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A Novel Approach For Coral Reef Disease Detection And Classification Using Deep Learning Techniques

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Abstract
Coral reefs are a significant and inevitable feature of the maritime environment. It has a significant impact on maintaining the ecosystem's equilibrium. For fish like tuna, dolphins, and other aquatic animals, coral reefs provide nutrition and protein. But the overall number of coral reefs has severely decreased as a result of bleaching, climate change, human activity, and industrial pollution. A hybrid ZeNet and VGG19 deep convolution neural network machine learning approach is proposed in this study effort to solve this concerning problem by identifying diseased or infected corals from movies. In the majority of classification tasks nowadays, deep neural network (DNN) models have supplanted the formerly manual feature extractors. Because of their domain independence and extensive dataset training, DNNs like ResNet, DenseNet, VGGNet, and Inceptions models provide unparalleled performance across a wide range of applications. The proposed framework extracts feature with a hybrid DCNN approach AlexNet and ZeNet and VGG19 used to further invariance that improves classification accuracy. Extensive evaluation has enabled the identification of the optimal patch, cluster size, kernel combination, and best-performing classifier.

Keywords: Deep learning; Coral reefs; Corel disease; marine ecosystem; CNN, ZeNet, VGG19, Hybrid DCNN.

1. INTRODUCTION

Coral reefs are living, colourful, multi-faceted structures, which are the part of marine ecosystem. Coral reefs are formed by calcium carbonates and are mostly present near the equator of the world. It lives in warm water and maintains a temperaturebetween 20 to 28 degrees Celsius It creates a colony-like structure to shelter species like fishes, crabs, sea stars, shrimps and algae [1]. It is estimated that around one lakh different species are living under the coral reefs. It also produces nutrition and proteins for the species that live in the ocean. Moreover, it also helps human beings by providing coral foods, shoreline protection and medicines. Based ona recent report from the National Oceanic and Atmospheric

Administration, the annual economic earning of coral reef mining is about 30 billion US dollars.

Coral reefs havethe most variety of all marine ecosystems. There are more than 2500 species of coral reefs in the world. Around 40%of coral are hard. It will not have any motion or movements in the ocean. They will look like a hard rock. On the other hand, the remaining 60% of corals are soft [2]. It will have skeletons that are flexible to make motions on the water. Though it gives several advantages to the ecosystem and human beings, coral reefs are now in great danger due to industry pollution, overfishing, destructive fishing and climate change. In some places on Earth, the coral reefs are destroyed and in many places, coral reefs are in an endangered situation.

Diseases spreading on the coral reefs are also an important reason for the degradation. Diseases like vibrio, white syndrome, white band, and rapid wasting disease. Here, the white syndrome and white band are the widespread disease in the entire world. These diseases forma white-colored foam on the surfaces of the coral reefs. Additionally, a clear separation between the exposed coral skeleton and the remaining coral tissue is seen. White layer diseases such as white band and syndrome in the coral reefs can be categorized into Type I and Type II diseases. Here, Type I, diseases don't show any bleaching on the upper layer of the coral reefs. But it changes the color slightly. Type II coral reef diseases bleach the surface completely [3]. In this research work, we intended to create a framework to identify the coral types and their disease automatically by performing deep learning techniques on the coral reef video dataset. Here, we have used a Deep Convolution Neural Network (DCNN) to identify the data coral type and its diseases.

Deep Convolution Neural Network (DCNN) is a type of neural network, which performs both forward and backward propagation to gather information, identify the relationship and detect patterns between the data. CNN has a fully connected multi-layer neuron structure, which has connections between every neuron in a layer and all the others in the layers that surround it. It uses linear convolution operation at least in any one of the layers. Convolution Neural Network (CNN) accepts input as images, classifies it, and gives different features of the image a different level of priority [4]. In this research work, a coral reef image dataset (downloaded from Mendeley open archive) is given as input to train and a video dataset from BBC Earth is used to test the proposed The proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network framework.

