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Performance Analysis of GA and PSO based Feature Selection Techniques for Improving Classification Accuracy in Remote Sensing Images

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Abstract

Background/Objectives: Feature Selection is applicable to decrease the number of features in various applications wherein the data include hundreds and thousands of features. The objective of this study is to choose Genetic Algorithm for feature selection to obtain better fitness function. **Methods/Statistical Analysis**: Particle Swarm Optimization (PSO) approach is used for selecting the subset from the combination of texture based features and providing the better fitness values. In this paper PSO is used to obtain the feature sets and the performance is compared with genetic algorithm. Support vector machine classifier is used to improve the classification accuracy. **Findings:** The experimental results shows that PSO overall accuracy is improved to LISS IV 1.7%, 1.4% and 2.9% and the kappa coefficient is improved to 0.06%, 0.012% and 0.39% as compared to GA. **Application/Improvements:** The Fitness value obtained by GA is more complex and not accurate. To reduce the complexity and increase the accuracy Particle Swarm optimization is used. Hence PSO improved the quality of texture based images.

Keywords: Artificial Neural Networks, Feature Extraction, Genetic Algorithm, Particle Swarm Optimization, Support Vector Machine

1. Introduction

Genetic Algorithm based[1,2] is complicated and not able to provide the better fitness values for the satellite images. Artificial Neural Networks[3,4] are not intelligent to recognize specific pattern and making an complex task on classification. To overcome the disadvantages of GA, Particle Swarm Optimization is used for random population of solutions and gives the global best values for optimum solutions which leads to better accuracy results. Due to the specifications of Particle Swam optimization, in this paper PSO based optimization is used to optimize the required problem which bringing out the candidates solution. The main advantage of the SVM classifier [5,6] is to analyze the data and recognize the specific pattern. Finally the combination of Particle Swarm Optimization along with SVM classifier gives the specific subsets and better accuracy for the classification of satellite images. The experimental results of previous methods used for feature extraction and the proposed method are compared.

2. Study Area and Data used

The multispectral satellite images from Linear Imaging Self Scanner LISS - IV in Figure 1, Figure 2, Figure 3 used in this study is of Madurai City in Tamil Nadu will be taken by the Indian remote sensing satellite P6. The topography of Madurai city is approximately about 101 m above mean sea level. The land cover features of images used in this study includes process of urban, wasteland, vegetation, water body and hilly region. The image details are

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Figure 1. LISSIV I.

Figure 2. LISS IV II.

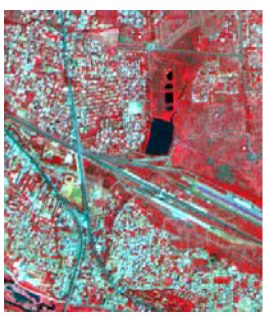

Figure 3. LISS IV III.

Resolution: 5.8 m
Band 2 (green): 0.52~0.59 μm
Band 3 (red): 0.62~0.68 μm
Band 4 (near-Infrared): 0.77~0.86 μm

3. Methodology

In this paper the performance of Particle Swarm Optimization for Feature selection is analyzed. Figure 4 shows the steps of the methodology for feature selection. The Scene was geometrically registered and given to the next stage.

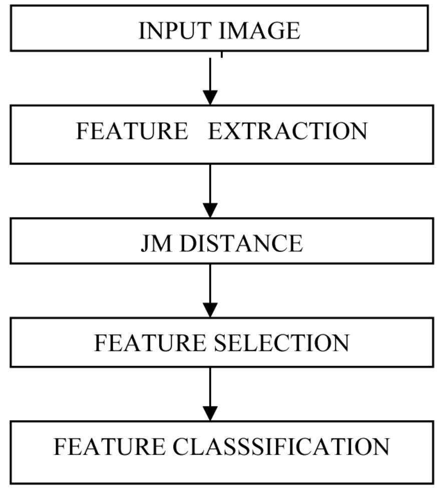

Figure 4. Methodology.

4. Genetic Algorithm

Genetic Algorithm represents the searching process of random once[7,8] which is used to solve the problem of optimization. Genetic Algorithm[9] is the function of solving embarrassed and uninhibited problems that depends upon the natural choice which will be lowering the growth of organisms. The Genetic Algorithm is[10,11] the type of models of specific machine signal that serves their behavior of the metaphor for the function of growth in nature. It includes various operations such as selection, crossover, mutation. Genetic algorithm does not provide the near optimum fitness solutions which was[12] classified by neural networks.

