ISSN 2278-3091
Volume 9, No.3, May - June 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse80932020.pdf
https://doi.org/10.30534/ijatcse/2020/80932020

An efficient image classification technique for Synthetic Aperture Radar (SAR) images

S.Rajkumar[1], G.Malathi[2]
[1]Assistant Professor (Senior), School of Computer Science and Engineering, VIT University, Chennai, India.
[1]rajkumar.srinivasan@vit.ac.in
[2]Associate Professor Senior, School of Computer Science and Engineering, VIT University, Chennai, India.
[2]malathi.g@vit.ac.in

ABSTRACT

The data processing in satellite is mostly treated in digital image processing techniques. Since, any satellite data are typically the digital image data. Further using the digital image processing algorithm, the remotely sensed information is measured for different applications. In recent years, the insinuation of extracting the Synthetic Aperture Radar (SAR) image features and classification are increasing. The classification in SAR images from remote sensing is the most effective scheme to extract and process the remote sensing data. Basically, the image classification is the process of assigning the individual pixels of an image into different categories and is one of the vital roles in satellite image processing today. Classifying the SAR image is the prerequisite for detecting and predicting the changes in geographical applications.

Accordingly, this paper focuses the features such as correlation, texture, color etc. in the spectral feature space. Here, a novel image classification method called ‘Adaptive Classifier (AC)’ is developed that accurately classifies the water body and non-water body regions in various places of India such as Berijam Lake (Kodaikanal) and Kochi over a period of 3 years from 2016 to 2018. In this paper, there are 8 different regions in SAR images such as lake, river, sea, forest, barren land, building, agricultural land and transport were identified and classified. Through, qualitative and quantitative measures the classified result is compared with Nearest Neighbor (NN), k-Nearest Neighbor (KNN) and Support Vector Machine (SVM) and further proved that the proposed classification outperforms the existing techniques.

Key words*:* Image classification, Adaptive Classifier, SAR image, Remote sensing, Satellite image, Feature extraction.

1. INTRODUCTION

The image feature extraction and classification are the most important key processes in remote sensing images. Since, the remote sensing data has been divided into two different classes namely biophysical and hybrid. The biophysical data are directly measured by the remote sensing systems without using other data such as temperature or soil moisture content. The hybrid data are created by systematically analyzing more than one biophysical variable such as detecting the different regions (water body and non-water body) in remote sensing images. Change detection is also an example of hybrid variable, because it requires the knowledge of several biophysical features such as color, texture, tone, location and so on.

The image classification is the process which categorizes every pixel in an image to a specific class (e.g., forest, agricultural, sea, lake, river etc.) based on statistical characteristics of the pixel value. It splits the feature space into different categories based on a decision rule. It uses the spectral information in terms of spectral class. It is a class which includes similar grey-level vectors in the multi-spectral space.

The proposed algorithm in [1] uses recurrent-CNN and feedback-CNN for multispectral image classification. This combined approach increases the accuracy of the classification rate. In [2], the quality of the SAR image is enhanced by using the HSB color model. The results of the histogram indicate the performance of the proposed approach is better. A convolutional neural network (CNN) based method namely Pyramid Scene Parsing Network [3] was proposed and is used to train the features from a huge data set, there by yielding the classification accuracy of 83%.

An unsupervised classification algorithm was developed in [4] using C language and integrated in the web based system developed using HTML5.0, Javascript, Ajax and Php to classify the airborne images. The proposed model in [5], is used to classify vacation images namely indoor and outdoor images. In this approach, Bayesian classification and Learning Vector Quantization were used to train the classes. Further, the color and edge histograms were developed to strengthen the classification process. An automatic technique was proposed in [6] to extract the water body area from Landsat remote sensing image and the method yield more accurate and discriminate the water body from other land cover areas.

Adopted a perceptron model in [6] was used to classify the water bodies in satellite images. The proposed method was tested with quickbird dataset and reported high accuracy of classification and less execution time. Weighted Average – Analytic Hierarchy Process was constructed in [7] and is combined into Multiple Classifier in turn comprised of minimum distance classifier, backpropagation network, fuzzy c-means, support vector machine and maximum likelihood classifier. This combined framework is used to classify the vegetable field and farm lands. The Netherlands area was chosen in [7] as the case study and using texture feature, the accuracy of the classification got improved.