Figure 1 Image captured through underwater video rovers

Figure 2 Image of Jellyfishrover

2. RELATED WORKS

In the early days, information related to coral reefs was collected from underwater visual censuses (UVC) by scuba divers. The accuracy of the collected information highly depends on the depth, duration and experience of the scuba divers. Identifying the type, growth, and disease in the coral reefs was difficult. However, after the rapid advancement in robotic technology and underwater cameras, information related to the coral reefs and marine ecosystem is captured using video supported by water rovers and automatic motion-capturing devices [5].However, collecting and observing information about the coral reefs needsan oceanic research specialist. Moreover, observing information from a long video is a time-consuming and expensive operation. So there is an immediate need to create a framework to perform automatic coral reef classification and disease prediction to improve the coral ecosystem. Images captured through underwater rovers are shown in Figure 1 and the example image of a jellyfish rover is shown in Figure 2.To achieve such an automated image classification method, deep learning techniques are used.One of the important subsets of deep learning techniques is Neural Networks (NN). It has been used in several applications text classification, paraphrase detection, facial recognition, speech recognition and much more. In recent times, it hasbeen used in oceans to keep track of ocean wave power, endangered fishes and temperature monitoring.

Likewise, deep learning techniques are also used in monitoring coral reefs. Countries like Australia,and the Philippines are using deep-sea ocean rovers to capture the images of the coral reefs at frequent intervals. In 2010, the government of Australia initiated automated tools for capturing and analyzing marine images and videos called CATAMI [6]. It used classification methods to classify the species in the marine ecosystem. However, due to the bad quality of images and improper preprocessing technique, the system doesn’t automate the classifying procedure.

Over the last decade, the performance of automatic identification of objects on images and videos has rapidly increased. Identifying the coral reefs inunderwaterimages is a challenging issue as it has a very low brightness and irrelevant information (i.e.) fishes covering the corals.

Shortis [7], proposed a fully automated technique to identify and measure the count of the fish in a particular place of the ocean. It proposed an algorithm for the detection of objects (fishes), identifying the trueness of objects, measuring the size of the fish, classifying the category of the fish and finding out the biomass value in underwater sequences. To classify the fish into different classes, Artificial Neural Network (ANN), Nearest Neighbor algorithm and Support Vector Machine (SVM) algorithms are used. Joly [8], suggested employing artificial neural networks (ANN) to collect precise information on the identity, location, and current state of species in the ocean via multimodal identification.

Furthermore, it assesses the difficulties associated with retrieving multimedia information and fine-grained categorization issues. Two supervised machine learning techniques were introduced by Villon [9] to automatically identify and detect fish and coral reefs underwater. It uses HOG machine learning and an SVM classifying algorithm to classify the object. Later, the results of both HOG and SVM are compared to predict the accurate result. It achieves 88% of F-Score within the same network architecture. Choi et al. [10], proposed a technique to perform video-based fish identification from the deep ocean. It extracts information about the fish item using a selective search and foreground detection approach. It also uses deep convolution neural networks to classify the fishes based on their size.

Kratzert et al. [11], presented an automatic fish species classification method to classify the underwater species for a FishCam video dataset. It uses Convolutional Neural Networks to classify the species. Raw data which are collected from video cameras are directly fed to the machine learning system. It also observed that by adding the additional metadata information the accuracy of the system is increased. It achieves the maximum accuracy of 93% (with additional metadata information like fish length, location, count, and migration details)

Ravanbakhsh [12], proposed a shape-based level sets framework for automatic fish detection. Principal Component Analysis is used to gather knowledge about the fishes. Fish head and snout positions are precisely determined using the HAAR classifier. It classified the semantic segmentation of the underwater photos of the coral reef environment using two popular deep learning techniques: patch-based convolutional neural networks (CNNs) and fully convolutional neural networks (FCNNs). Semantically segmented output from the input images is produced using FCNN, while single-entity classification is enabled using patch-based CNN. In order to enhance the classification and semantic segmentation accuracy of the input images, it additionally contrasts patch-based CNN with FCNN.

