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IMPLEMENTATION OF DEEP LEARNING TECHNIQUES TO ADDRESS CORAL REEF DISEASES

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***Abstract*— Coral reefs is an important, unavoidable attribute of the marine ecosystem. It plays a major role in keeping the ecosystem balanced. Coral reefs produces nutrition and proteins to the fishes like tuna, dolphin and other pelagic species. But, due to industrial pollution, human-related activities, climate change, bleaching, the total amount of the coral reefs has drastically reduced. According to the report of Global Coral Reef Monitoring Network (GCRMN) around 19% of coral reefs in the world has lost in last 30years and it is expected to lose another 17% by 2030. It has also predicted that, in 2050, all the coral reefs in the world will be in danger. To address this alarming issue, this research work proposes a deep convolution neural network machine learning technique to identify the infected or diseased corals from videos. Here, two datasets are used. One is used to train the neural network to predict the type of the coral reef downloaded from Mendeley open source archive and second dataset is used to predict whether the particular coral is affected from white plague disease or not. The second video dataset is downloaded from official BBC Earth YouTube web channels in HD 720 pixel. These data are given as input to the Deep Convolution Neural Network (DCNN) to perform image classification. The proposed system automatically predicts the diseases in the coral reefs and helps in improving the coral ecosystem.**

***Keywords*— Deep learning; Coral reefs; Disease prediction; Coral ecosystem; neural networks.**

1. INTRODUCTION

Coral reefs are living, colorful, multi-faceted structure, which are the part of marine ecosystem. Coral reefs are formed by calcium carbonates and are mostly present near equator of the world. It lives in warm water and maintains a temperature between 20 to 28 degree Celsius It creates a colony-like structure to shelter species like fishes, crabs, sea stars, shrimps and algaes [1]. It is estimated that around one lakh different species are living under the coral reefs. It also produces nutrition and proteins to the species that live on the ocean. Moreover, it also helps human being by providing coral foods, shorelines protection and medicines. On the basis of recent report from National Oceanic and Atmospheric Administration, the annual economy earning of coral reef mining is about 30 billion US dollars.

Coral reefs has most variety of all marine ecosystem. There are more than 2500 species of coral reefs in the world. Around 40 percent coral are hard in nature. It will not have any motion or movements in the ocean. They will look like a hard rock. On the other hand, remaining 60 percent of corals are soft in nature [2]. It will have a skeletons that are flexible to make motions on the water. Though, it gives several advantages to the ecosystem and human being, 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 entirely destroyed and in many places coral reefs are in 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. In here, the white syndrome and white band are the wide spread disease in the entire world. These diseases forms a white colored foam in the surfaces of the coral reefs. It also exhibits a pronounced division between the remaining coral tissue and the exposed coral skeleton. White layer diseases such as white band and syndrome in the coral reefs can be categorized into Type I and Type II diseases. In here, Type I, diseases doesn't show any bleaching on the upper layer of the coral reefs. But it changes the color slightly. Type II coral reef diseases bleaches the surface completely[3].

In this research work, we intended to create a framework to identify the corals types and its

disease automatically by performing deep learning techniques on the coral reef video dataset. Here, we have used 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 perform both forward and backward propagation to gather information, identify the relationship and detects patterns between the data. CNN has a fully connected multi-layer neuron structure, in which each neurons in a layer is connected with all the neurons in the adjacent layers. It uses linear convolution operation at least in any one of the layer. Convolution Neural Network (CNN) takes input as image and assign importance to various aspects in the image and classifies it [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 DCNN framework.

This research work is organized as, Section 2, describes the related works that are carried out on predicting the type and the disease spread in the coral reefs. Section 3, explains the proposed implementation and framework of proposed Deep Convolution Neural Network used. Section 4, evaluates the performance of the proposed approach and Section 5 concludes and discusses about the future work.

2. RELATED WORKS

In early days, information related to coral reefs are collected from underwater visual censuses (UVC) by scuba divers. The accuracy of the collected information is highly depends on the depth, duration and the experience of the scuba divers. Identifying the type, growth, disease in the coral reefs were difficult. But, after the rapid advancement in robotic technology and under water cameras, information related to the coral reefs and marine ecosystem are captured using video supported under water rovers and automatic motion capturing devices [5].

However, collecting and observing information about the coral reefs need an oceanic research specialists. 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 is shown in Fig. 1 and the example image of jelly fish rover is shown in Fig.2.

In order to achieve such an automated image classification method, deep learning techniques are used.

Fig. 1 Image captured through underwater video rovers

Fig. 2 Image of jelly fish rover

One of the important subset of deep learning technique is Neural Networks (NN). It has been used in several applications text classification, paraphrase detection, facial recognition, speech recognition and much more. In recent time, it has been used in oceans to keep track of ocean wave power, endangered fishes and temperature monitor.