A multiscale road extraction scheme called atrous spatial pyramid pooling was developed in [8], which solves the road connectivity problem in Yinchuan city. The proposed method in [9] was splitting the image into square tiles and then extracting features on these tiles. Then, these features are passed into fully connected neural network with semi-supervised learning, in turn extracts the structural information contained in the unlabeled tiles**.**

In [10], Wishart-ML classifier was developed to classify three different types of water body regions namely lake, pond and canal and this method was yielding an overall accuracy of 89.40%. A region in Rajasthan (Sambhar Lake), India was chosen as the dataset in [11], for detecting the changes in water bodies. A two-tier image labeling scheme has been formulated by keeping the changes in climate acquired through a monsoon in tier-1 and the variation of water body through assessing the area in tier-2 to identify the impact of variation in water body.

A novel approach developed in [12], was using adaptive contextual information via composite kernel to increase the efficiency of the classification. The results of the work was compared in terms of qualitative and quantitative analysis and thus proved the algorithm works well. In [13], enhanced modified normalized difference water index was proposed to extract the very narrow river water region. This method was compared with modified normalized difference water index and is producing better segmentation results. Ensemble classifier was developed in [14] is used to classify 4 different classes namely water, barren land, agricultural land and green land. Further, the changes were detected in terms of area of different regions. A novel model in [15] namely faster region convolutional neural network was proposed to detect the ocean internal wave stripes at various scales.

The proposed Time-fitting algorithm and pixel classification method were used [16] to classify the vegetation dynamics in Landsat image and the quantitative analysis proved that the technique is more powerful in terms of accuracy.

The experimental result in [17] examines the building damages through satellite images using CNN classification technique. This approach was using the multi-resolution image data as the inputs. A region oriented boundary detection technique was proposed in [18], to detect the boundaries of different degrees of complexity in polarimetric satellite images. A deep neural network based classification technique was implemented in [19] to classify the remotely sensed images and this work yields an accuracy of 94.12%. The Constant False Alarm Rate was used in [20] to detect bright pixels of target. Further, the pixel classification method was developed to classify 4 different classes namely grass, shadow, tree and road. The Maximum Likelihood Classifier is used in [21] to enhance the accuracy of the classification and minimize the variance while measuring the damage during the disaster period. A band selection algorithm was developed in [22] for classifying three different types of hyperspectral images and the results of the experiment proves that the proposed method yields better accuracy Bhattacharyya distance.

The Section 2 of this manuscript highlights the motivation of the research work. The proposed Adaptive Classification (AC) algorithm is illustrated in Section 3. The Section 4 deals with the results of the proposed work. Finally, Section 5 elaborates the conclusion.

2. MOTIVATION OF THE PROPOSED WORK

SAR image classification is an important technique in remote sensing and earth observatory field with growing applications. Since, detecting and monitoring the changes in natural resources such as water body and non-water body are purely depends on the image classification techniques. Similarly pattern recognition, object recognition and tracking are evolved from the direct result of classification methods. Also, the accurate classification decides to predict the changes occurred in geo-spatial natural resources in future.

Because of these wide applications, the image classification is of great significance in satellite image processing. Hence, there is no great initiative was taken, an effort has been made through this paper to address this research issue.

3. PROPOSED ADAPTIVE CLASSIFICATION (AC) ALGORITHM

While interpreting the SAR image, there are certain most important properties that enable the observer to detect and recognize the objects from the surroundings. In this paper, the color, texture and correlation were considered for extracting the features from the image and is further used for image classification.

Color feature is more effective and convenient for the identification of object details. It measures the electromagnetic radiation reflected by the terrain areas. The colors are emphasizing various surface properties and enhance the human ability to interpret surface materials. High intensity returns appear as light tones on an image, while low signal returns appear as dark tones on the imagery. SAR image color can be defined as the average intensity or strength of the backscattered signal.

Texture is the property of arrangement of repetitions of tone or color in an image, refers to the visual quality of the roughness or smoothness of an image region. It is often used to identify objects which are too small to resolve individually from satellite, i.e., road region and trees in a forest. The textures can be classified into rough and smooth textures. The grey level in rough textures change abruptly whereas the smooth textures are mostly even and uniform surfaces, such as tiles of a floor, fields, grasslands and mountains.

