matrices were generated and the percent accuracy was estimated (at 90% confidence level) based on the number of points verified on ground and the number of failures. During the study period, we have collected Line Intercept Transect method (Nayak et al., 2003) based data. Line intercept transects of various lengths (ranging from 100m to 500m) were laid on the reef stretching from the beach seawards to the edge of the reef. After every 20m or at each change in zone the observations are recorded. The geographic locations of different points sampled along transect were noted using pre-calibrated Magellion GPS (stand-alone GPS) instrument with accuracy of 10m. From each sampling unit substrate characteristics, depth of water, percentage coral, algae and seagrass cover, coral species, size of coral colonies, column of water, sea surface temperature were recorded. We are collecting ground data for the coral reef in the Gulf of Kachcch every year since 1998. We collected the ground data during the low tide condition. During the low tide condition water depth is below 1m and it is easy to walk on the coral reef from landward to the seaward side (along the transect). During the analysis of remote sensing data, it was found that the reflectance patterns of different features i.e. live corals, dead coral; algal ridge and macro algae vary significantly in their spectral behavior (Nayak et al., 2003). However, it needs to be mentioned here that these patterns are not representative spectral signatures of the features. The ground-based radiometric studies are required in order to obtain a specific signature of coral reefs. An attempt is being made to develop methodologies for classifying the coral reefs using satellite data and Neural Network. The spectral behaviour of live coral, dead coral, algal ridge, macro algae, micro algae, mangroves, mud and sand studied for classification. The digital signatures were taken from the least heterogeneous categories and named as the pure samples. The pure samples are, then, taken as training samples for the Neural Network. The trained Neural Network, then, has been used to classify the Image.

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The four layer artificial neural network (1 input layer, 2 hidden layer, 1 output layer) is considered as the basic training classifier. A sigmoid function is used for the synapse function of the neuron, with back propagation (BP) training of the IRS LISS-III sensor data.

Artificial Neural Network Based Coral Cover Classifiers using Indian Remote Sensing (IRS LISS-III) Sensor Data: A Case Study in Gulf of Kachcch, India

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Abstract
Artificial neural network have become popular in classification of remotely sensed satellite data where they demonstrate better accuracy than conventional methods. A back propagation neural network algorithm has been developed to classify eco-morphological zonation of coral reef as well as benthic communities. IRS P6 LISS III satellite data of March 2, 2006 has been used to map coral reefs using hybrid analysis of user based knowledge. The traditional method used for classification of coral reefs gives substantial amount of mis-classifications due to the similarity in reflectance values. The optimized neural network, made for the classification of coral reef image with high rate of noise, shows a better accuracy, as it is able to remove mis-classifications up to certain extent. The developed classifier uses the radiance values of 300 homogeneous pure pixels per class as training samples from a radiometrically and geometrically corrected image of the study area. The optimized network was applied on the complete coral reef image. Accuracy was checked by cross validating ground truth data which showed considerable improvement (84% at 90% confidence level to 91.14% at 90% confidence level) in mis-classifications.