Likewise, deep learning techniques are also used in the monitoring coral reefs. Countries like Australia, Philippines are using a deep sea ocean rovers to capture the images of the coral reefs at frequent interval. In 2010, the government of Australia initiated an automated tools for capturing, 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. But identifying the coral reefs on under water image is a challenging issues 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 the 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 finds out the biomass value in underwater sequences. To classify the fishes into different classes, Artificial Neural Network (ANN), Nearest Neighbor algorithm and Support Vector Machine (SVM) algorithms are used. Joly [8], proposed a multimedia identification to gather accurate knowledge about the identity, geographic location and the living species in the ocean using Artificial Neural Networks (ANN).

In addition to that, it also evaluates the challenges related to multimedia information retrieval and fine-grained classification problems. Villon [9], presented two supervised machine learning method to automatically detect and recognize coral reef and fishes under water. It uses HOG machine learning and 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 uses a foreground detection method with selective search to extract information about the fish object. It also uses deep convolution neural networks to classify the fishes based on its 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 camera are directly fed to the machine learning system. It also observe that by adding the additional metadata information the accuracy of the system is increased. It achieves the maximum accuracy as 93% (with additional metadata information like fish length, location, count, migration details)

Ravanbakhsh [12], proposed an automated approach for fish detection using shape based level sets framework. Principal Component Analysis is used to gather the knowledge about the fishes. The HAAR classifier is used identify the precise location of the head and the snout of the fishes. It used two major deep learning techniques, such as patch based convolutional neural networks (CNNs) and fully convolutional neural networks (FCNNs) to classify the semantic segmentation of the underwater images of the coral reef ecosystem. In here, patch based CNN are used to enable single entity classification and FCNN is used to generate a semantically segmented output from the input images. It also compares the patch based CNN and FCNN to improve the accuracy of classification and semantic segmentation of the input images.

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%. Deep Learning methods can thus perform efficient fish identification on underwater images and offer promises to build-up new video-based protocols cheaply and effectively in short time.

3. PROPOSED FRAMEWORK

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

The proposed deep learning technique uses two different data set. 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 consist 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 hours video download from official BBC Earth YouTube web channel in HD 1080p.

To train the Deep Convolution Neural Network (DCNN), the chosen image dataset has to undergo a preprocessing method to purify the error data from the dataset. Raw image dataset might have low quality as the images are captured under water. The preprocessing technique will improve the quality and accuracy of the image dataset, which will impacted on the overall accuracy of the proposed deep learning technique.

3.1 Data Pre-processing of test dataset

Pre-processing is an important feature of deep learning technique which process the raw data and converts in a knowledgeable format which are later given as the input to the Deep Convolution Neural Network(DCNN). Under water image will have noises like,

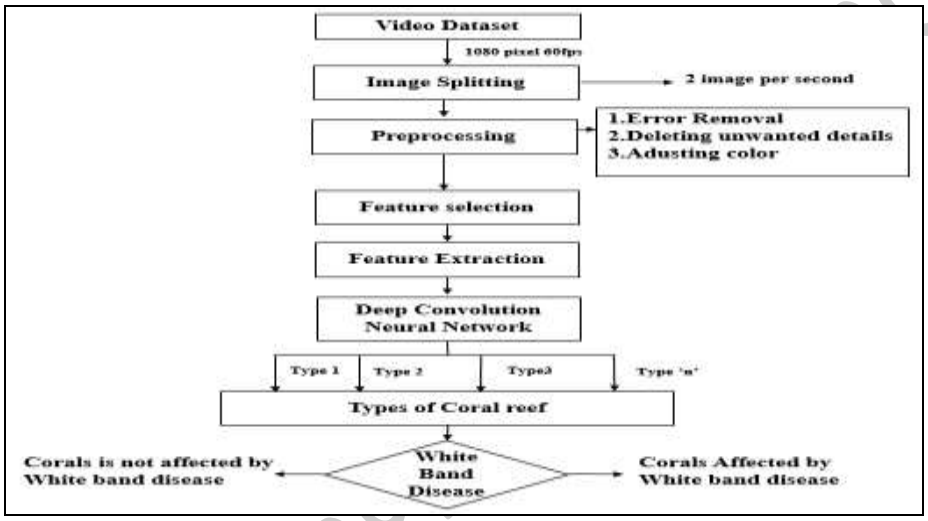

Fig. 3. Workflow to identify the type and condition of white band diseases affected in coral reefs using DCNN

Gaussian noise, Salt and pepper noise, shot noise, quantization noise, film grain noise, low light noise, anisotropic and periodic noise.

To remove these noise and improve the quality of image two important method 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-noising 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 (fishes) are fed as the input along with the image.