Correlation feature decides how far one pixel dependent on neighboring pixels and it specifies the spatial arrangement of pixels in an image. It indicates the closeness of pixels in an image and is the most important feature to extract the features from real time images such as SAR and Landsat images. If one pixel is dependent of its neighbouring pixels, it is known as correlated, otherwise it is called as uncorrelated.

Earlier, the SAR images were classified using NN, KNN, SVM, deep learning and machine learning techniques. But, those techniques does not able to classify different regions, also its performance becomes poor in terms less accuracy.

The deep learning and machine learning techniques yields more complex and time consuming methods. In order to troubleshoot these drawbacks, minimize the outlier effects and enhance the accuracy of the classification, in this paper an Adaptive Classification technique is introduced. Here, an adaptive strategy is incorporated in k-Nearest neighbor algorithm and is effectively improves the rate of accuracy and minimizes the mis-classification rate even when the huge dataset is used.

The proposed Adaptive Classification algorithm comprised of the following steps:

Assume that $\boldsymbol{X} = \{\boldsymbol{X_1}, \boldsymbol{X_2}, \ldots \boldsymbol{X_N}\}$ is a training set and Y= $(\boldsymbol{Y_1}, \boldsymbol{Y_2})$ is a test input. The each element $\boldsymbol{X_i} = (\boldsymbol{x_{i1}}, \boldsymbol{y_{i1}}, \boldsymbol{l})$ of $\boldsymbol{X}$ is a 3-dimensional vector. The first and second elements in $\boldsymbol{X_i}$ is a 2-dimensional data and the third element '$\boldsymbol{l}$' is a class number of the data.

Input: Filtered SAR Image

Output: Classified SAR Image

for i = 1 to N **do**
    $D[i] = \sqrt{(x_{i1} - y_1)^2 + (y_{i1} - y_2)^2}$
end for
Sort the Array D in ascending order
for i = 1 to k **do**
    $S[i] = D[i]$
    $C[i] = x_i[3]$
end for
for i ← 2 to k **do**
    $AC(x_i) = ((D_{max} - D[i]) / ((D_{max} - D_{min}))$
end for
$AC(x_1) = \max(AC(x_i))$
for i ← 1 to k **do**
    fw[i] ← 0
end for
for i = 1 to k **do**
    for j = 1 to k **do**
        if(C[j]! = 0)**then**
            if(C[i] == C[j])**then**
        C[j] = 0
        $fw[i] = fw[i] + AC[X_i]$
            end if
        end if
    end for
end for
Compute the maximum value in the array fw
The test input y belongs to the corresponding class of fw_{max}.

4. EXPERIMENTAL RESULTS

In this research, the color, correlation and texture features were calculated from real time SAR images. Based on these features, 8 different types of regions were classified using proposed Adaptive classification algorithm. All the images are captured by the Indian Metrological Department-Government of India, Satellite Imaging Corporation, Digital Globe- vendor of space imagery and geospatial content. The Table 1 shows the color features, Table 2 shows the texture features and Table 3 shows the correlation features.

Table 1: Extraction of Color Features

S.No	Class name	Minimum			Maximum			Average		
		R	G	B	R	G	B	R	G	B
1	River	15	15	0	24	22	15	19.5	18.5	7.5
2	Forest	15	22	15	65	80	70	40	51	42.5
3	Barren land	108	92	85	160	135	135	134	113.5	147.5
4	Building	107	105	98	193	195	191	150	150	149.5
5	Sea	50	78	104	76	101	161	63	89.5	132.5
6	Transport	81	75	65	114	111	103	97.5	93	84
7	Agricultural Land	53	77	70	90	93	90	71.5	83.5	80
8	Lake	0	17	33	15	36	53	7.5	26.5	43

Table 2: Extraction of Texture Features

S.No	Class name	Grayscale (MIN)	Grayscale (MAX)	Avg. Gray	Texture (MIN)	Texture (MAX)	Avg Texture
1	River	14	22	18	3	6	4.5
2	Forest	20	76	48	7	11	9
3	Barren Land	95	140	117.5	5	12	8.5
4	Building	105	194	149.5	16	32	24
5	Sea	74	100	87	1	3	2
6	Transport	76	111	93.5	19	38	28.5
7	Agricultural Land	71	92	81.5	10	25	17.5
8	Lake	15	33	24	1	5	3

Table 3: Extraction of Correlation Features

S.No	Class name	R(mean)	G(mean)	B(mean)	Correlation
1	River	19.5	18.5	7.5	0.75
2	Forest	40	51	42.5	0.814
3	Barren Land	134	113.5	147.5	-0.999
4	Building	150	150	149.5	0.798
5	Sea	163	89.5	132.5	-0.511
6	Transport	97.5	93	84	0.556
7	Agricultural Land	71.5	83.5	80	0.399
8	Lake	7.5	26.5	43	-0.352

The image classification plays vital role in image and signal processing applications. The change detection of geo-spatial natural resources, climate change, locating natural resources such as water regions, forests, vegetation areas, land covers, pattern recognition and object identification are purely lies on the results of image classification algorithms.

