the difficulties encountered with the marine data and utilizations of associated deep learning approach. This survey also discusses the upcoming research direction within the domain of deep learning and marine image analysis. Elawady [9] has proposed an “Atlantic deep sea” coral reef labelled dataset. This work has presented a supervised sparse-based classification method using Convolutional Neural Networks (CNN) for feature extraction and classification of coral reef species. Gomez-Rios et al. [10] have proposed two two-level classifiers using structureRSMAS dataset and RSMAS dataset. The first level classifier has been utilized to classify the dataset whether the input image belongs to the texture dataset or structure dataset. The second classifier has been used for species classification.

Shihavuddin et al. [11] have focused their study toward feature extraction and classification of coral reef species. It has presented a comparative analysis of various methods of feature extraction and classification with benthic and texture datasets. Rivero et al. [12] have emphasized the cost-effective approach for coral reef monitoring. This work has evaluated the performance of deep CNN for automated image analysis on a global coral reef monitoring dataset. Sagar et al. [13] have focused their study on the classification of stony (scleractinian) corals with RGB and gray scale approaches. It has presented a coral reef image dataset that has been manually annotated and categorized by marine experts for stony coral classification.

3 Methodology

The major steps involved in proposed approach are dataset collection, pre-processing, data augmentation, model training, classification, and classification performance evaluation. The steps are shown in Fig. 1.

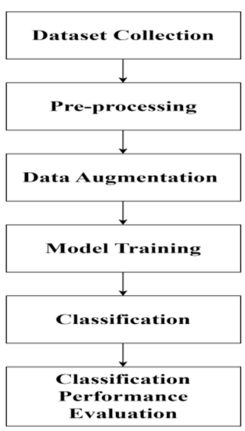

Fig. 1. Major steps involved in the proposed approach

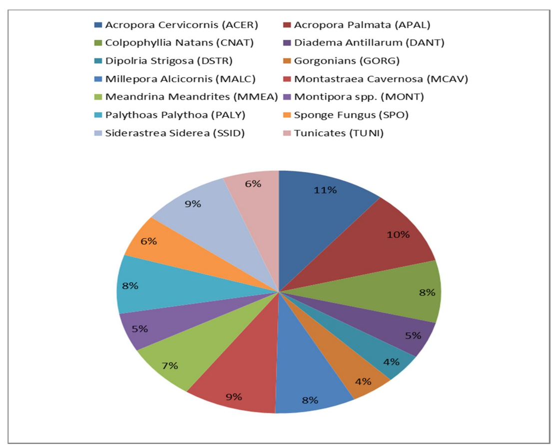

Fig. 2. Details of Percentage description of each species in StructureRSMAS dataset

3.1 Dataset Collection

The StructureRSMAS dataset [10] has been collected for the proposed work. It contains 409 structure images and comprises of 14 different species that captures diverse coral reef characteristics. The percentage distribution of total dataset across coral species of the structureRSMAS dataset has been shown in Fig. 2, offering a comprehensive overview of the dataset composition.

3.2 Pre-processing and data augmentation

The Pre-processing method includes a normalization technique to standardize the pixel values range as [0, 1] by dividing the image pixel value with 255. Simultaneously, data augmentation has been employed to prevent the over fitting problem. It has utilized the on-the-fly data augmentation approach [15] to introduce variations in the training dataset by employing techniques includes rotation range (0 to 180 degrees), Shear range (60%), height and width shift range (60%), zoom in and zoom out range (60%), horizontal flip, and fill mode (constant).