Villion [13], proposed a method to identify and count the number of fishes from videos using Convolution Neural Networks. It also compares the human ability interns of speed and accuracy with CNN trained with different photographic databases. The rate of accuracy of CNN-based prediction is about 94.6% and human (manual) identification is 89.3%. Thus, deep learning techniques may efficiently identify fish from underwater images and hold potential for rapidly and affordably developing new video-based procedures.

3. PROPOSED FRAMEWORK

The proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network approach intends to create a design for detecting the types of coral reefs and the effect of white band diseases in the coral ecosystem from a video dataset. The workflow of the proposed deep learning technique is shown in Figure 3.

Data Sets

Two datasets are utilized here. The first dataset is used to train the neural network to identify the type of coral reef that was downloaded from the Medley open-source collection, and the second dataset makes predictions about whether or not the specific coral is afflicted by the white plague disease. The second video dataset, in HD 720 pixels, was obtained from the official BBC Earth YouTube channels. These data are given as input to the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network proposed to perform image classification. To enhance the coral ecosystem, the suggested system automatically detects and categorizes diseases that affect coral reefs.

The proposed deep learning technique uses two different data sets. To train the proposed DCNN model we have used, an open-source image dataset which is collected from Mendeley Open Archives from Universitat de Girona - Campus de Montilivi. The dataset consists of a huge amount of images and information about the different coral reef species. We have also used a second dataset to test the performance of the proposed method. The second dataset is a 10-hour video download from the official BBC Earth YouTube web channel in HD 1080p.

To train the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network, the chosen image dataset has to undergo a preprocessing method to purify the error data from the dataset. Raw image datasets might have low quality as the images are captured underwater. The preprocessing technique will improve the quality and accuracy of the image dataset, which will impact on the overall accuracy of the hybrid proposed deep learning technique.

3.1 Data Pre-processing of the test Dataset

Pre-processing is an important feature of deep learning techniques which processes the raw data and convertsit into a knowledgeable format which is later given as the input to the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network. Under water images will have noises like Gaussian noise, Salt and pepper noise, shot noise, quantization noise, film grain noise, low light noise, anisotropic and periodic noise.

To remove this noise and improve the quality of the image two important methods are used to preprocess the underwater images. They are image restoration and image enhancement. In image restoration, an arithmetic mean filter is used to de-noise the underwater images and then an iterative deconvolution method is used to filter out the images. Information like attenuation, coefficients, scattering and depth estimation of the object (fish) is fed as the input along with the image.

$$\mathrm{I_{pre}} = \mathrm{P}(\mathrm{I_{raw}})$$

Where $\mathrm{I_{raw}}$represents the raw input images from the dataset, and P is the preprocessing function that enhances image quality through techniques like denoising and contrast adjustment.

Later in the image enhancement preprocessing method, disturbances or noises in the images are corrected sequentially. Initially, it removes the over-applied effects using the homomorphic filters on the image to improve the quality of the image. It is also used to remove the defects of non-uniformity of illumination and improve the contrasts. Figure 4 represents the preprocessed image and raw image.