In this research, there are 8 different types of classes were classified using proposed Adaptive Classification algorithm. All the images are captured by the Indian Metrological Department - Government of India and Digital Globe- vendor of space imagery and geospatial content.

The table 4 shows the color legends used for different geo-spatial natural resources as per the GIS manual. In this research, there are 8 different types of classes namely, barren land, agricultural land, forest land, transport region, building region, sea region, river region and lake region were classified using proposed AC algorithm.

Here, Figure.1, Figure.3, Figure.5 are the input SAR images. In this work, a set of 3 images are captured in the same time slot at the same region across the year 2016, 2017 and 2018. The SAR images of scale 867 x 516 as shown in Figure.1 Figure.3 and Figure.5 are captured in 'Egmore Chennai'. Then, the AC algorithm is applied to all these SAR images separately and the resultant classified images are given below in the format: classified image- input image Figure.2-Figure.1, Figure.4-Figure.3 and Figure.6-Figure.5.

Table 4: Color Legends for different geo-spatial classes

Class name	Color value with name (As per GIS manual)	Color Pattern (As per GIS manual)
Sea	0,0,255 (Blue)	
River	65,105,255 (Royal Blue)	
Lake	30,144,255 (Dodger Blue)	
Building	255,255,0 (Yellow)	
Barren land	255,255,255 (White)	
Forest	0,255,0 (Green)	
Agriculture	140,181,0 (Apple/Citrus/Lime Green)	
Transport	0,0,0 (Black)	

Figure 1:SAR Input Image (2016)

Figure 2: Classified Image (2016)

Figure 3: SAR Input Image (2017)

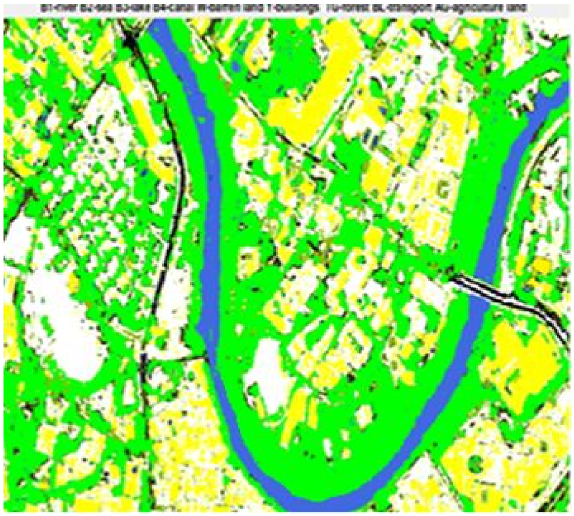

Figure 4: Classified Image (2017)

Figure 5:SAR Input Image (2018)

Figure 6: Classified Image (2018)

The SAR image of 'Chennai Egmore' region which is captured in the year 2018 is classified by proposed AC algorithm and is shown in Figure 9. Then, the classified image is compared with Nearest Neighbor classifier in Figure.7. Further, the image is compared with K-Nearest Neighbor algorithm in Figure.8.

