International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-3, January 2020

Land Cover Classification of Multispectral Remotely Sensed Data Based On Channel Relative Spatial Pattern

M. Christy Rama, D. S. Mahendran, T. C. Raja Kumar

***Abstract:** Land spread grouping of remotely detected pictures includes characterizing the satellite pictures into various land use/land spread classes, for example, water, urban region, crop land, backwoods and so on. To screen the ecological effects. Highlights like shading and surface assume a prevalent job in land spread grouping. Picking an appropriate shading space is a significant issue for shading picture order. The quality of various shading spaces, for example, RGB, HSV, LUV have been coordinated successfully to make sense of the element vector. In this paper, another Channel Relative Spatial Pattern (CRSP) is proposed for separating the surface highlights. The extricated highlights are prepared and tried with Random Forest (RF) classifier. Examinations were directed on IRS LISS IV datasets and the outcomes were assessed dependent on the disarray grid, characterization exactness and Kappa insights. The proposed surface example is additionally contrasted and the (LBP), (LDP) and (LTrP) surface techniques and the precision appraisal results have demonstrated exceptionally encouraging outcomes for the CRSP surface example.*

***Keywords:** Confusion matrix, chromaticity, color percentile, entropy, integrative co-occurrence matrix, random forest.*

I. INTRODUCTION

Remote detecting picture arrangement is a significant research territory in the field of ethereal and satellite picture investigation to order pictures into a discrete arrangement of important land spread classes as per the picture substance. Exceptional endeavors have been taken in creating different remote detecting picture arrangement techniques due to its critical job for a wide scope of uses, for example, geospatial object identification, regular perils location, geographic picture recovery, LULC assurance, vegetation mapping, condition checking and urban arranging [1].

Revised Manuscript Received on January 30, 2020.
* Correspondence Author
M. Christy Rama*, Research Scholar, Department of Computer Science, Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli, Tamil Nadu, India. E-mail: christyrama@gmail.com.
D. S. Mahendran, Principal, Aditanar College of Arts and Science, Tiruchendur, Tamil Nadu, India E-mail: dsmahe65@yahoo.com.
T. C. Raja Kumar, Associate Professor, Department of Computer Science, St. Xavier's College, Tirunelveli, Tamil Nadu, India. E-mail: rajazion@yahoo.co.in.

Shading is an essential factor in extricating data from pictures and shading histograms are normally utilized in content-based recovery frameworks and have demonstrated to be extremely valuable.

Be that as it may, the worldwide portrayal is poor as it needs data about how the shading is conveyed spatially. It is critical to bunch shading in confined locales and to combine shading with textural properties. Both shading and surface are remarkable highlights of the picture [2]. Picture characterization calculations ought to be intended to separate solid segregating power highlights and preparing the fitting classifier to group the picture. Characterization of pictures into semantically characterized classes is an essential issue in remote detecting. Every area in the preparation information is spoken to by a component vector. The component vector and name are then applied to some factual learning structure that maps highlight vectors to probabilities of having a place with various classes [3].

II. LITERATURE SURVEY

An assortment of surface models are appeared in writing. As per include significance investigations, multispectral force highlights dependent on a few channels were more helpful than those dependent on one channel [4]. Hopkinson et al. (2016) establish the cover in single-channel force esteems among various land spread classes was much to the point that it keeps precise order from single channel information [5]. Spatial phantom techniques can develop the precision of the land-spread/usage order for remote detecting symbolism [6]. Dark level co-event lattice (GLCM) [7], nearby double examples (LBP) [8] and gabor include [9] and so on. Are the generally utilized surface highlights for breaking down satellite pictures [10, 11]. Neighborhood paired example (LBP) administrator has been displayed for turn invariant surface arrangement. Nearby stage quantization and LBP have been dissected for surface portrayal of land-spread order of remote detecting picture information [12]. Wei et al. utilized a component level combination that links a couple of various highlights, for example, Gabor, LBP highlights and ghastly includes for characterization of hyper unearthly symbolism [13]. In (14) the prevailing level parallel example (DLBP) is applied to catch the commanding examples in surface pictures. The DLBP highlights come up short on the thought of far off pixel connection. B. Uma Shankar et al.

indicated that the wavelet highlights got from wavelet change on a picture gives spatial and ghastly qualities of pixels and improves the order precision [15]. The LBP able to considered as a common definition to create miniaturized scale designs in nearby neighborhoods. LBP technique isn't caught the prevailing data in huge scale structures because of scanty purposes of the pixels. To beat this confinement, Zhanget al.