3.3 Model Training

In this work, the Xception network [14] has been utilized with an additionally modified layer as shown in Fig. 3. The input image of dimension 224×224×3 has been used in this work. In the proposed approach the top layer has been removed and added with the flatten layer, dense layer, dropout layer, and softmax layer. The Xception network which has been trained on ImageNet database has been considered. The transfer learning approach in a pre-trained Xception network has been utilized for feature extraction. The output of Xception network has been flattened using a flattened layer. A flattened layer has been added to transform the 3D output tensor from the Xception model into a 1D tensor output. After that dense layers with 128 units and ReLU activation have been added. The ReLU activation function introduces a non-linearity to the model and learns complex patterns in the flattened feature representation. This dense layer has been accompanied by a dropout layer with a dropout rate of 0.2. During training, this dropout layer randomly drops 20% of the units, helping to prevent over fitting by adding in a form of regularization. The final layer is a dense layer with 14 units of 14 classes with a softmax layer. This softmax layer ensures that the predicted output values are normalized to represent probabilities, and each unit corresponds to the likelihood of the input belonging to a particular class.

3.4 Classification and performance evaluation

After completion of the training procedure for the proposed model, the next step is to test the proposed approach on the test dataset. The proposed method of multi-class coral reef species classification system has been evaluated by considering evaluation parameters includes accuracy, precision, recall, and ROC-AUC score as mentioned in Eq. 1 to Eq. 5.

$$\text{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP + TN + FP + FN}} \tag{1}$$

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP + TN + FP + FN}} \tag{2}$$

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \tag{3}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{Precision + Recall} \tag{4}$$

$$\text{False Positive Rate} = \frac{\mathrm{FP}}{\mathrm{FP + TN}} \tag{5}$$

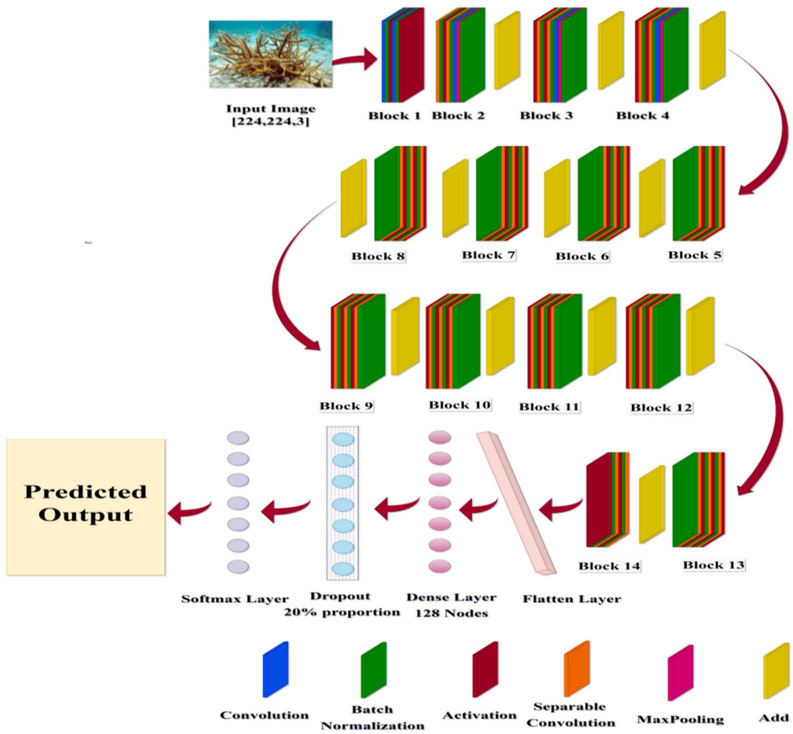

Fig. 3. Proposed Modified Xception network

4 Results and Discussion

The Experimental setup of the proposed approach incorporates Google Colab, Python 3.9, Keras with version 2.14.0 for the implementation. The structureRSMAS dataset has been divided into a training set of 70%, a validation set of 20%, and a testing set of 10% of the total dataset for the experimentation. The Hyper-parameters such as learning rate of 0.00001, batch size of 32 and 64 along with the categorical crossentropy loss function have been tuned using the adam optimizer. The proposed approach has been executed using the above experimental setup, both with the utilization of early stopping and without early stopping criterion. The training process involved in this experiment has been monitored between the ranges of 100-500 epochs for considering the best performance for the respective models in the condition of without early stopping. Early stopping approach automatically stops the training process as per the mentioned 'patience' level with the monitoring of 'validation-loss'. Early stopping with patience level of 10 and regularization techniques such as dropout rate of 20% have been utilized to prevent the proposed model from over fitting.