Figure 7: Classified Image (2016) usingNearest Neighbor Nearest algorithm

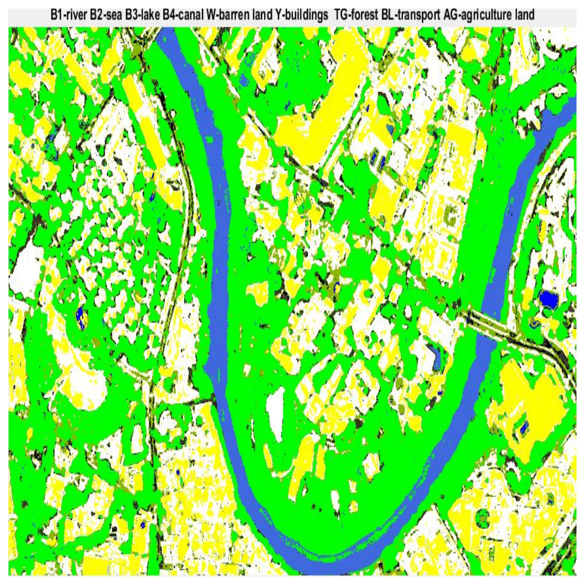

Figure 8: Classified Image (2016) using K- Nearest Neighbor Nearest algorithm

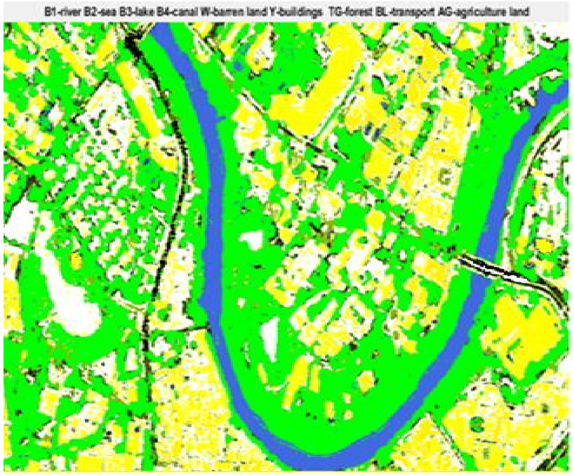

Figure 9: Classified Image (2016) using proposed Adaptive Classifier

The Figure.10 shows the SAR input image of size 175 x 180, which is captured in 'Kochi' region. The image is subjected to combined PCA based K-Means Clustering with Support Vector Machine (SVM) and the classified output is shown in Figure.11. Then, the same input image is classified through the proposed Adaptive Classifier and is shown in Figure 12.

Figure 10: Input Image(Kochi region)

Figure 11: Classified Output Image using combined PCA based K-Means clustering with SVM

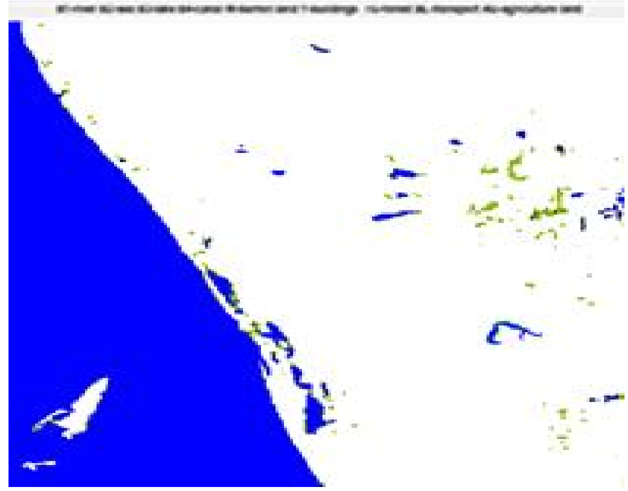

Figure 12: Classified Output Image using Proposed Adaptive Classifier

The SAR image classification accuracy is computed by using following relation:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

In this paper, 198 SAR images were considered as training inputs. Out of 198 images, the proposed AC algorithm classifies 93 images were True positives, 94 images were True negatives, 9 images were False Positives and 2 images were False negatives.

Therefore the accuracy of the classification is

$$= \frac{93 + 94}{93 + 94 + 9 + 2} = 94.44\%$$

Table 5: Comparative results of Overall Accuracy

S.No	Methods	Overall Accuracy in %
1	NN	86.36 (Tested with 198 images)
2	KNN	90.40 (Tested with 198 images)
3	SVM	91.97 (Tested with 198 images)
4	Proposed AC algorithm	94.44 (Tested with 198 images)

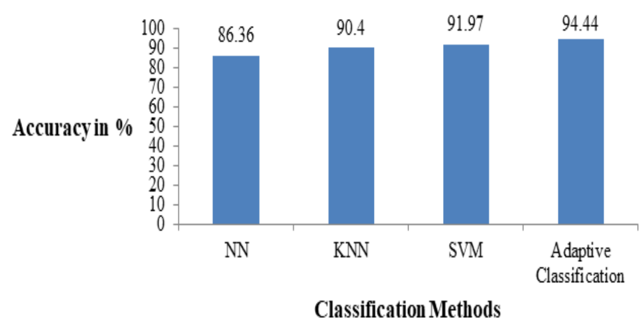

Figure 13: Graphical representation of Classification accuracy of different algorithms

The Table 5 shows the comparative results of overall accuracy of the classification. The accuracy of the Nearest Neighbor algorithm is 86.36%, the accuracy of the K-Nearest Neighbor Algorithm is 90.40%, the SVM produces 91.97% of accuracy and the proposed AC algorithm produces 94.44% of accuracy. The graphical representation of Classification accuracy of different algorithms is shown in Figure.13.