Proposed another descriptor called the (LDP) which encodes the higher-request subsidiary data that contains increasingly itemized discriminative highlights that the principal request LBP can't get from a picture [16]. Murala et al. discovered that the single high request subsidiary heading association of LDP be able to reached out to the two higher request subordinate course (2D) connections as far as the LTrP which receives both the level and vertical high request subordinate bearings. LTrP encodes with four unmistakable qualities by utilizing 0 & 90 headings which eliminates more discriminative data than the LDP which just thinks of one as dimensional bearing with two particular qualities [17]. Li et al. investigated deliberately the exhibition of different normally utilized regulated classifiers under various conditions and regarded that RF was the directed classifier generally reasonable for picture arrangement. RF classifiers perform better at handling excess highlights [18]. RF is better than standard arrangement strategies, for example, a straightforward choice tree since it allows an expanded separation between the various classifications of the examination zone [19]. The RF methodology is of incredible enthusiasm for multispectral picture grouping since this methodology is nonparametric and it additionally gives an approach to deciding the significance of the individual factors in arrangement. Arbitrary woodlands are effective to assess and their great order execution has been demonstrated in numerous concentrates in remote detecting just as picture handling [20, 21].

In this paper, a Channel Relative Texture Pattern (CRSP) is proposed to separate the surface highlights and the relationships between's the shading channels are considered while registering the surface highlights. The characterization exactness of the proposed surface example is additionally contrasted and the well-known surface examples, for example, LBP, LDP and LTrP.

III. PROPOSED METHODOLOGY

A. Architectural Model

The proposed land spread request approach has concealing and surface segment extraction part and portrayal part. The planning tests are removed randomly beginning from the soonest phase of unquestionable land spread classes of remotely distinguished pictures. These planning tests are used to recognize the parameters of the classifiers. Resulting to studying the classifier, to assemble the land fronts of the entire picture. Concealing and surface features expelled from various concealing spaces are used to set up the unpredictable boondocks Classifier. The classifier reestablishes the class names reliant on its previous learning of planning tests. The healthiness of portrayal based upon the selection of features.

The going with figure (Fig-1) shows the designing model of the suggested work and the component extraction procedures for land spread request.

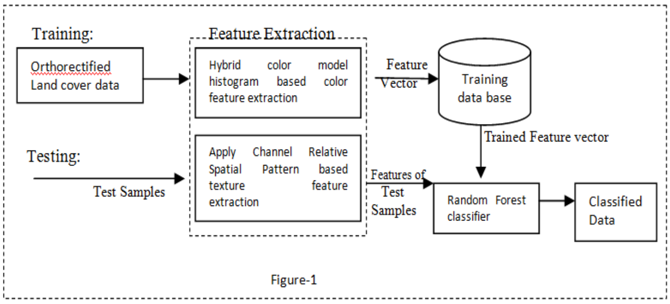
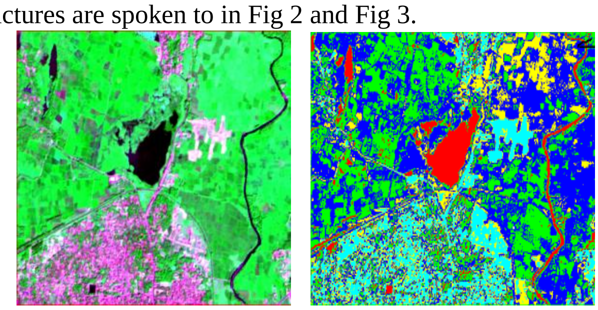