1. Introduction

Coral reefs of the Indian coast have been studied for their extent, ecological condition as well as morphological zones using satellite data (Nayak et al., 1992, Bahuguna and Nayak, 1998 and Bahuguna et al., 2002). The Indian reefs are in degrading condition. The current reliance on measuring the percentage of live coral cover for assessing degradation is, however, sufficient for comparisons among coral reefs, although change in live coral cover is an important indicator at a single location for coral reef health (Burke et al., 2002). A coral reef environment is known as optically, spatially and temporally complex presenting difficulties in extracting information on ecology and vitality of coral reef communities using remote sensing data. While coral reef remote sensing promises to address some of these difficulties, still there are challenges to integrate remote and in-situ observations for coral reef monitoring. Hence, there is a need to consider these factors in understanding images obtained from different sources taken at various periods. The satellite images are analyzed with specialized software's which help in generating theme based maps of the study area. Remote sensing data has an edge over other means of generating maps as these help in getting a synoptic view of the study area. Today, techniques like knowledge classifiers, Artificial Neural Network (ANN) etc. have been established that use both user-based knowledge as well as inherent remote sensing data to classify the satellite images. The effectivity of ANN in satellite image classification is due to its intrinsic ability to generalize the non-dependance on stastical distribution of data, and capability to form highly nonlinear decision boundaries in the space (Lippmann, 1987; Hush and Horne, 1993). In multisource remote sensing data classification, ANN does not require any priori specifications of the weight of each data source models. The procedure involved with neural network spectral classification are more closely associated with supervised classification as opposed to unsupervised classification techniqiues. Lippmann (1987) concluded that neural network classifiers are non-parametric and are more robust when distributions are strongely non-Gaussian. Neural networks have been used in a number of studies to classify remotely sensed data (Benediktsson et al., 1990, Tzeng and Chen, 1997; Sangle and George, 2005).

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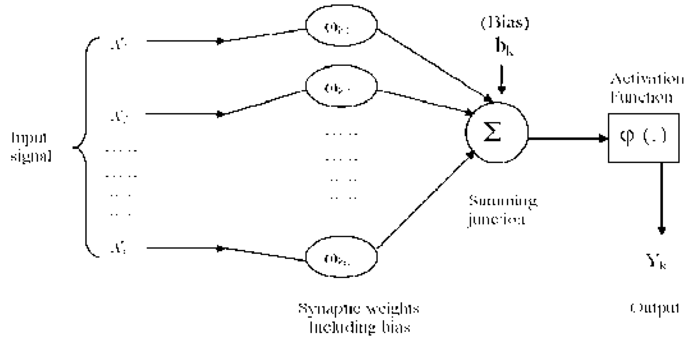

Figure 1: Basic structure of an artificial neural network

Yoshida and Omatu (1994) proposed a neural network classification method for remotely sensed data analysis in order to improve neighborhood relation between pixels and to decrease error probability for pattern classification. Artificial Neural Networks (ANNs), according to Haykin (2004), are massive parallel distributing systems that can store experimental data and make use of it in extracting meaningful patterns from it by creating relationship amongst the data (Figure 1). The most widely used ANN is known as Back Propagation ANN. This type of ANN is excellent at prediction and classification. ANN algorithms are computer programs, which use similar function like biological neurons. Learning of biological systems involves adjustments to the synaptic connections that exist between the neurons. Learning typically occurs by examples through training, or exposure to a truthed set of input/output data where the training algorithm iteratively adjusts the connection weights (synapses). These connection weights store the knowledge necessary to solve specific problems. Techniques like Artificial Neural Network can be used in order to obtain better quality of results and accuracies of the order of pixel and sub-pixel. Neural networks are essentially non-parametric data transformations that are not restricted by underlying assumptions and can account for nonlinear effects given a sufficiently complex partitioning of the classification space (Atkinson and Tatnall, 1997). A key benefit in ANNs is that a model of the system can be built just from the data such as the digital signatures. To correlate spectral image features to actual information such as living coral distribution, image processing, pattern recognition and water column correction are needed, as evidenced by numerous studies on this field (Purkis, 2005, Hochberg and Atkinson, 2000 and Green et al., 1996). Some studies show the use of feed forward back propagation neural network to classify close-up images of coral reef components into three benthic categories: living coral, dead coral and sand (Marcos et al., 2005). Furthermore, neural networks are more likely to learn the complex variability in the signature of the coral reef. If a stable algorithm is developed which can be applied on coral reefs in general then it would increase the accuracy of the present techniques for classification. In this study, an algorithm is developed which is able to classify the satellite data with the help of Artificial Neural Network (ANN).