5. Feature Vector Extraction

As Compare to GA, PSO has been used for the initial population and the required subsets will be deployed by the JM distance. Here, fitness is depending upon the JM distance. It does not involve crossover and mutation. The operation is depending upon only velocity of the particle. Only best solution generates the information from the subsets. It also involves one way information sharing. But in GA chromosome generates the information and the population it moves from one group to another in which the obtained fitness function is not near optimum. The following parameters are extracted and stored in the digital library.

$$\text{Mean} \quad \bar{x} = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N} x_{i,j} \tag{1}$$

$$\text{Variance} \quad V = \frac{1}{N^2}\sum_{i=0}^{N}\sum_{j=1}^{N}\left(x_{i,j} - \bar{x}\right)^2 \tag{2}$$

$$\text{Co variance} \quad \operatorname{cov}(x,y) = \frac{\sum_{i=n}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{n-1} \tag{3}$$

$$\text{Standard deviation} \quad \sigma = \sqrt{\frac{\sum\left(x - \bar{x}\right)^2}{n}} \tag{4}$$

5.1 JM Distance

The JM distance[13] is calculated in order to give the best distance of each subsets of the input images. The average JM distance is obtained as

$$J_{ave} = \sum_{i=1}^{L}\sum_{j>i}^{L} p(w_i)p(w_j)J_{ij} \tag{5}$$

$$J_{ij} = \sqrt{2\left(1 - e^{-b_{ij}}\right)} \tag{6}$$

$$b_{ij} = \frac{1}{8}\left(M_i - M_j\right)^T\left(\frac{C_i + C_j}{2}\right)^{-1}\left(M_i - M_j\right) + \frac{1}{2}\log\left(\frac{\left|C_i + C_j\right|/2}{\sqrt{\left|C_i\right|\left|C_j\right|}}\right) \tag{7}$$

6. Feature Selection

6.1 Particle Swarm Optimization

PSO is tool for stochastic population based optimization in which it is related to the social behaviour. PSO is based upon the movement and intelligence of swarms. Particle Swam Optimization is form of computation tool used to optimize the required problem which bringing out the specific candidates. The basic concept of PSO shown in Figure 5 lies in accelerating each particle toward its particle best and the global best locations. It is the method of dealing with the candidate solution and it can be improved to obtain the quality of the input image.

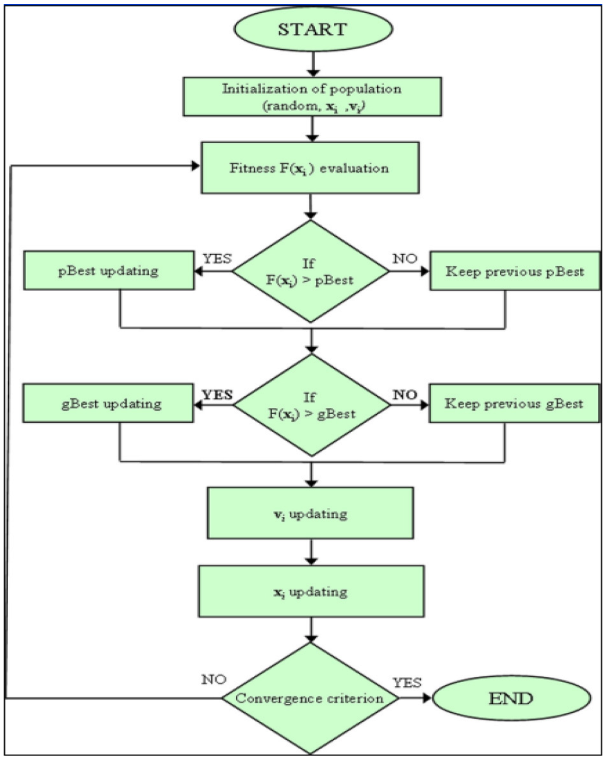

Figure 5. Flow chart of PSO optimization.

6.2 Particle Best

In PSO, particles which will have potential solutions can fly in problem space following the current particle which gives nearby optimum solution. These optimum particles keep track its co-ordinates associated with the best solutions. From this the nearby fitness value will be achieved. This obtained value is known as Pbest.

6.3 Local Best

The best value that can be tracked by the PSO will be the specific values of the each individuals in the search space. This location is known as lbest.

6.4 Global Best

The specified particle include the topological neighbours, the obtained best value is termed as gbest.