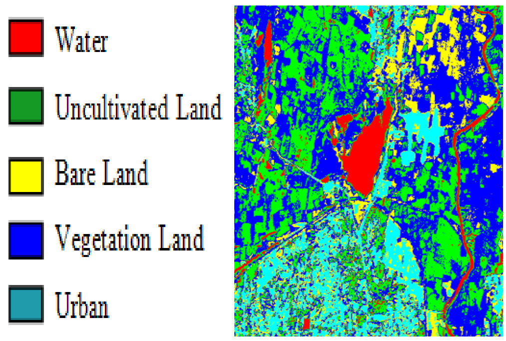
Fig 1 Architectural model of the proposed land spread course of action procedure.

B. Study Area and Datasets

The remotely detected pictures under investigation are Resouresat2 satellite, LISS-IV (sensor) orthorectified pictures provided by (NRSC), Hyderabad, India. The pictures were reserved in Jan. 2012 with a spatial goals of 5.8m. Groups 2, 3 and 4 of LISS-IV information are joined together to shape a RGB picture. The investigation zone centers the territories in and around the spots Nagarcoil, Thuckalai in Kanyakumari locale of Tamil Nadu, India. The picture of Nagercoil locale of size 552 X 414 spreads the scope of 8.2145236 to 8.195756 and longitude of 77.4189782 to 77.443809. Picture of Thuckalai of size 786 X 643 spreads the district of scope 8.254797 to 8.2255779 and longitude 77.302411 to 77.3378509. The Ground Truth (GT) of these investigation territories have been taken from ENVI. The pictures of the examination region, their GT and the arranged pictures are spoken to in Fig 2 and Fig 3.

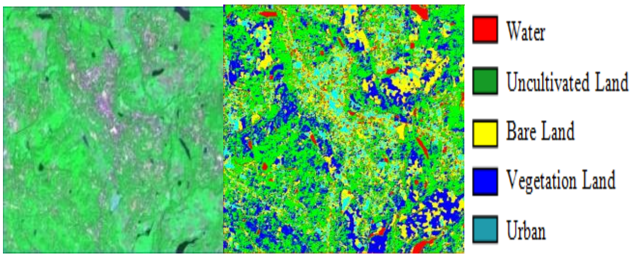


2. A Nagercoil-RGB Image 2.b. GT

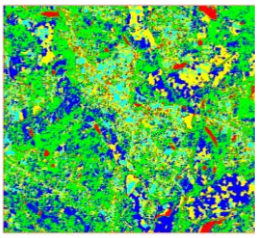


2. c GT label. 2. d Classified Data.

Fig 2 IRS LISS IV RGB image, labeled GT and classified image of Nager-coil data.



3a Thuckalai-RGB Image 3b GT 3 c GT Label



3 d Classified Data

Fig 3 IRS LISS IV RGB image, labeled GT and classified image of Thuckalai data.

C. Feature Extraction Techniques

Color Features - Hybrid Color Model

Shading highlights are commonly spoken to by the shading histogram. HSV shading space is utilized in this work since it is more perceptually uniform than other shading spaces. A half and half shading model in which the (H) estimations of HSV shading gap spaces and luminance (L) estimations of LUV shading space are joined organized to build the histogram of 90 containers utilizing (Eqn-1) as given beneath [23].

$$H=\begin{cases} 0 & h \in [340, 20] \\ 1 & h \in [20, 50] \\ 2 & h \in [50, 75] \\ 3 & h \in [75,140] \\ 4 & h \in [140,160] \\ 5 & h \in [160,195] \\ 6 & h \in [195,285] \\ 7 & h \in [285,305] \\ 8 & h \in [305, 340] \end{cases} \qquad L=\begin{cases} 0 & l \in [0, 10] \\ 1 & l \in [10, 20] \\ 2 & l \in [20, 30] \\ 3 & l \in [30, 40] \\ 4 & l \in [40, 50] \\ 5 & l \in [50, 60] \\ 6 & l \in [60, 70] \\ 7 & l \in [70, 80] \\ 8 & l \in [80, 90] \\ 9 & l \in [90,100] \end{cases} \quad (1)$$