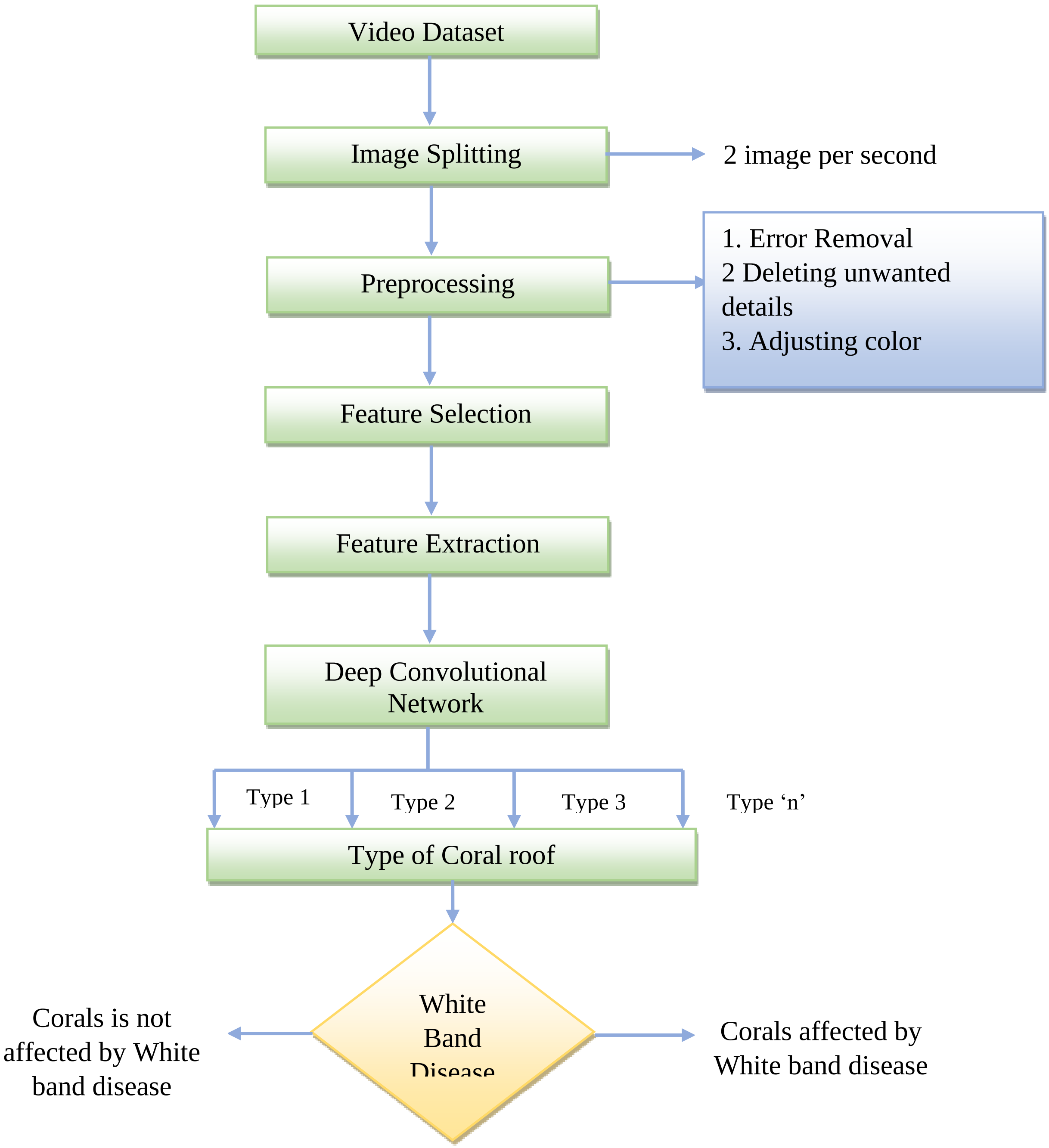

Figure 3 Workflow to identify the type and condition of white band diseases affected in coral reefs using DCNN

Later the preprocessed data are fed to a specified Uniform Ratio Aspect (URF) module to crop the images into a square shaper. Because most of the neural networks perform on the square-shaped image. For cropping the images, the middle part of the image is chosen. The preprocessing algorithm takes the middle part of the image draws multiple square-shaped crops and finds the best fit.

Figure 4 (a) Raw extracted image

Figure 4 (b) Preprocessed image

4. Proposed DCNN Methodology

4.1 AlexNet CNN Architecture

The architecture of the AlexNet network was quite similar to that of LeNet, but it was larger, deeper, and contained convolutional layers layered on top of one another. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) was won in 2012 using AlexNet, the first large-scale CNN. Large-scale image collections were the target of the AlexNet architecture's design, and it produced cutting-edge results. Five convolutional layers, including three fully connected layers, two dropout layers, and a combination of max-pooling layers, make up AlexNet. Relu is the activation function used in every layer. Softmax is the activation function that is used in the output layer. This design has around 60 million parameters in total.