The process that can generate six fixed random values such that inertia, variable parameter, damp ratio, maximum iteration method, velocity such as C1, C2 variables. Each pixels has seperate X values including both higher and lower values that can be obtained for the feature extraction. Extracting the various features like variance, mean, co-variance, and standard deviation retains the variant combination of subsets present in the input images. Based upon the parameters found in the feature extraction the different kind of subsets are obtained. JM distance gives the concept of approaching the band pair potentials that segregate between the different class regions. It provided the best subsets and applied to PSO optimization. By utilizing the different stages in the PSO the near fitness function is obtained. PSO selects the global best values of the input images and classify by Support vector machine. The advantage of having this type of selection is to minimize the additional features and can able to attain the high accuracy of input images. The parameter that obtained from the original image will be shown in Table 1.

7. Feature Classification

Support Vector Machine is the type of supervised learning[14] which can be apply to various classification and can able to calculate the respective values of the specific variables. The main advantage[15,16] of the SVM classifier is to determine the data and recognize the patterns present in the input images. SVM is also used for regression analysis. This[17] clustering algorithm can be widely used in various application areas. SVM serves the main function to define the decision boundaries in the decision planes. The different[18] class of subsets can be seperated by the decision panel. The classified output image of GA and PSO using SVM shown in Figure 6, Figure 7, Figure 8.

8. Experiments and Results

The experimental study of Madurai LISSIV images are used for feature extraction. First, the 3×3 matrix is generated and the combinations of features are shown in Table 1. From this it analyses with all combinations in order to get the best values for selection of subsets. The parameter involves in the experiment study is that

C1 = 1.5
C2 = 4-C1
Inertia = .3
DampRatio = .95
ParticleSize = 40
MaxIter = 30

The convergence graph illustrates that the function of JM distance in order to get the best fitness images.

Tabel 1. Parameters of PSO

Parameter	values	maximum	Minimum
G	30	30	30
GB	<1×30 double>	19,2553	30,7352
N	40	40	40
Pmut	0.1200	0.1200	0.1200
VarHigh	[399,399,399, 399.......	399	399
VarLow	[2,2,2,2,2,2,2,2]	2	2
Br	400	400	400
Cx	0.3000	0.3000	0.3000
File	'400×400'tif	0	0
Fitness	<1×40 double>	19.2533	28.0490
Fitmessoff	[28,4310,28, 4314,22....	22.9073	30.6270
Genl	8	8	8
H	3	3	3
I	8	8	8
Ii	4	4	4
Imorig	<400×400×3 unit8>	0	255
Imout	<400×400×3 unit8>	20	200
J	8	8	8
K	40	40	40
Len	400	400	400
Ma	30	30	30
Newfit	<1×48double>	19,2533	31,1229
Newpop	<48×48 double>	10	399
Off	0	0	0
Offspring	<8×8double>	248	367
P	<48×48 double>	8	8
Parent	0	225	375
Pop	<8×8double>	10	399
Res	0	0	0

The value of JM distance is 1.414 by comparing to this value the best subset is obtained. For each iteration the JM distance keeps on increasing which relates to the fitness values. Depend upon the fitness the JM distance is used to calculate the distance of the each subsets. The Convergence graph of the GA is shown in Figure 9,

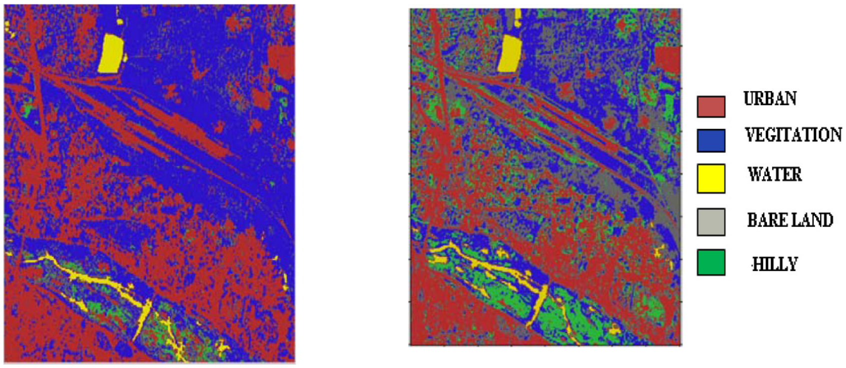

Figure 6. a) Classified output image of GA using NN for LISSIV I. b) Classified output image of PSO using SVM for LISSIV I.