Texture Feature (Proposed Method - Channel Relative Spatial Pattern (CRSP))

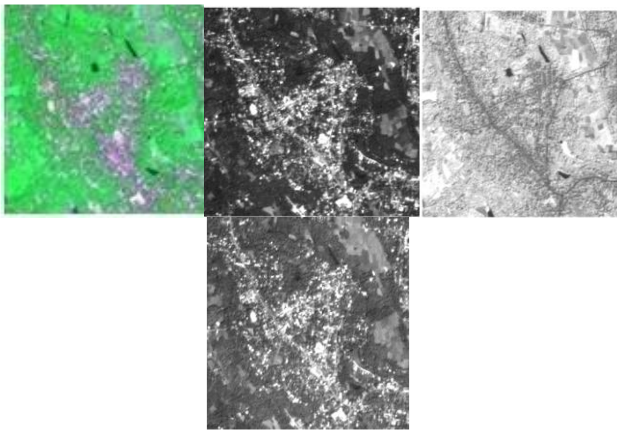
In this paper surface highlights are extricated utilizing the proposed Channel Relative Spatial Pattern (CRSP). The RGB picture of size (345x313) M X N is taken and the pixels are masterminded in a vector group. For every pixel 'I', three sorts of CRSPs are separated for the RGB channels dependent on the accompanying formulae 2-4.

$$R_{CRSP\,(i)} = \max((G_{i-1}), (B_{i+1})) \quad (2)$$

$$G_{CRSP\,(i)} = max((B_{i-1}), (R_{i+1})) \quad (3)$$

$$B_{CRSP\,(i)} = max((R_{i-1}), (G_{i+1})) \quad (4)$$

Give us a chance to take the RGB picture of size 345x313 in figure 4a (Part of Thuckalai Image). The RG B Channel esteems for an arrangement of 10 pixels of this picture are recorded in Table-1. The pictures comparing to the RGB diverts are appeared in fig 4.



4 a RGB Image 4 b. R Channel 4 c. G Channel 4 d. B Channel.

Fig 4 The RGB Channel images of the sample RGB image.

Table-1 R G B Channel values for a list of pixels in RGB image.

R: (i)

62	53	56	68	71	62	50	53	53	53

G: (i-1)

218	215	228	238	225	202	206	221	218	224

B: (i+1)

106	98	106	110	110	98	81	81	85	85

For each pixel, the RCRSP, GCRSP and BCRSP values are extracted as per equations (2 to 4) and are exhibited in the following table (Table-2). The images of such channels are also shown in Fig-5.

Table-2 RCRSP, GCRSP and BCRSP Channel prices of the R G B Channels.

R_{CRSP}

225	218	215	228	238	225	202	206	221	218

G_{CRSP}

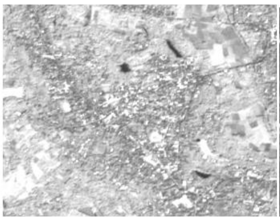
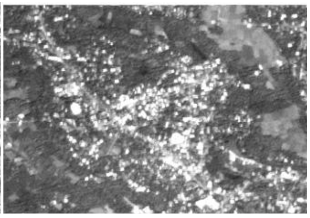
93	106	98	106	110	110	98	81	81	85

B_{CRSP}

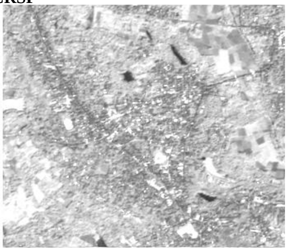
215	228	238	225	202	206	221	218	224	242

Retrieval Number: B7230129219/2020©BEIESP
DOI: 10.35940/ijitee.B7230.019320
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication (BEIESP)

5.a R_{CRSP} 5.b G_{CRSP}



5. c B_{CRSP}

For every district, histograms of 256 canisters are taken for each RCRSP, GCRSP and BCRSP designs and a surface component vector of 768 containers is extricated by connecting these histograms. This surface element and the cross breed shading model based shading highlight vector of 90 canisters are joined together to dole out class names for every district.