2. Study Area

The Gulf of Kachchh has an assemblage of different ecologically sensitive ecosystems consist of coral reefs, mangroves, seagrasses and algae/seaweeds (Figure 2). It is the largest inlet (approx. 7350 km^2) of the Arabian Sea, about 60 km wide at its widest and 170 km long. Due to its rich diversity and fragile nature, the Govt. of Gujarat, in 1983 declared an area of about 457.92 sq km as the Marine Sanctuary and 162.89 sq km as Marine National Park. The southern coast of the Gulf of Kachchh is the only region in Gujarat, which houses coral reefs. They are geographically in the northernmost limits of coral formations in the Indian Ocean (excepting the northern portions of the Red sea). The reef flat is narrow, houses seasonal algae/seaweed growth and is followed by a deposition of mud on it. Many dead reefs occur 2-7 m above present-day sea level extending 2 km inland (Lyall and Reddy, 1982). Their origin is due to coastal uplift (Krishnan, 1997). Buried coral reefs are located off the northern Saurashtra coast and off Narara bet around 32 m and 8-20 m below present sea level (Lyall and Reddy, 1982). Using satellite data, the reefs have been classified into fringing reefs (North of Okha, Bet Shankodhar, Dhani bet to Sikka, Jindra and Chad, Pirotan and Valsura), platform reefs (Paga, Bural Chank, Ajad, Gandhio Kuddo, Panero, Kaubhar and Munde ka bet) and coral pinnacles (north-east, north-west and south of Bural., Changri, south of Goos reef). In the present study Munde ka bet reef (Platform reef) was used to classify using ANN model. The fluctuation in high and low tides in the Gulf is phenomenal unlike those of other coastal regions of the country. Because of the shallow depth and its agitation during the tides, heavy load of silt and clay particles get suspended along the coast.

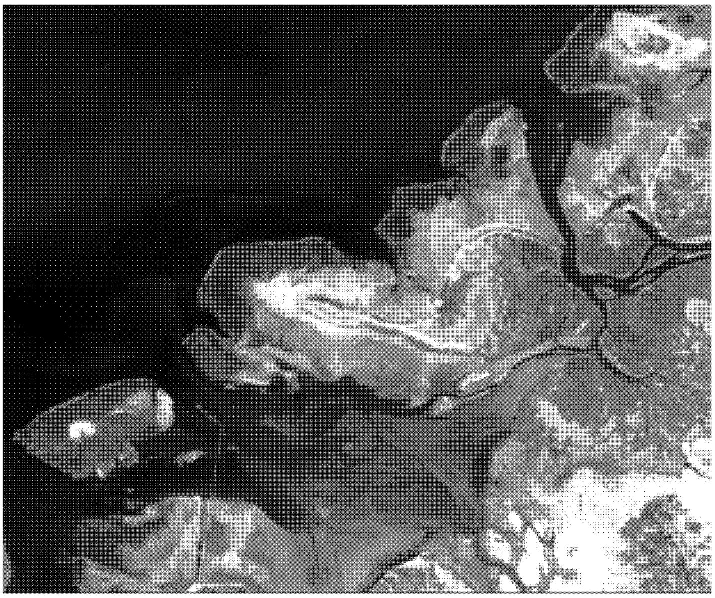

Figure 2: Location of the study area

3. Data used and Methodology

IRS LISS III data (23 m resolution), consist of 4 bands (green, red, NIR and MIR) of 2006 has been used for mapping the Munde ka bet coral reef in order to know its ecological status. Required sub-image was extracted from the data set and was subjected to geo-referencing using Survey of India topographical map (base map). The image was subjected to radiometric corrections, viz., conversion of DN values to spectral radiance (at the sensor) and removal of atmospheric effects due to absorption and scattering (atmospheric correction) in the ERDAS IMAGINE environment, prior to subjecting the images for ANN classification. The DN values were converted to radiance values by a simple process wherein the conversion in radiance image is basically correcting the image for its sensor parameters. Therefore, gain and off-set values of the sensor are used in the following equation (each band of the image is processed separately) using modeler available in the ERDAS IMAGINE (Nayak et al., 2003),