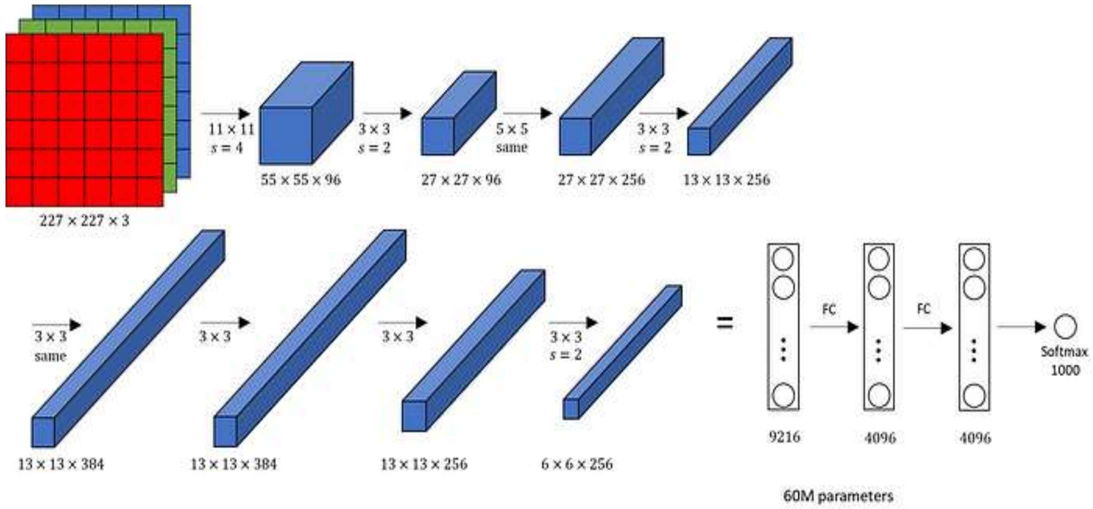

Figure 5: AlexNet Architecture

4.2 ZF Net

ZFnet is a CNN architecture that combines CNNs with fully-connected layers. Through adjustments to the architectural hyperparameters, namely enlarging the intermediate convolutional layers and reducing the stride and filter size on the first layer, the network surpassed AlexNet with comparatively less parameters. Using the ImageNet dataset, the Zeiler and Fergus model served as its foundation. There are seven levels in the ZF Net CNN architecture: The fully connected output is applied after the convolutional layer, stride one, concatenation layer, max-pooling layer (downscaling), convolutional layer with linear activation function, and dropout for regularization. In terms of computation, this CNN model outperforms AlexNet.

4.3. VGGNet – CNN Architecture with Large Filters

The CNN architecture is called VGGNet. The acronym for "VGG16" is "Visual Geometry Group 16." This neural network design was created at the University of Oxford's Visual Geometry Group, thus the name. The number 16 in the model's name denotes that it has 16 weighted layers, including fully connected and convolutional layers. Training on more than one billion images (1000 classes), VGGNet is a 16-layer CNN with up to 95 million parameters. It contains 4096 convolutional features and can process large input images with a pixel size of 224 × 224. CNN architectures like GoogLeNet (AlexNet architecture) outperform VGGNet for the most of image classification tasks with input images with sizes ranging from 100 x 100 pixels to 350 x 350 pixels. This is mostly because CNNs with such large filters are costly to train and need a lot of data. As it can be used for a wide range of tasks, including object identification, the VGG CNN model is computationally efficient and serves as the basis for many computer vision applications. YOLO, SSD, and other neural network designs leverage its deep feature representations. The following diagram shows the typical VGG16 network architecture:

4.4. VGG-19 Architecture

Three fully connected layers and 16 convolutional layers make up the 19 weight layers of the deep convolutional neural network VGG-19. The architecture is simpler to comprehend and apply since it conforms to a simple, repeating pattern.