5. CONCLUSION

The SAR image classification is the most noticeable process in the area of satellite image processing. Here, the color, correlation and texture features were extracted from SAR images and as based on the extracted features, 8 different classes in SAR image namely, lake, river, sea, forest, barren land, building, agricultural land and transport regions were classified successfully. The AC algorithm was formulated through this paper to categorize these 8 different classes.

Based on the inference from the results, the Nearest Neighbor algorithm is producing more mis-classification rate in road and river regions also it failed to classify the building regions. Hence, it is less accuracy rate in classifying the above regions. The K-Nearest Neighbor algorithm is producing more outliers in river and building regions as well. Hence, the accuracy of K-Nearest Neighbor algorithm is poor. The Support Vector Machine leads to more mis-classification rate in barren land region also it works only for very limited number of classes broadly water body and non-water body.

As based on the results, the proposed Adaptive Classification algorithm attains best performance in classifying more number of classes (8 different classes). Also, it is more accurately differentiates these classes and the accuracy rate of the proposed algorithm outperforms the existing classification algorithms namely NN, KNN and SVM. Therefore, the proposed AC algorithm effectively eliminates the above mentioned limitations in NN, K-NN and SVM and proved the results with outstanding while classifying multiple number of classes. The other key aspect of this algorithm is that it works well on real time color image.

ACKNOWLEDGEMENT

We wish to duly acknowledge Indian Metrological Department, Digital Globe and Satellite Imaging Corporation for providing satellite data used in this research work. We express our sincere thanks and gratitude to the reviewers for their constructive comments, valuable inputs and suggestions. We also highly pleased to our university for providing such a platform to carry out this research paper.

REFERENCES

1. NevrezImamoglu, PascualMartínez -Gomez, Ryuhei Hamaguchi, Ken Sakurada, Ryosuke Nakamura, **Exploring Recurrent and Feedback CNNs for Multi-Spectral Satellite Image Classification**, in *Int. Conf. Complex Adaptive Systems, Elsevier*, pp. 162–169, 2018. https://doi.org/10.1016/j.procs.2018.10.325
2. DebabrataSamanta, GoutamSanyal, **A novel approach of SAR image processing based on Hue, Saturation and Brightness (HSB),***Procedia Technology, Vol.4, Elsevier*, pp.584-588, 2012. https://doi.org/10.1016/j.protcy.2012.05.093
3. Xuemei Zhao, Lianru Gao, Zhengchao Chen, Bing Zhang,Wenzhi Liao, **CNN-based Large Scale LandsatImage Classification**, *in Proc. of Int. Conf. APSIPA*, pp.611-617, 2018.
4. Angel Ferran, Sergio Bernabe, Pablo G. Rodríguez and Antonio Plaza, **A Web-Based System for Classification of Remote Sensing Data**, *IEEE of Selected topics in Applied Earth Observations and Remote Sensing*, Vol.6, No.4, pp.1934-1948, August 2013.
5. Aditya Vailaya, Mario A. T. Figureueiredo, Anil K. Jainand Hong-Jiang Zhang, **Image Classification for Content-Based Indexing**, *IEEE Trans.Image Process*, Vol.10, No.1, pp.117-130, January 2001.
6. Kshitij Mishra and P. Rama Chandra Prasad, **Automatic Extraction of Water Bodies from Landsat Imagery Using Perceptron Model**, *Journal of Computational Environmental Sciences, Hindaw*i, pp.1- 9, 2015. https://doi.org/10.1155/2015/903465
7. Rob J.Dekker, **Texture Analysis and Classification of ERS SAR Images for Map Updating of Urban Areas in The Netherlands,** *IEEE Trans. on Geoscience and Remote Sensing*, Vol.41, No.9, pp.1950-1958, September 2003.
8. AziguliWulamu, Zuxian Shi ,Dezheng Zhang and Zheyu He, **Multiscale Road Extraction in Remote Sensing Images**, *Computational Intelligence and Neuroscience, Hindwai*, Vol. 2019, pp.1-9. https://doi.org/10.1155/2019/2373798
9. HaikelAlhichri , Essam Othman , Mansour Zuair , NassimAmmour and YakoubBazi, **Tile-Based Semisupervised Classification of Large-Scale VHR Remote Sensing Images**, *Journal of Sensors, Hindawi*, pp.1-14, 2018. https://doi.org/10.1155/2018/6257810
10. Lei Xie, Hong Zhang and Chao Wang, **Water-body Types Classification Using Radarsat-2 Fully Polarimetric SAR Data**, in *Proc. of Int. Conf. on Aerospace Electronics and Remote Sensing Technology (ICARES)*, 2015.
11. R. Jenice Aroma and KumudhaRaimond, **A novel two-tier paradigm for labeling water bodies in supervised satellite image classification**, in *Proc.of International Conference on Signal Processing and Communication (ICSPC'17)*, pp.384-388, 2017.