$$L_{rad} = \{[\text{DN/max grey}] \times [L_{max} - L_{min}]\} + L_{min}$$

Equation 1

Where DN is the digital number of each pixel; max grey = 255 for LISS III sensors of Indian Remote Sensing Satellite. L_{max} is obtained from the header file of each scene and L_{min} is zero for the above sensor. The image was then subjected to atmospheric correction (Kaufman, 1989 and Green et al., 2000). Among several methods available we have employed here the Dark Pixel Subtraction (DPS) method. In this method, the path radiance is removed by identifying the minimum pixel value (as far as possible from the deep clear water) in each band. Bi-plots of infrared band against the green and red bands are generated for pixels of the dark regions. Regressions techniques are then used to calculate the y-intercept, which represents the path radiance in bands green and red. This is then subtracted from all pixels in the imagery. High tides modify and reduced the signature coming from the reef-scape, so, it is preferred to choose the data acquired at low tides and clear sky conditions. We used the low tide condition satellite image of the study area, so we did not performed the water column correction. The coral reef habitats were classified using the eco-morphological classification system evolved earlier at the Space Applications Centre, Ahmedabad (Bahuguna and Nayak, 1998) that includes type of reef, eco-morphological classes (reef edge, reef flat, sand deposition in reef flat, mud deposition on reef flat, sandy beach), backwash deposit on reef flat, high and low tide line. Live corals that mostly occur on the reef edge, reef crest, in the shallow pools on reef flats and near algal ridge, are the site of maximum bio-diversity and productivity. Similarly, algal ridge and reef flat consisting of seagrass, algae/seaweeds etc., are very important for coral reef productivity. On the basis of the spectral properties ANN was performed to classify the image. Digital classification accuracy was ascertained by estimating the overall classification accuracy and Kappa Coefficient. Error matrices were generated and the percent accuracy was estimated (at 90% confidence level) based on the number of points verified on ground and the number of failures. During the study period, we have collected Line Intercept Transect method (Nayak et al., 2003) based data. Line intercept transects of various lengths (ranging from 100m to 500m) were laid on the reef stretching from the beach seawards to the edge of the reef. After every 20m or at each change in zone the observations are recorded. The geographic locations of different points sampled along transect were noted using pre-calibrated Magellion GPS (stand-alone GPS) instrument with accuracy of 10m. From each sampling unit substrate characteristics, depth of water, percentage coral, algae and seagrass cover, coral species, size of coral colonies, column of water, sea surface temperature were recorded. We are collecting ground data for the coral reef in the Gulf of Kachcch every year since 1998. We collected the ground data during the low tide condition. During the low tide condition water depth is below 1m and it is easy to walk on the coral reef from landward to the seaward side (along the transect). During the analysis of remote sensing data, it was found that the reflectance patterns of different features i.e. live corals, dead coral; algal ridge and macro algae vary significantly in their spectral behavior (Nayak et al., 2003). However, it needs to be mentioned here that these patterns are not representative spectral signatures of the features. The ground-based radiometric studies are required in order to obtain a specific signature of coral reefs. An attempt is being made to develop methodologies for classifying the coral reefs using satellite data and Neural Network. The spectral behaviour of live coral, dead coral, algal ridge, macro algae, micro algae, mangroves, mud and sand studied for classification. The digital signatures were taken from the least heterogeneous categories and named as the pure samples. The pure samples are, then, taken as training samples for the Neural Network. The trained Neural Network, then, has been used to classify the Image.