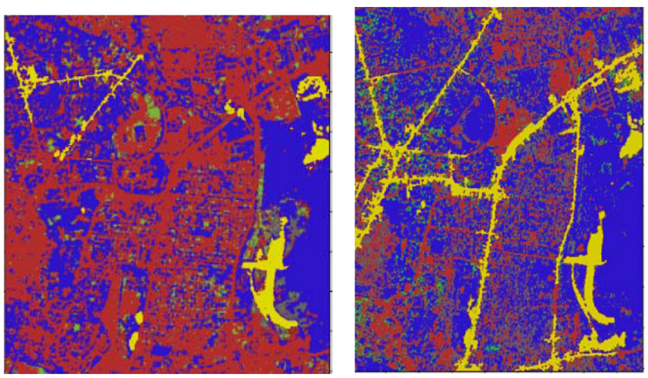

Figure 7. a) Classified output image of GA using NN for LISSIV II. b) Classified output image of PSO using SVM for LISSIV II.

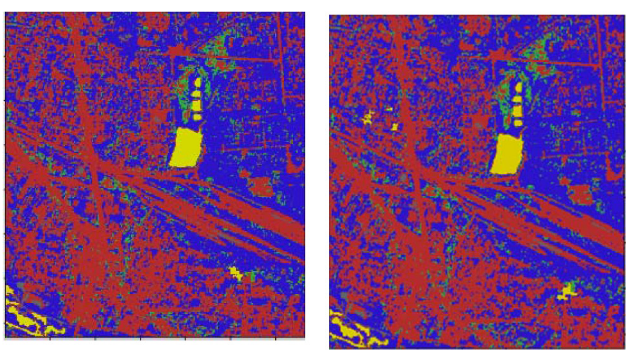

Figure 8. a) Classified output image of GA using NN for LISSIV III. b) Classified output image of PSO using SVM for LISSIV III.

Figure 10, Figure 11, Compare to GA PSO has an frictional distance that will be define in each iteration is shown in Figure 12, Figure 13, Figure 14.

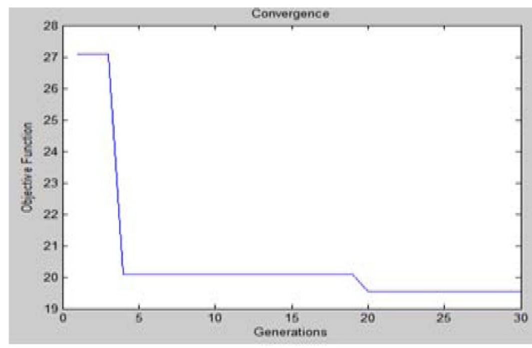

Figure 9. Convergence graph for the GA LISSIV I.

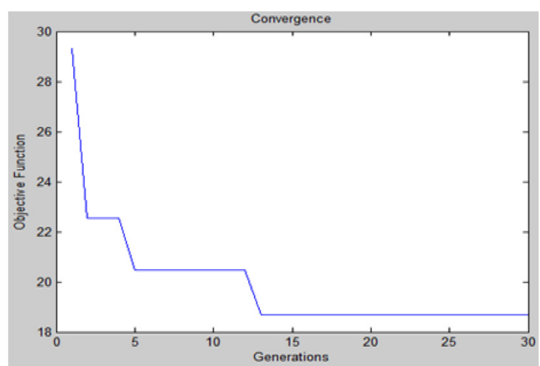

Figure 10. Convergence graph for the GA for LISSIV II

The 660 field visit data are collected and the classification accuracy is computed by the performance of the confusion matrix. Comparing the classified data with the reference data which gives the overall and kappa accuracy of GA and PSO algorithms. Figure 15, Figure 16, Figure 17 shows the actual pixels versus GA and PSO classification.

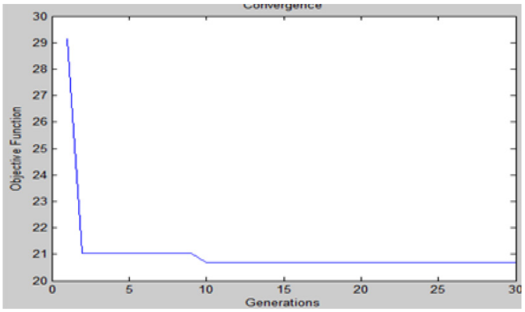

Figure 11. Convergence graph or the GA for LISSIV III.