Later in image enhancement preprocessing method, disturbance 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 also used to remove the defects of non-uniformity of illumination and improves the contrasts. Fig. 4 represents the preprocessed image and raw image.

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 performs on the square shaped image. For cropping the images, the middle part of the image is chosen. The preprocessing algorithm takes middle part of the image and draws multiple square shaped crops and find the best fit.

Fig. 4 (a) Raw extracted image

Fig. 4 (b) Preprocessed image

3.2 Feature selection

Feature selection is also an important and unavoidable task in Deep learning. It aims to find a small number of features that describes the image dataset

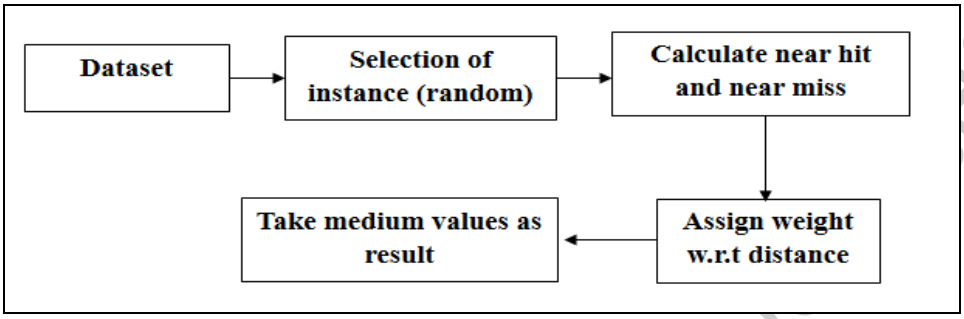

Fig. 5 Relief feature selection algorithm of image dataset

better than the original set of features. This can be achieved by removing irrelevant and redundant features according to importance criterion in feature selection. To remove the irrelevant data from the raw dataset, relief feature selection algorithm is used. The images on the dataset is consider as instances and the object belonging to a known classes are called as feature of the dataset. Let us consider, 'n' instances and 'p' features in a dataset. Each features in the dataset is scaled between the value 0 and 1. Now, take the feature vector X from a random instance and another feature vector X from its nearest instance using Euclidean distance. This operation is performed in an iterative manner. The closest instance is considered near-hit and the longest distanced instance is considered as near-miss. At each iteration, the weight of the vector is updated. Weight of the feature vector can be calculated from,

$$\text{Weight}_{(i)} = \text{Weight}_{(i-1)} - (X_i - \text{near hit}_i)^2 + (X_i - \text{near miss}_i)^2$$

After find out the weight for each feature vector, the median value is set as threshold for feature selection. Fig. 5, shows the procedure of feature extraction.

3.3. Deep Convolution Neural Networks

Deep Convolution Neural Network is a subset of deep neural networks, which is used to analyze, classify the image and video dataset. It is also called as Shift Invariant Neural Network (SIANN). It has been used in face recognition, image classification, recommendation system, medical image analysis.

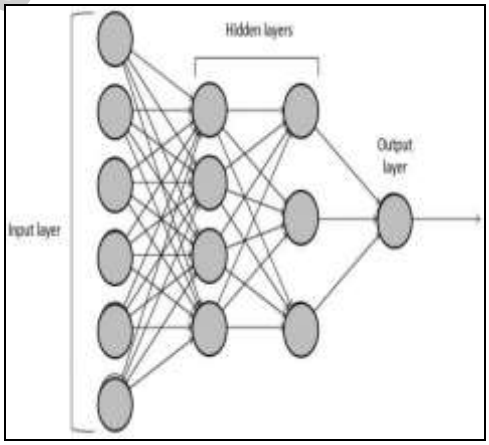

Fig. 6 Structure of the Neural Networks

Every layer in neural networks will have several neurons in each layer. CNN system takes input as images, process it and classifies the input dataset into classes based on the features of the image. In here, the result produced by the feature extraction algorithm is processed and separates the images based on the type of the corals reefs. Each input in the dataset will undergo through a series of convolutions layers, where each layer will have a kernel filters, pooling and softmax function to classify the image with probabilistic value of 0 to 1. Convolution uses the relationship between the pixels and small-square as input to learn the

features on the image. Filters in each layer perform task like edge detection, blur handling, sharpening the image.

Meanwhile, the classification based on the convolution filters alone can't give a perfect result. To improve the prediction result in the convolution layer, padding is also used. For example, if the size of the filter used is 3*3 matrix and the input image size is 8*8, then the filter can't efficiently process the input data. In such scenario, padding can be used.