Algorithm

The remotely detected pictures have been separated into districts of different classes dependent on their ground truth. Shading and surface highlights are separated from every locale. The separated highlights are prepared and tried by irregular timberland classifier. In the testing stage, the classifier allocates class marks to the areas dependent on its earlier learning of preparing tests.

Input:

The Slightly Detected image RS_{img}

Output:

Classified Image

// Block-1Training Phase -Feature Extraction from each region of the image

For each Training ROI (Component c) ε RS_{img}

$HSV_c \leftarrow$ RGB2HSV (c) // RGB to HSV

$LUV_c \leftarrow$ RGB2LUV (c) // RGB to LUV

$Colorfeat_{(90)} \leftarrow$ HCM-H (HSV_c, LUV_c) // hybrid color model Histogram

$Textfeat_{(768)} \leftarrow$ Channel Relative Spatial Pattern CRSP (RGB_c)

$TrainingFeat_{(858)} \leftarrow$ TrainingFeat U {Colorfeat, Textfeat}

End for

IV. PERFORMANCE EVALUATION

GT of the investigation zones have been taken from ENVI. The datasets are part into districts dependent on their ground truth. Shading and surface highlights are removed from every area. Preparing tests (districts) are chosen arbitrarily from unmistakable land spread classes of remotely detected pictures. Shading surface highlights of 858 containers are utilized to prepare and order the dataset agreeing to the calculation in area 4. RF classifier with 160 trees is utilized in this examination. A disarray network is utilized as the quantitative technique for portraying picture order precision. The misclassification is likewise related to perplexity network. The size of perplexity framework is c x c where "c" is the measure of classes. In the event that a locale that has a place with class ci is effectively characterized, at that point an include is included passage (i,i) of perplexity lattice. On the off unplanned that a locale has a place with class ci is mistakenly characterized to class cj, at that point a check is added to the section (i,j) of disarray framework. The corner to corner sections mark right characterizations while the upper and lower slanting passages mark erroneous groupings. The exhibition of this characterization strategy is assessed utilizing different measurements, for example, exactness, explicitness, affectability and f-score and are classified (Table 3 and Table 4). The general precision (OA) is the level of effectively characterized pixels though the normal exactness (AA) speaks to the normal of the individual class correctnesses. Kappa coefficient additionally endeavors to increase current standards for surveying the exactness of the arrangement strategy. The standard surface techniques, for example, LBP, LTrP are applied to group the Nagercoil dataset by taking the shading highlight from the half and half shading model as in eqn-2 and the outcome is appeared in table-5 . The proposed calculation delivers promising outcomes when contrasted with the current LBP, LDP and LTrP surface examples and is additionally spoken to as a diagram in fig-6.

Accuracy

The ratio of correctly classified instances to total amount of instances.

Accuracy= (TP+TN)/ (TP+FP+TN+FN)

Where:

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

The above functions values are acquire from the confusion matrix

Sensitivity

The sensitivity or True Positive Fraction is defined as the ratio among the Amount of true positive estimates and the Amount of positive instances.

Sensitivity = TP/(TP+FN)

Specificity

The specificity or True Negative Fraction is defined as the ratio between the Quantity of true negative predictions and the Amount of negative illustrations.