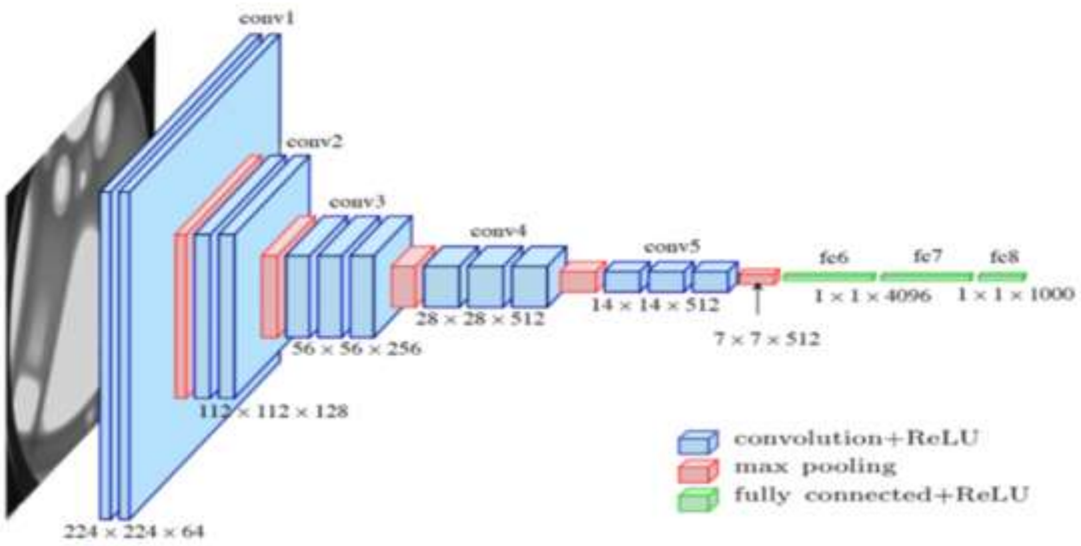

Figure 6: VGG 19 Architecture

The key components of the VGG-19 architecture are:

6.1 Use in Transfer Learning

The excellent feature extraction capabilities of VGG-19 have led to its extensive application in transfer learning. Object identification, image segmentation, and style transfer are only a some of the computer vision tasks for which pre-trained VGG-19 models on massive datasets like ImageNet are often optimized.

6.2 Characteristics of VGGNet-19

Model Simplicity and Effectiveness: The VGG-19 architecture is a very successful and simple model for a variety of computer vision applications due to its repeated block structure and consistent usage of 3×3 convolution filters. Computing Requirements The VGG-19 model has a high computing requirement, which is one of the most significant trade-offs that it presents. The fact that it demands a substantial amount of memory and processing capacity is due to the fact that it is deep and makes use of small filters. As a result, it is better suited for settings that have robust hardware capabilities.

6.3 Robust Feature Extraction

The VGG-19 model is a great feature extractor because of its depth, which enables it to capture complex characteristics in images. The capability to fine-tune pre-trained VGG-19 models for particular tasks by using the rich feature representations acquired from extensive datasets is very useful in transfer learning.

6.4Data Augmentation

To enhance the performance and generalization capability of VGG-19, data augmentation techniques such as random cropping, horizontal flipping, and color jittering are often employed during training. These techniques help the model to better handle variations and improve its robustness.