The system artificially adds, n*n zero matrix values to the image to equals the inputs data size. The added pixel will have the zero value and doesn't affect the convolution neural network in any means. The process of kernal filter and padding are continuously performed in an iteration manner and allows the input data to propagate forward and backward and makes the system to learn about the input image.

Once after the DCNN is learned about the coral reefs and its type. The second dataset (i.e.) test dataset (video files) is given as input the DCNN. Later, the video dataset is extracted in scale of 2 images per second (120 image per minute) of a total 10hours videos. These frame extraction is performed using video capturing function in OpenCV. These test dataset is fed to the CNN again to check the accuracy of the proposed DCNN based automatic prediction technique.

Once after finding out the type of the coral reefs, an separate support vector machine (SVM) base machine learning technique is used to classify whether the coral reef has affected from white band disease or not.

4. EXPERIMENTS

The proposed 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 Mendeley Imaging Archive site. The downloaded data had several information related to the type of the coral reef. The total number of the coral reef images present in the first dataset is around 1,512, in which 80% of images (i.e.) 1,259 images is chosen as training images and 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 the coral reefs. The second dataset used to train the neural networks is a video dataset, which is downloaded from the BBC Earth YouTube Channel consist of a total run time of 3.12 hours of oceanography and underwater videos shot beneath the sea. 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 image derived from the video. Later in these 3,000 videos, 80% are used as training data set and 20% are used as test data. The second dataset is used to identify whether the coral reefs is infected by the white band diseases are not.

The implementations were carried out on an i7 Intel processor system with 8GB with the computing power and 1TB storage space. The overall performance of the proposed DCNN is measured using three major evaluation aspects of the ML algorithm such as accuracy of the results, precision and recall.

To measure the accuracy of the proposed DCNN method, 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 belong to a particular type and DCNN fails to find it. The false positive is the case where the coral reef is not belong to a particular type and DCNN results the same. False negative is the case, where the coral reed doesn't belong to a type, but DCNN wrongly predicts that the coral reef belong to particular type. The formula to measure the accuracy of the proposed system is,

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

The measured accuracy of the proposed model DCNN model is 92.1%. In total of 253 test set images, the DCNN system correctly predicted the type of 233 images. However, accuracy of SVM algorithm to predict the same is 80.6%, (i.e.) 203 images. The accuracy of the proposed DCNN method is measured and compared with other existing methods. Likewise, the sensitivity is also measured. Sensitivity is a measure of the proportion of actual positive cases that got

predicated as positive. It is measured by the following formula,

$$Sensitvity = \frac{Ture\ Positive}{Ture\ Positive + False\ Negative}$$

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

$$Specificity = \frac{Ture\ Positive}{Ture\ Positive + False\ Positive}$$

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

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

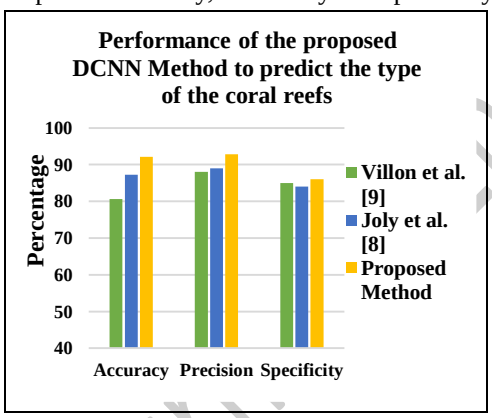

Fig. 7 Comparison of the proposed DCNN method with existing approaches to predict the type of the coral reefs

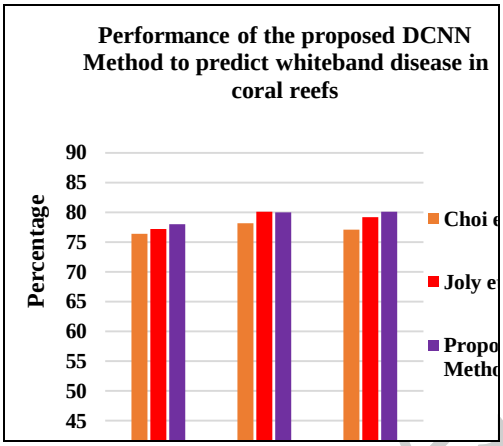

Fig. 8 Comparison of the proposed DCNN with existing approaches to predict the white band diseases in coral reefs

5. Conclusion

This research work creates an efficient deep convolution neural network 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 feature are detected from the images and extracted to train the neural network. Once after the training phase, the test data are given as an input to the DCNN to perform image classification. The proposed system efficiently predicts the type of the coral reefs and later it also predicts the whether the coral is infected by the white band or not. The proposed method helps in improving the coral ecosystem, with the accuracy of 92.1%, sensitivity of 92.8% and specificity of 86.2%. The proposed methods outperforms the existing methods and makes in practical to implement on real time.

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