Specificity=TN/(TN+FP)

F-Score

F-Score is a grouping of recall and accuracy.
FScore=(2*Precision*Recall)/(Precision+Recall)
Where
Recall=TP/(TP+FN).
Table-3 shows that the Presentation of proposed model using RF – IRS Dataset- Nagercoil region. The analysis shows for various class such as Water, Uncultivated land, Bare Land, Vegetation land, and Urban. From analysis the proposed system provides 99.21% of average accuracy, 96.61% of average sensitivity.
like the Tabel.3. Performance, table 4. Shows that the performance analysis for proposed system using RF – IRS Dataset - Thuckalai region. From the analysis the proposed system archive 99.84% of average accuracy, 99.60% of sensitivity, 99.88% of specificity and the proposed system averagely archive 99.67% of false score.
Tabel.5. and Figure 6. The investigations showed that the proposed surface model performs reliably well when contrasted with the current surface techniques LBP, LDP and LTrP feature extraction technique on various IRS datasets. From the analysis the LTrP based system archive 59.22% of overall accuracy, which is very lower compared to LBP and LDP. From the Kappa score analysis LDP technique archive 53.56% which is very higher compared to LBP and LTrP.

Table-3 Presentation of proposed model using RF – IRS Dataset- Nagercoil region.

NAGERCOIL DATA							
CLASS	ACCURACY	SENSITIVITY	SPECIFICITY	PRECISION	FSCORE	OVERALL Accuracy	KAPPA
Water	0.990196	0.857143	1	1	0.923077	0.9804	0.9739
Uncultivated land	0.980392	0.973684	0.984375	0.973684	0.973684		
Bare Land	0.990196	1	0.98765432	0.954545	0.976744		
Vegetation land	1	1	1	1	1		
Urban	1	1	1	1	1		
Average	0.992157	0.966165	0.99440586	0.985646	0.974701		

Table-4 Performance of proposed system using RF – IRS Dataset - Thuckalai region

THUCKALAI DATA							
CLASS	ACCURACY	SENSITIVITY	SPECIFICITY	PRECISION	FSCORE	OVERALL Accuracy	Kappa
Water	1	1	1	1	1	0.9961	0.9947
Uncultivated land	0.996109	0.98	1	1	0.989899		
Bare Land	0.996109	1	0.994318	0.987805	0.993865		
Vegetation land	1	1	1	1	1		
Urban	1	1	1	1	1		
Average	0.998444	0.996	0.998864	0.997561	0.996753		

Table -5 Performance Accuracy of LBP, LDP and LTrP Methods – IRS Nager-pcoil Dataset.

Class	LBP	LDP	LTrP
Water	0.9271845	0.9466019	0.9320388
Uncultivated land	0.7281553	0.7621359	0.6553398
Bare land	0.8106796	0.8203884	0.8349515
Vegetation land	0.8446602	0.8543689	0.8252427
Urban	0.9417476	0.9466019	0.9368932
Average Accuracy	0.8504854	0.8660194	0.8368932
Overall Accuracy	0.6262	0.665	0.5922
Kappa	0.4738	0.5356	0.4101

Retrieval Number: B7230129219/2020©BEIESP
DOI: 10.35940/ijitee.B7230.019320
Journal Website: www.ijitee.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication (BEIESP)

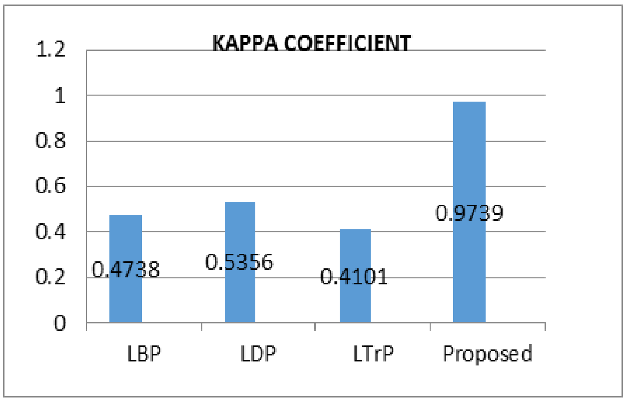


Fig- 6 Relationship of Kappa Co-efficient for the existing and proposed Texture methods.

From the experiments, it is proved that the planned color and smoothness model based RF classifier earnings higher classification accuracy and outperforms other simulations taken for training based on several parameters.