7. EXPERIMENTS

The proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network experiment to identify the type of the coral reef and to derive the information about the white band disease on the surface of the coral reefs are carried out on an open source software called, Tensor Flow software. The dataset used for the implementation is taken from the Mendeley Imaging Archive site. The downloaded data had several pieces of information related to the type of coral reef. The total number of coral reef images present in the first dataset is around 1,512, in which 80% of images (i.e.) 1,259 images are chosen as training images and the remaining 20% of images are used as the testing dataset. The first dataset is used to train the neural network to classify the type of coral reefs. The second dataset used to train the neural networks is a video dataset, which is downloaded from the BBC Earth YouTube Channel and consists of a total run time of 3.12 hours of oceanography and underwater videos shot beneath the sea. A total of 22,462 images are derived from the video (i.e.) two images per second. Due to the limitation of processing capacity in the computer system, a total of 3000 images were chosen from 22,462 images derived from the video. Later of these 3,000 videos, 80% are used as a training data set and 20% are used as test data. The second dataset is used to identify whether the coral reefs are infected by the white band diseases are not.

To measure the accuracy of theproposed hybrid ZeNet and VGG19 Deep Convolution Neural Network, four major factors are considered, such as true positive (TP), true negative (TN), false negative (FN) and false positive (FP). The true positive is the case, in which the type of the coral reef is identified correctly. The true negative is the case, where the coral relief belongs to a particular type and proposed hybrid DCNN fails to find it. The false positive is the case where the coral reef does not belong to a particular type and hybrid DCNN results the same. A false negative is the case, where the coral reed doesn’t belong to a type, but hybrid DCNN wrongly predicts that the coral reef belongs to a particular type. The formula to measure the accuracy of the proposed system is,

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

The measured accuracy of the proposed model hybrid DCNN model is 98.02%. In a total of 253 test set images, the hybrid DCNN system correctly predicted the type of 233 images. Likewise, the sensitivity is also measured. Sensitivity is a measure of the proportion of actual positive cases that were predicated as positive. It is measured by the following formula,

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Moreover, the specificity (i.e.) proportion of actual negatives, which was predicted as negative. Specificity of the proposed hybrid DCNN-based coral reef classification is calculated from the following formula,

$$\text{Specificity} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The performance metrics (accuracy, sensitivity and specificity) of the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network method to predict the type of coral reefs are diagrammatically compared with existing methods and shown in Figure 7 Likewise, the accuracy, sensitivity and specificity of the proposed hybrid DCNN to predict whether the coral reef is infected by the white band diseases or not is diagrammatically shown in Figure 8.

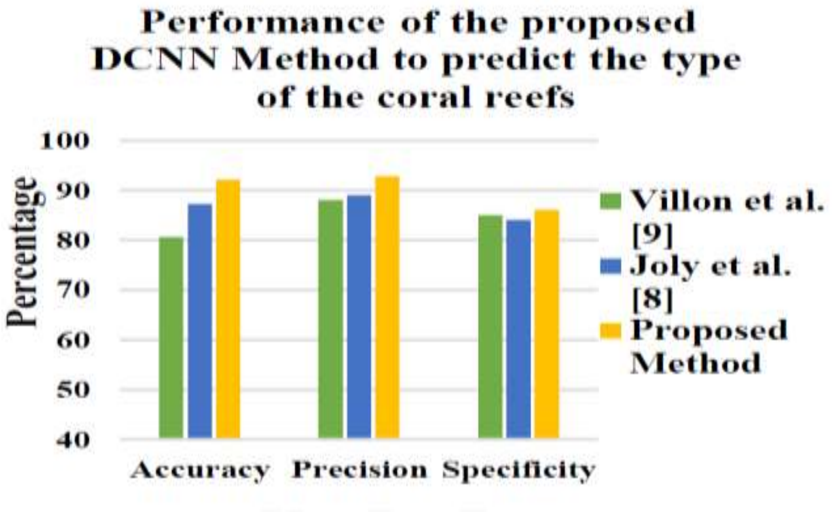

Figure 7 Comparison of the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network with existing approaches to predict the type of the coral reefs

From the above results, it is clear that the proposed method outperforms the existing methods concerning accuracy, sensitivity and specificity.