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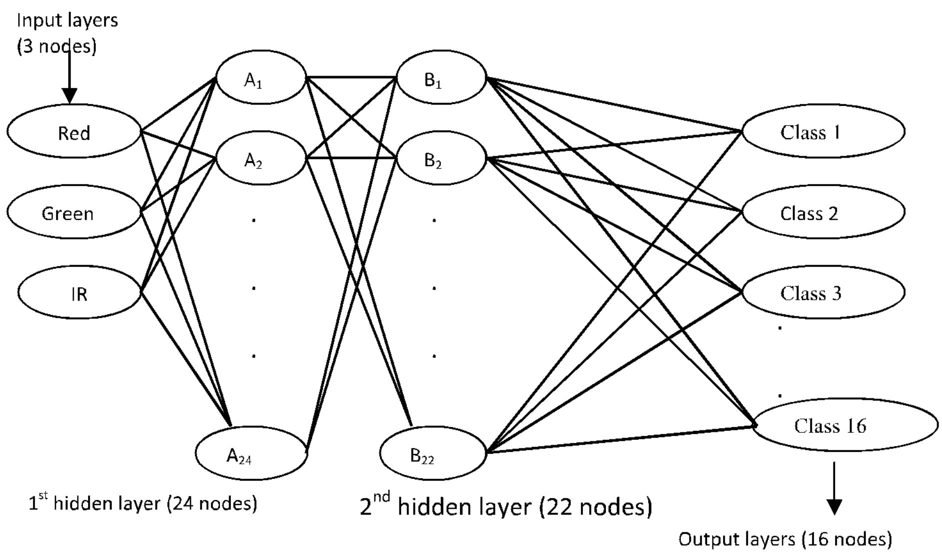

Figure 3: Architecture of neural network with grey values

- A sigmoid function was used *f(x)*:

$$f(x) = 1/1+e^{-x}$$

Equation 2

- Initialization of weight parameters to random values.
- Calculating the error term for each output unit as:

$$\delta_j = y_j\,(1-y_j)\,(\delta_j - y_j)$$

Equation 3

Where δ_j is the desired output of the node j and y_j is the actual output.

- A rate parameter, r is picked. Until performance is satisfactory for each sample input β is computed for nodes in the output layer using:

$$\beta_z = d_z - o_z$$

Equation 4

Where d_z is desired output and o_z is obtained output

- Then β is computed for all other nodes using the formula:

$$\beta = \sum_k w_{j\to k} o_k (1 - o_k) \beta_k$$

Equation 5

Where k, j are variables

- Next the weights changes are computed for all weights using:

$$\Delta w_{i\to j} = r o_i o_j (1 - o_j) \beta_j$$

Equation 6

Where Δw is the differential of the initial weight and the final weight. Then all the weight changes are added for all weights for all sample inputs, and then the weights are changed to reduce the error.

This iterating program is run until the error reduces and no over learning is seen. Learning rate parameters are also added to keep the network iteration in check. The algorithm was built in 'C' language. As the inputs were provided in separate band files so the outputs were also obtained in separate band files which were written in a single file along with the header information which was obtained from the original image subset. The output file obtained in the form of classes. This newly obtained image file was made suitable for viewing in Image processing software like ERDAS Imagine.

4. Results and Discussion

The main emphasis of the present work is to develop the ANN for better classification of coral reefs. Final corrected image after applying ANN is shown in Figure (4a and b). After classification, statistical analysis of the classifier's accuracy has been carried out. Producer's and user's accuracy of each extracted class are shown in (Table 2), while Kappa statistics are shown in (Table 3). It is noticed through these tables that by the use of neural network, the accuracy of the classified image was improved. The classification obtained was for the major sixteen classes. These show the live and dead regions of the coral reef as well as the mangroves, algae and mud covered regions. There are mergings seen between some of the classes. These mergings are mainly due to the similar digital signatures of the classes identified as algae with mangroves and the suspended sand with dead coral. Due to the validation routine and neural network algorithm the specific region of the study area could be improved and the mis-classification was successfully removed in some extent. Although the error in classification was removed up to a certain extent still merging of some of the minor classes and suspended sand with dead coral reef region was found. Kappa coefficient is a statistical measure of the agreement, beyond chance, between two maps (e.g. output map of classification and ground-truthed map). Correctly assigned pixels may have been assigned by chance and not based on the classification decision rule. The kappa value indicates how accurate the classification output is after this chance, or random, portion has been accounted for. The overall obtained classification accuracy is 91.41% (Table 2). The over all classification was achieved from the classification product with contextual editing. Kappa coefficient obtained is 0.9030 (Table 3).