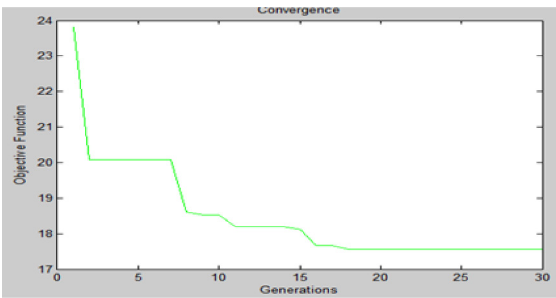

Figure 12. Convergence graph for the PSO LISSIV I.

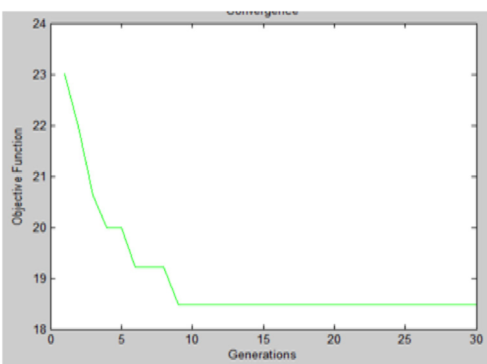

Figure 13. Convergence graph or the PSO for LISSIV II.

In confusion matrix, the kappa and overall accuracy of PSO shown in Table 2 and Table 3. PSO gives the increased accuracy for LISSIV Madurai images.

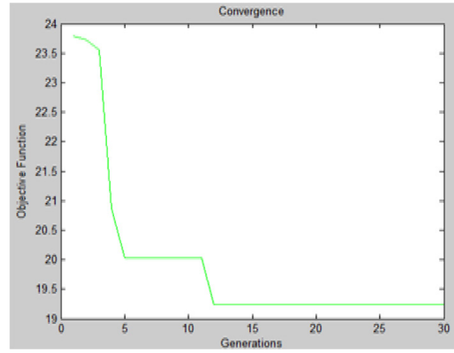

Figure 14. Convergence graph for the PSO for LISSIV III.

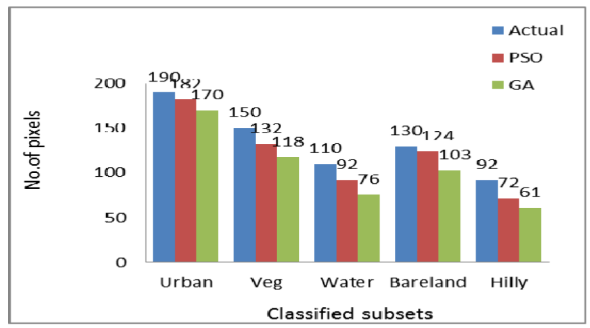

Figure 15. Comparison of pixels classification by using GA and PSO for LISSIV I

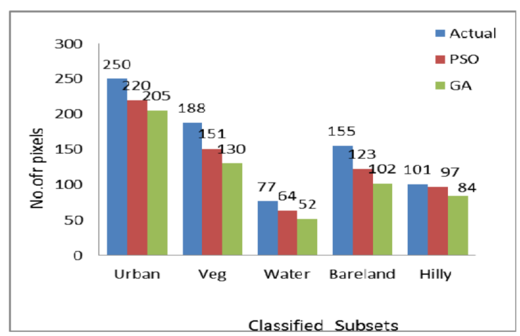

Figure 16. Comparison of pixels classification by using GA and PSO for LISSIV II.

9. Conclusion and Discussion

In this study, the paper presented that PSO based algorithm can able to achieve an optimum selection of feature subset, that can be used to trained and classified by using support vector machine. The obtained results shows that PSO gives the optimum fitness values for all classified subsets such as urban, vegetation, water, bare land and hilly areas which is obtained by the SVM classifier. The proposed method shows that by using PSO which reduces the complexity of optimization. The experimental result shows that PSO has effective activity on LISSIV Madurai image which describes increased overall accuracy and kappa coefficient than GA.

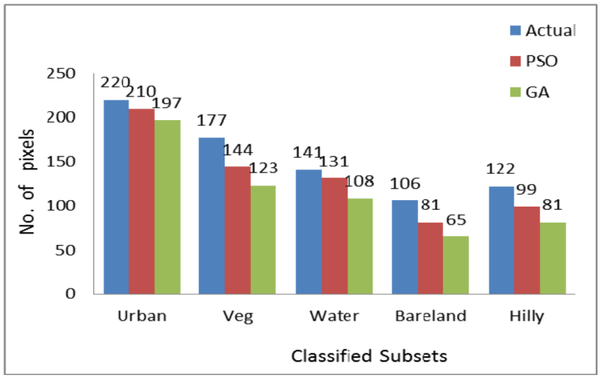

Figure 17. Comparison of pixels classification by using GA and PSO for LISSIV III.