4.1 Classification assessment of proposed approach

The classification assessment of the proposed approach has been done utilizing the batch size of 32 and 64 with and without the condition of early stopping criterion. At the batch size of 32, the classification accuracy of the proposed approach has been achieved as 86.54% with early stopping and 82.69% without early stopping. Similarly, with a batch size of 64, the classification accuracy has been achieved as 88.46% with early stopping and 86.54% without early stopping as indicated in Table 1.

Table 1. Classification accuracy of the proposed approach at the different conditions

Batch Size	Utilization of Early Stopping	Accuracy
32	YES	86.54%
	NO	82.69%
64	YES	88.46%
	NO	86.54%

The proposed approach has shown better classification accuracy at a batch size of 64 for both early stopping and without early stopping condition as compared to a batch size of 32. Hence, the batch size of 64 has been finalized for the proposed approach to detect the coral reef species. The multiclass confusion matrix and ROC-AUC curve have been evaluated for both with and without early stopping condition to show the detailed performance assessment of the proposed model as shown in Fig. 4 to Fig. 7. Based on the multiclass confusion matrix, classification report with precision, recall, and F1-score parameters for batch sizes 64 in both the condition of with and without early stopping have been evaluated for all 14 classes of coral reefs as indicated in Table 2, and table 3.

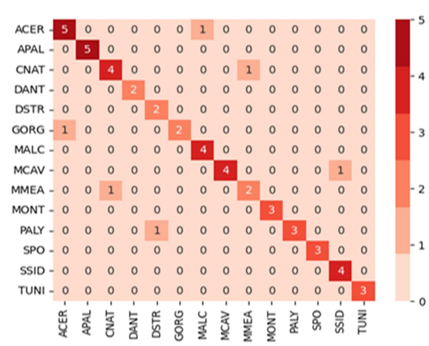

Fig. 4. Multiclass confusion matrix of the finalized proposed model with the involvement of early stopping

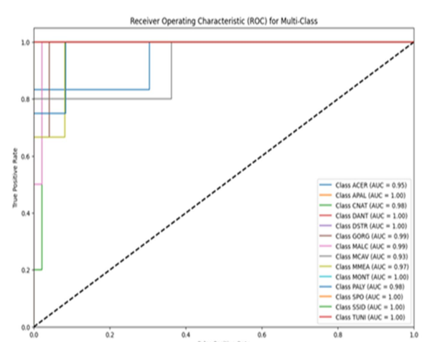

Fig. 5. ROC-AUC curve of the finalized proposed model with the involvement of early stopping

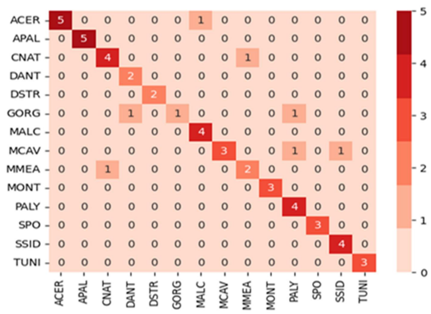

Fig. 6. Multiclass confusion matrix of the finalized proposed model without the involvement of early stopping

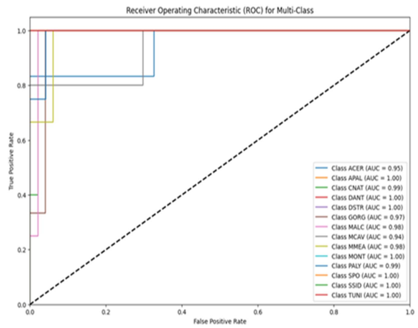

Fig. 7. ROC-AUC curve of the finalized proposed model without the involvement of early stopping

4.2 Comparison with other Deep CNN Networks

The proposed approach performance has been compared with the performance of other deep CNN Networks such as VGG16, VGG19, and ResNet101, for the coral reef species detection. Also the proposed Xception based model performance has been compared with the Xception model without the added modification. The classification accuracy of the Xception model by utilizing the early stopping criteria has achieved 82.69% while the proposed Xception based network has achieved 88.46% as indicated in Table 4. Similarly, the classification accuracy of the Xception model without the early stopping criteria has achieved 75.00% and the proposed Xception based network has achieved 86.54% as indicated in Table 4. These comparative analysis at batch size of 64 demonstrates that the proposed Xception based network has shown the superior performance in coral reef species detection as compared to the original Xception network.