This result however, suggests mixing of few particular classes, which can be further improved. By the use of supervised classification method one can give the much required real life information which actually describes the study. This method involves the input from the user that gives the complete picture about the problem. Thus problem specific solutions could be developed by this method which can be of high accuracy but are difficult to apply on a generalized scenario. The supervised classification has a definite advantage of defining the exact difficulties faced in the classification step and also outlining the possible solutions for such misclassifications. In an earlier results, Indian Remote Sensing Satellite LISS III sensor data of periods 1998, 2000 and 2005 were analysed to zone the eco-morphological zones of the Pirotan coral reef in nine classes with an accuracy of 89% to 92% at 90% confidence level using supervised classication method (Sharma et al., 2009). Paola and Schowengerdt (1995) also demostrated the advantages of the neural network method over traditional classifiers for classification of remotely sensed multi spectral imagery.

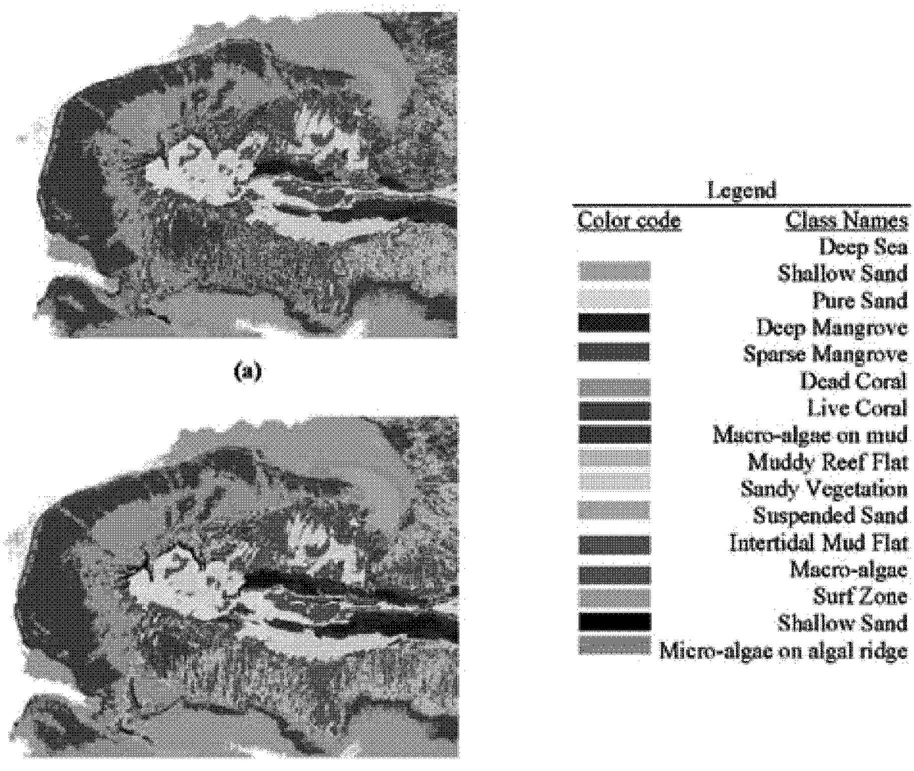

Figure 4: (a) Image obtained after applying ANN (b) Final image after correction

Table 1: Major specifications LISS III data

1	LISS III	23.5 m	Band 1 (0.52-0.59) Band 2 (0.62-0.68) Band 3 (0.77-0.86) Band 4 (1.55-1.7)	7 bits

Table 2: Classification accuracy assessment report

Deep Sea	42	39	39	-------	------
Shallow Sea	30	35	30	100.00	85.71
Pure sand	10	11	10	100.00	90.91
Deep Mangrove	2	2	2	100.00	100.00
Sparse Mangrove	3	3	3	100.00	100.00
Dead Corals	35	36	31	88.57	86.11
Live Corals	36	37	34	94.44	91.89
Macro Algae	11	7	6	54.55	85.71
Muddy Reef Flat	33	34	30	90.91	88.24
Sandy Vegetation	15	15	14	93.33	93.33
Suspended Sand	5	5	4	80.00	80.00
Inter-tidal Mud Flat	24	24	24	100.00	100.00
Macro Algae	1	1	1	100.00	100.00
Surf Zone	1	0	0	-------	-----
Shallow Sand	4	3	3	75.00	100.00
Micro Algae on algal ridge	4	4	3	75.00	75.00
Totals	256	256	234		
Over all Classification accuracy = 91.41%					

Table 3: Calculated Kappa Statistic for each classified class using ANN

Deep Sea	1.0000
Shallow Sea	0.8382
Pure Sand	0.9054
Deep Mangrove	1.0000
Sparse Mangrove	1.0000
Dead Corals	0.8391
Live Corals	0.9057
Macro Algae	0.8507
Muddy Reef Flat	0.8649
Sandy Vegetation	0.9292
Suspended Sand	0.7960
Intertidal Mud Flat	1.0000
Macro Algae	1.0000
Surf Zone	0.0000
Shallow Sand	1.0000
Micro Algae on algal ridge	0.7460
Overall Kappa statistics	0.9030

The classes that are chosen for classification from this study area are distinct from each other, while they showed the mis-classification with each other in some cases. Though they are distinct and are placed in different regions of the study area few of them gives the same spectral readings. As these spectral reading or digital signatures are the basic inputs for the Neural Network, the classes with similar signatures are seen to merge and hence, giving mis-classifications. These classes are mainly the algae found on the algal ridge in the seaward direction with the mangroves seen on the landward direction of the coral reef. The other