V. CONCLUSION

In this paper another Channel Relative Spatial Pattern is applied for the choice of powerful shading surface highlights for arrangement of multispectral remote-detecting pictures and the examination shows high grouping precision. The separated highlights secure data of the pixel alongside its neighbors both in spatial and phantom spaces. This paper intelligences a solid relationship between's the shading channels. Relationship between's shading channels merits being utilized as a shading descriptor likewise with highlights processed inside shading groups. The investigations showed that the proposed surface model performs reliably well when contrasted with the current surface techniques LBP, LDP and LTrP on various IRS datasets.

REFERENCES

1. Jenicka and Suruliandi A (2016), Texture based land cover classification algorithm using gabor wavelet and anfis classifier. ICTACT Journal on Image and Video Processing, Vol.6, Issue.4, pp.1273-1279.
2. Vadivel A, Shamik Sural, Majumdar A K (2007), An integrated Color and Intensity Co-occurrence Matrix, Pattern Recognition Letters vol.28, pp. 974–983.
3. Jiangye Yuan, DeLiang Wang and Rongxing Li (2014), Remote Sensing Image Segmentation by Combining Spectral and Texture Features, IEEE Transactions on Geoscience and Remote sensing, vol. 52, No.1, doi:10.1109/tgrs.2012.2234755
4. Leena Matikainen, Kirsi Karila, Juha Hyyppa, Paula Litkey (2017) Object-based analysis of multispectral airborne laser scanner data for land cover classification and map updating. ISPRS Journal of photogrammetry and Remote Sensing, Vol.128, pp. 298–313.
5. Hopkinson C, Chasmer L, Gynan C, Mahoney C, Sitar M (2016), Multisensor and multispectral LiDAR characterization and classification of a forest environment. Can. J. Remote Sens. 42 (5), pp. 501–520.
6. Jun Li, Xin Huang, Jose M, Bioucas Dias and Jon Atli (2015) Multiple feature learning for hyperspectral image classification. IEEE transactions on Geoscience and remote sensing, vol.53, No.3, pp.1592 -1606, https://doi.org/10.1109/tgrs.2014.2345739
7. Xin Huang, Xiaobo Liu and Liangpei Zhang (2014), Multichannel Gray Level Co-occurrence Matrix for Multi/Hyperspectral Image Texture Representation, Remote Sensing, vol.6, No.9, pp.8424-8445.
8. Huang L, Chen C, Li W and Du Q (2016), Remote Sensing Image Scene Classification Using Multi-Scale Completed Local Binary Patterns and Fisher Vectors. Remote Sensing, vol.8, no.6, pp.483
9. Jain A, Ratha N K and Lakshmanan S (1997), Object detection using Gabor filters, Pattern Recognition, vol. 30, no. 2, pp. 295-309.
10. Aptoula E (2014), Remote sensing image retrieval with global morphological texture descriptors, IEEE Trans. Geosci. Remote Sens. Vol. 52, no.5, pp. 3023 - 3034.
11. Huang X, Zhang L and Wang L (2009), Evaluation of morphological texture features for mangrove forest mapping and species discrimination using multispectral IKONOS imagery, IEEE Geosci. Remote Sens. Lett., vol. 6, no. 3, pp. 393-397.
12. Musci M, Feitosa R O, Costa G A (2013), Velloso M L F, Assessment of binary coding techniques for texture characterization in remote sensing imagery, IEEE Geosci. Remote Sens. Lett., Vol. 10, No. 6, pp. 1607–1611.
13. Wei Li, Chen Chen, Hongjun Su, Qian Du (2015), Local Binary Patterns and Extreme Learning Machine for Hyperspectral Imagery Classification, IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, Issue.7, pp.3681 – 3693, Doi: 10.1109/TGRS.2014.2381602
14. Liao S, Law WK, Chung CS (2009), Dominant local binary patterns for texture classification. IEEE Trans Image Process,18(5):1107–1118
15. Uma Shankar B, Saroj K. Meher, Ashish Ghosh (2011), Wavelet-fuzzy hybridization: Feature-extraction and land-cover classification of remote sensing images, Applied Soft Computing, vol.11, pp. 2999–3011.
16. Zhang B, Gao Y, Zhao S, and Liu J (2010), Local derivative pattern versus local binary pattern: Face recognition with higher-order local pattern descriptor, IEEE Trans. Image Process., vol. 19, no. 2, pp. 533–544.
17. Murala S, Maheshwari R. P, and Balasubramanian R (2012), Local tetra patterns: A new feature descriptor for content-based image retrieval, IEEE Trans. Image Process., vol. 21, no. 5, pp. 2874–2886.
18. Li M, Ma L, Blaschke T, Cheng L, Tiede D(2016), A systematic comparison of different object-based classification techniques using high spatial resolution imagery in agricultural environments. Int. J. Appl.Earth Obs. Geoinf. 49, pp. 87–98.
19. Rodriguez-Galiano V F, Ghimire B, Rogan J , Chica-Olmo M, Rigol-Sanchez J P (2012), An assessment of the effectiveness of a random forest classifier for land-cover classification, ISPRS Journal of Photogrammetry and Remote Sensing, Vol.67, No.1, 93–104.
20. Gislason P O, Benediktsson J A and Sveinsson J R (2006), Random forests for land cover classification, Pattern Recognition Letters, vol.27, no.4, pp. 294–300.
21. Dongping Ming, Tianning Zhou, Min Wang, Tian Tan (2016), Land cover classification using random forest with genetic algorithm-based parameter optimization, J. Appl. Remote Sens. 10(3), doi: 10.1117/1.JRS.10.035021.
22. Silvén O, Niskanen M, Kauppinen H (2003). Wood inspection with non-supervised clustering, Machine Vision and Applications, 13(5-6) pp. 275-285.
23. Christy Rama M, Mahendran D.S. and Raja Kumar T.C. (2018), A hybrid colour model based land cover classification using random forest and support vector machine classifiers, Int. J. Applied Pattern Recognition, Vol. 5, No. 2, pp.87–100. DOI: 10.1504/IJAPR.2018.092517