Table 2. Classification report of the finalized proposed model with the involvement of early stopping

Classes	Precision	Recall	F1 score
ACER	83%	83%	83%
APAL	100%	100%	100%
CNAT	80%	80%	80%
DANT	100%	100%	100%
DSTR	67%	100%	80%
GORG	100%	67%	80%
MALC	80%	100%	89%
MCAV	100%	80%	89%
MMEA	67%	67%	67%
MONT	100%	100%	100%
PALY	100%	75%	86%
SPO	100%	100%	100%
SSID	80%	100%	89%
TUNI	100%	100%	100%

Table 3. Classification report of the finalized proposed model without the involvement of early stopping

Classes	Precision	Recall	F1 score
ACER	100%	83%	91%
APAL	100%	100%	100%
CNAT	80%	80%	80%
DANT	67%	100%	80%
DSTR	100%	100%	100%
GORG	100%	33%	50%
MALC	80%	100%	89%
MCAV	100%	60%	75%
MMEA	67%	67%	67%
MONT	100%	100%	100%
PALY	67%	100%	80%
SPO	100%	100%	100%
SSID	80%	100%	89%
TUNI	100%	100%	100%

Additionally, the proposed Xception based network has been also compared with other CNN models at the batch size of 64 as indicated in Table 5. It shows that proposed Xception based network has outperformed the other CNN models as shown in Fig. 8.

Table 4. Comparison of proposed modified Xception network with the original Xception network

Models	Utilization of Early Stopping	Accuracy
Modified Xception network	YES	88.46%
	NO	86.54%
Original Xception network	YES	82.69%
	NO	75.00%

Table 5. CNN models classification Performance accuracy

Models	Utilization of Early stopping	Accuracy
VGG16	YES	57.69%
	NO	69.23%
VGG19	YES	53.85%
	NO	61.54%
ResNet 101	YES	73.08%
	NO	63.46%

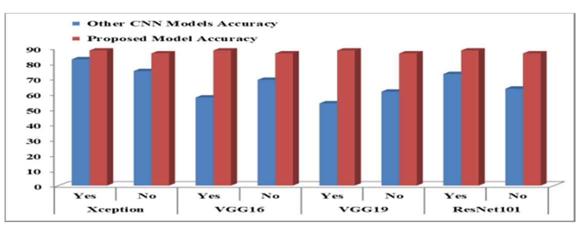

Fig. 8. Comparative performance evaluation of different CNN models with the Proposed Xception based network

4.3 Comparison with the state-of-the-art work

The finalized proposed approach i.e. with early stopping criterion and without early stopping criterion at a batch size of 64 has been used for comparison with the state-of-the-art work. The coral reef species classification result of the proposed approach has outperformed the state-of-the-art work as indicated in Table 6.

Table 6. Comparison with state-of-the-art work

Authors	Methods	Accuracy
A. Gómez-Ríos et al.[10]	ResNet 50	85.263%
Proposed Method (Without Early Stopping)	Proposed Modified Xception model	86.54%
Proposed Method (With Early Stopping)	**Proposed Modified Xception model**	**88.46%**

5 Conclusions

This work has proposed the Xception network based deep learning approach for the detection of coral reef species. This work has focused towards the detection of 14 different species of coral reef based on the structureRSMAS dataset. The proposed Xception based network has achieved the highest accuracy of 88.46% with the early stopping and 86.54% accuracy without the early stopping. The result obtained in the proposed experiment with the hyper-parameter optimization shows that the proposed Xception based network exhibits superior performance in coral reef species detection compared to the state-of-art work. Future work will be dedicated towards proposing the generalized approach by utilizing large size dataset of coral reef species to overcome the limitation of small dataset utilization of this work.