part of the reef which is seen to have mis-classified is the suspended sand towards the edge of the coral reef and the dead coral region in the inner section of the reef flat. By the use of Neural Network the accuracy has improved but these mis-classifications are still found though in lower amount. They are removed by validation routine which takes the user input to overlay the correct classes in their correct positions. By doing so the accuracy improves greatly. Other minor classes that have merged are micro algae on mud and muddy reef flat. This is found while collecting ground truth. They also give similar signatures but as they are located in the same region they do not effect the major mapping misclassification.

5. Conclusion

The results presented here add to the growing support for the use of neural networks in remote sensing studies. It also demonstrates the superiority of ANN methods and its edge over spectral characteristics based supervised classification. The study shows superior results than those obtained previously when judged in statistical terms. This increased accuracy is an indication that the specific algorithm to study a biological environment gives better accuracy than that of general algorithms. The neural network classification reduces the merging of the thematic categories. This merging cannot be removed only by taking the digital signatures of the respective classes as their digital signatures are similar. There is a future scope for the improvement of the developed algorithm so that it can be applied on a general scenario as well as to reduce the merging. This study can be cited as an attempt to test an artificial neural network algorithm as an optimization technique specifically developed to deal with the merging problems seen during coral reef classification. It can be suggested that the use of hybrid algorithms may give an overall accuracy but to attain a very high level of accurate classification study specific algorithms should be developed. Such that, they are able to use user given specifications in turn increasing the accuracy of the classification. The accuracy obtained after cross validation with ground truth shows considerable improvement in the classified output. The over all classification accuracy shows 91% accuracy at 90% confidence level which is acceptably good. The problem of hill climbing and over training found in ANN algorithms are not seen in the present study. These problems should not be overlooked as it might in turn give false results when this algorithm is used in new study areas. The major limitation seen in this study is the less availability of the different types of training data. Only digital signatures or spectral readings may create problems as some of the classes have very similar spectral readings. This classes merge and cannot be effectively separated. As neural networks has rapidly become established in remote sensing it is likely that they will be used increasingly and in a broader range of activities that will help to exploit more fully the potential of remote sensing as a useful tool in coastal habitat research.

Acknowledgement
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