AUTHORS PROFILE

Mrs. M. Christy Rama, is the Associate Professor of the Department of Computer science in Rani Anna Government College, Tirunelveli, Tamil Nadu, India. She is doing Ph.D. (Part Time) in Computer Applications at Manonmaniam Sundaranar University, Abishekapatti, and Tirunelveli. She has published research papers in many International journals and conference proceedings.

Dr. T. C. Raja Kumar has been working as Associate Professor of the Department of Computer Science in St. Xavier's College (Autonomous), Tirunelveli. He has completed his M.Sc. (Computer Science) in Bharathidasan University, Tiruchirappali, M.Phil., (Computer Science) in Alagappa University, Karaikudi and Ph.D. (Computer Science) in Manonmaniam Sundaranar University, Tirunelveli.

He is a member of IEEE and also a member of curriculum development committees of various Universities and autonomous Colleges of Tamil Nadu. He has attended so many National and International Seminars, Conferences and published more than 20 scientific papers in National and International Journals. His area of research is Digital image processing and Data mining.

Dr. D. S. Mahendran is the Principal of Aditanar Arts and Science College, Tiruchendur. He did his Ph.D in Computer Science in Alagappa University, Karaikudi. He has organized many Workshops and participated in 20 National and International Conferences. He has acted as a Resource Person in 35 Seminars / Workshops. His papers have been published in 22 National and International journals. 12 students have got their M.Phil., degree and 6 scholars are doing their Ph.D. under his supervision. He has three books to his credit as an editor. He served as an Associate NCC Officer (Naval Wing) for nearly 23 years from 1992 to 2015. He was a member of Board of studies in many Colleges and Universities. His areas of research includes Networking, Image processing and Data mining.

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication (BEIESP)