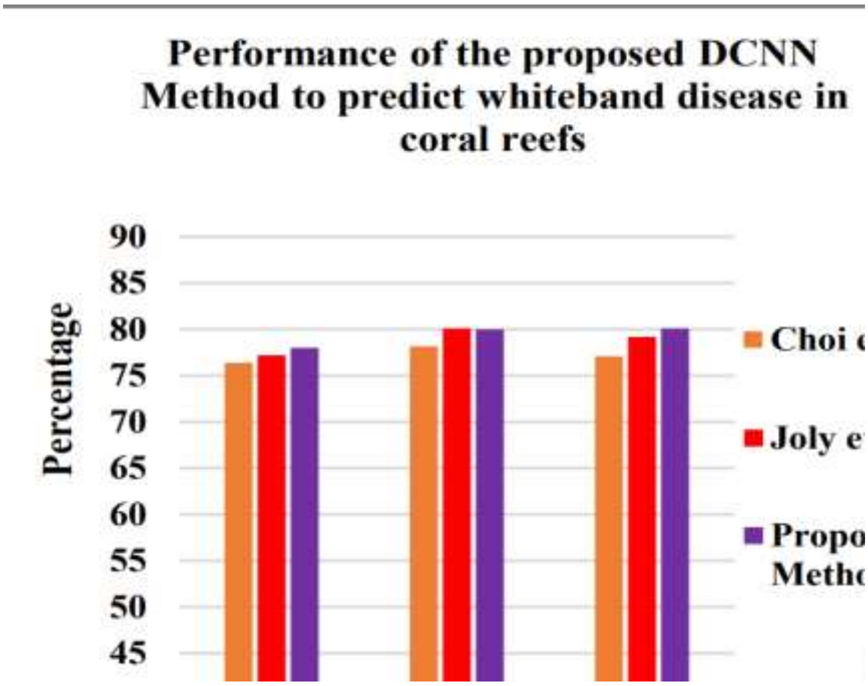

Figure 8. Comparison of the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network with existing approaches to predict the white band diseases in coral reefs

Different Methods	Accuracy	Specificity	Sensitivity
Inception	93.80	88.04	90.01
AlexNet	85.88	85.19	91
Inception + AlexNet	90	86.15	91.02
ResNet101	94.25	87.18	90
GoogleNet	95.35	87.75	91.03
ResNet101+GoogleNet	96.33	88	92.76
ZeNet	96.88	82.65	93
VGG19	97.45	84.78	94.56
ZeNet+VGG19	98.02	87.65	95.6

Table 1: Comparison of the proposed hybrid ZeNet and VGG19 Deep Convolution Neural Network with existing approaches to Classification Performance.

8. Conclusion

This research work creates an efficient proposed hybrid Deep Convolution Neural Network (ZeNet and VGG19) to identify the type of the coral reef and also it identifies the coral which are infected by the white band diseases. Initially, the images were preprocessed using image restoration and image enhancement techniques. Later, the image features are detected from the images and extracted to train the neural network. Once after the training phase, the test data are given as input to the hybrid DCNN to perform image classification. The proposed system efficiently predicts the type of coral reefs and later it also predicts whether the coral is infected by the white band or not. The proposed method helps in improving the coral ecosystem, with an accuracy of 98.02%, sensitivity of 95.6% and specificity of 87.65%. The proposed methods outperform the existing methods and make in practical to implement in real time.

Future Work

One potential area of improvement is the integration of advanced image augmentation techniques to further increase the diversity and robustness of the training dataset, thereby enhancing model generalization. Additionally, the incorporation of transfer learning from pre-trained models on larger, related datasets could reduce training time and improve accuracy. Exploring other state-of-the-art neural network architectures, such as transformers or attention-based models, may also yield better performance. Furthermore, deploying the system in real-time underwater monitoring environments with good, waterproof hardware can validate its practical utility and resilience. Another critical direction is the integration of environmental and contextual data (e.g., water temperature, depth, and salinity) to provide a more comprehensive assessment of coral health.

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