Table 2. Accuracy of GA for input images

	User Accuracy	Producer Accuracy	Overall Accuracy	Kappa
LISSIV I	81.8	79.8	82.9	0.8311
LISSIV II	83.35	82.78	86.0	0.8746
LISSIV III	86.49	84.13	87.7	0.8832

Table 3. Accuracy of PSO for input images

	User Accuracy	Producer Accuracy	Overall Accuracy	Kappa
LISSIV I	82.5	81.2	84.6	0.8377
LISSIV II	85.1	83.4	88.3	0.8871
LISSIV III	89.27	85.0	90.60	0.9224

10. References

1. Rajesh S, Arivazhagan S, Pratheep MK, Abisekaraj R. Land cover/land use mapping using different wavelet packet transforms for LISS IV Madurai imagery.Journal of the Indian Society of Remote Sensing. 237–248. doi:10.1007/s12524-012-0208-5.
2. Goldberg E. Reading, MA, USA: Addison-Wesley: Genetic Algorithms in Search, Optimization, and Machine Learning. 1989; p. 37.
3. Foody GM, Arora MK. An evaluation of some factors affecting the accuracy of classification by an artificial network. International Journal of Remote Sensing. 1997; 18(4):799-810.
4. Hansen VLK, Salamon P. Neural network ensembles IEEE Trans. Pattern Anal. Mach. Intell. 1990; 12(10):993-1001.
5. Kaliyamurthie K, Parameswari D. Remote Sensing Imaging for Satellite Image Segmentation. Indian Journal of Science and Technology. 2015; 8(31):1-5.
6. Tseng MH, Chen SJ, Hwang GH, Shen MY. A genetic algorithm rule-based approach for land cover classification. ISPRS Journal of Photogrammetry and Remote Sensing. 2008; 63(2):202-12.
7. Bandyopadhyay S, Pal SK. Pixel classification using variable string genetic algorithms with chromosome differentiation. IEEE Trans Geosci Remote Sens. 39(2):303–8.
8. Brindha BG, Rohini G, Gnanakousaly C. Genetic Algorithm based Optimization of Single Node in Reformed-Digital Micro Fluidic. Indian Journal of Science and Technology. 2015; 8(29):1-8. **Doi:** 10.17485/ijst/2015/v8i29/71888.
9. Huang CL, Wang CJ. A GA-based feature selection and parameters optimization for support vector machines. Expert Systems with Applications. 31:231-40.
10. Goldberg DE. Addison Wesley: Genetic algorithms in search optimization and machine learning. 1997; p. 41.
11. Smitha P, Paul V, Shajy L, Sujathan K. Feature Extraction from Immunohistochemistry Images to Classify ER/PR Scores. Indian Journal of Science and Technology. 2015; 8(34):1-7.
12. Qingfeng JW, Huailin D. A random feature selection approach for neural network ensembles: Considering diversity. In Proc. IEEE Int. Conf. Comput. Intell. Software Eng. (CiSE). 2010; p. 1-4.
13. Roli BLF, Serpico SB. An extension of the Jeffreys-Matusita distance to multiclass cases for feature selection. IEEE Trans. Geosci. Remote Sens. 1995; 33(6):1318-21.
14. Bigdeli F, Samadzadegan, Reinartz P. A multiple SVM system for classification of hyperspectral remote sensing data. J Indian Soc Remote Sens. 2013; 41(4):763-76.
15. Melgani F, Bruzzone L. Classification of hyperspectral remote sensing images with support vector machines. IEEE Trans Geosci Remote Sens. 2004 Aug; 42(8):1778-90.
16. Waske B, Linden S, Benediktsson JA, Rabe A, Hostert P. Sensitivity of support vector machines to random feature selection in classification of hyperspectral data. IEEE Trans. Geosci Remote Sens. 2010; 48(7):2880-89.
17. Perumal K, Bhaskaran RS. VM-based effective land use classification system for multispectral remote sensing images. International Journal of Computer Science and Information Security. 2000; 6(2):549-63.
18. Venkateswaran K, Kasthuri N, Balakrishnana K, Prakash K. Contourlet-Based Multiband Image Fusion for Improving Classification Accuracy in IRS LISS III Images. Artificial Intelligence and Evolutionary Algorithms in Engineering Systems of the series Advances in Intelligent Systems and Computing. 2014; 325:201-11.