References

1. Mahmood A, Bennamoun M, An S, Sohel F, Boussaid F, Hovey R, Kendrick G, Fisher RB (2017) Deep Learning for Coral Classification. Handbook of Neural Computation 383–401. https://doi.org/10.1016/b978-0-12-811318-9.00021-1
2. Indo ocean project (2020), "Coral Identification Manual," https://indooceanproject.org/wp-content/uploads/2020/08/Coral-Identification-Manual.pdf
3. A. El-Naggar H (2021) Human Impacts on Coral Reef Ecosystem. Natural Resources Management and Biological Sciences. https://doi.org/10.5772/intechopen.88841
4. Raina J-B, Tapiolas DM, Forêt S, Lutz A, Abrego D, Ceh J, Seneca FO, Clode PL, Bourne DG, Willis BL, Motti CA (2013) DMSP biosynthesis by an animal and its role in coral thermal stress response. Nature 502:677–680. https://doi.org/10.1038/nature12677
5. Haydon TD, Seymour JR, Suggett DJ (2018) Soft corals are significant DMSP producers in tropical and temperate reefs. Marine Biology 165:. https://doi.org/10.1007/s00227-018-3367-2

6. Comeau S, Cornwall CE, DeCarlo TM, Krieger E, McCulloch MT (2018) Similar controls on calcification under ocean acidification across unrelated coral reef taxa. Global Change Biology 24:4857–4868. https://doi.org/10.1111/gcb.14379
7. Jokiel PL (2013) Coral reef calcification: carbonate, bicarbonate and proton flux under conditions of increasing ocean acidification. Proceedings of the Royal Society B: Biological Sciences 280:20130031. https://doi.org/10.1098/rspb.2013.0031
8. Cooper EL, Hirabayashi K, Strychar KB, Sammarco PW (2014) Corals and Their Potential Applications to Integrative Medicine. Evidence-Based Complementary and Alternative Medicine 2014:1–9. https://doi.org/10.1155/2014/184959
9. Elawady, Mohamed. (2014). Sparse Coral Classification Using Deep Convolutional Neural Networks. 10.13140/RG.2.1.1623.7206.
10. Gómez-Ríos A, Tabik S, Luengo J, Shihavuddin ASM, Herrera F (2019) Coral species identification with texture or structure images using a two-level classifier based on Convolutional Neural Networks. Knowledge-Based Systems 184:104891. https://doi.org/10.1016/j.knosys.2019.104891
11. Shihavuddin ASM, Gracias N, Garcia R, Gleason A, Gintert B (2013) Image-Based Coral Reef Classification and Thematic Mapping. Remote Sensing 5:1809–1841. https://doi.org/10.3390/rs5041809
12. 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, Markey K, Neal BP, Osborne K, Reyes-Nivia C, Sampayo EM, Stolberg K, Taylor A, Vercelloni J, Wyatt M, Hoegh-Guldberg O (2020) Monitoring of Coral Reefs Using Artificial Intelligence: A Feasible and Cost-Effective Approach. Remote Sensing 12:489. https://doi.org/10.3390/rs12030489
13. Sharan, Sumit , Harsh and Kininmonth, Stuart and Mehta, Utkal V. (2021) Automated CNN based coral reef classification using image augmentation and deep learning. International Journal of Engineering Intelligent Systems, 29 (4). pp. 253-261. ISSN 1472-8915
14. Chollet F (2017) Xception: Deep Learning with Depthwise Separable Convolutions. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). https://doi.org/10.1109/cvpr.2017.195
15. Mishra M, Pati UC (2023) A classification framework for Autism Spectrum Disorder detection using sMRI: Optimizer based ensemble of deep convolution neural network with on-the-fly data augmentation. Biomedical Signal Processing and Control 84:104686. https://doi.org/10.1016/j.bspc.2023.104686