12. Dongdong Guan , Deliang Xiang , Ganggang Dong , Tao Tang ,Xiaoan Tang, and GangyaoKuang, **SAR Image Classification by Exploiting Adaptive Contextual Information and Composite Kernels**, *IEEE Trans. on Geoscience and Remote Sensing*, Vol.15, No.7, pp.1035-1039, 2018.
13. Putu Virga NantaNugraha, Sunu Wibirama1, RisanuriHidayat, **River Body Extraction And Classification using Enhanced Models of Modified Normalized Water Difference Index At YehUnda River Bali**, *International Conference on Information and Communications Technology (ICOIACT)*, pp.337-342, 2018.
14. K. Radhika, S. Varadarajan**, A neural network based classification of satellite images for change detection applications,***Cogent Engineering*, pp.1-9, 2017. https://doi.org/10.1080/23311916.2018.1484587
15. BaoSude , MengJunmin , Sun Lina, Liu Yongxin, **Detection of ocean internal waves based on Faster R-CNN in SAR images**, *Journal of Oceanology and Limnology*, Vol.38, No.1, pp.55-63.
16. Jiaxing Xu, Hua Zhao, Pengcheng Yin, Duo Jia and Gang Li, **Remote sensing classification method of vegetation dynamics based on time series Landsat image: a case of opencast mining area in China**, *EURASIP Journal on Image and Video Processing*, pp.1-10, 2018.
17. D.Duarte, F.Nex, N. Kerle, G. Vosselman, **Satelliteimage classification of building damages using airborne and satellite image samples in a deep learning approach**, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume IV-2, pp.89-96, 2018. https://doi.org/10.5194/isprs-annals-IV-2-89-2018
18. Alejandro C. Frery, Julio Jacobo-Berlles, Juliana Gambini, Marta E. Mejail, **Polarimetric SAR image segmentation with B-splines and a new statistical model**, *Journal of MultidimSyst Sign Process*, 2010, pp.319-342.
19. S. Jayanthi, C. Vennila, **Advanced Satellite Image Classification of Various Resolution Image Using a Novel Approach of Deep Neural Network Classifier**, *Wireless Personal Communications*, Springer, pp.357-372, 2019. https://doi.org/10.1007/s11277-018-6024-7
20. ShyamKuttikkad and Rama Chellappa, **Statistical modeling and analysis of high-resolution SyntheticAperture Radar images**, *Journal of Statistics and Computing*, Vol.10, pp.133–145, 2000. https://doi.org/10.1023/A:1008994309819
21. Darala Siva, PolaiahBojja, **MLC based Classification of Satellite Images for Damage Assessment Index in Disaster Management,** *International Journal of Advanced Trends in Computer Science and Engineering*, 8(6), 2825 – 2830, November - December 2019. https://doi.org/10.30534/ijatcse/2019/24862019
22. Mohammed Lahlami , MounirAitKerroum , Youssef Fakhri, **Band Selection by Divergence Distance Based on Gaussian Mixture Model for Hyperspectral Image Classification,** *International Journal of Advanced Trends in Computer Science and Engineering*, 8(5), 2330-2338, September - October 2019. https://doi.org/10.30534/ijatcse/2019/72852019