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Enhanced Classification Algorithms for the Satellite Image Processing

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Abstract

Background and objectives: Region based approach to determine the used land details of Vellore district to improvise the vegetation in future. **Methods and Statistical Analysis:** To classify the used lands Modified KNN and Modified SVM algorithm are applied to get the classification. Accuracy is measured by producer's accuracy, user's accuracy, commission error and omission error. **Results:** MOKNN and MOSVM produce the improved accuracy in classification to determine the exact land use details. **Conclusion:** Proposed MOKNN and MOSVM give the improved accuracy to predict used land details. This work may be extended with combined data set to get more improved accuracy.

Keywords: Classification, Fuzzy, KNN, MOKNN, MOSVM, SVM

1. Introduction

In remote sensing images, lot of predictions can be made without any intervention of the human being. Remotely sensed image is digital representations of the Earth, by using this, places which cannot be accessed is viewed by the remote sensing images, this will encourage the process of those interior parts. In a remotely sensed image data, each pixel represents an area of the Earth at a specific location. If a pixel satisfies a certain set of criteria then that pixel is assigned to the class that corresponds to those criteria. This process is referred as image classification. Presently, image classification method can be grouped into two main categories depending on the image primitive i.e. pixel based and object based method. Pixel based methods classify individual pixels without taking into account any neighbourhood or spatial information of the pixel. Object/ Region based methods are also able to handle high resolution imagery which aggravates the classification process for most pixel based methods. Depending on the type of information extracted from the original data, classes will be identified with the known features on the ground. An example of a classified image is a land cover map, showing vegetation, bare land, pasture, urban, etc. In remote sensing imagery, a pixel might represent a mixture of class covers, within-class variability, or other complex surface cover patterns that cannot be properly described by one class. Finding about vegetation indices level is very important to know about the used lands and agricultural levels in the particular region. To achieve this, the remote sensing image has to be taken for processing, in this work LANDSAT image is taken and it is processed to identify the used land. In the processing initially LANDSAT image is checked for noise freeness. Using this image the required features are extracted. For this feature extraction the different features like vegetation indices, used land, forest and unused land are considered. After extracting the features from the image, classification algorithms are applied to get the different classification groups, in this KNN, SVM, Fuzzy algorithms are applied to get the classified image. These results were compared with the MOKNN and MOSVM. Modified algorithms which gives the better result comparing with the existing algorithms. To predict the overall accuracy of the algorithms, different metrics are used like user's accuracy, producer's accuracy, omission error and commission error.

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2. Literature Review

In remote sensing images, the important features can be extracted only when the details of the image are properly classified. Classification of an image is very important to extract the fine details for further processing. Many researchers were concentrated on identifying the best classification algorithm in the recent years, active learning algorithm were used to find the best classifier in hyper spectral images and this work identifies that SVM, KNN algorithms were tested in the hyper spectral images[1]. K-nearest neighbourhood algorithm used vastly in the classification of images. An improved KNN for high resolution remote sensing is used and it permits to combine the locality using the maximum margin classification[3]. KNN is used with artificial immune B-cell network is used and it proves that reduction of data for processing[2]. Later K-nn is used with maximal margin principle and is proved with the satisfactory results[4]. KNN applied in hyper spectral images and it is used with the genetic algorithm and it produces good decision boundaries in an accurate way[5]. Above rational work concludes that KNN gives good results in classification with the help of maximum marginal classification, artificial immune B-Cell network and genetic algorithm. The other algorithm which is taken for the classification is support vector machine. SVM also applied on hyper spectral images with the feature reduction based approach and compared with the other classifier[6]. High efficient classification on remote sensing image is done with the SVM classifier with the metric distance function and it is less sensitive to the class label uncertainty[7]. SVM is moved from the pixel based representation to the object based representation for the classification in remote sensing images[8]. In semi supervised one class support vector machines for the classification of remote sensing data is done with the free parameter selection for the crop monitoring and cloud monitoring[9]. From the various research work SVM also proved to provide better classification in remote sensing images. The other algorithm fuzzy used for classification is Neuro fuzzy approach with the combination of different methods given as input for neural network[10]. Fuzzy rule based classification of remotely sensed images on LANDSAT TM scene is done with the rule system derived from training set using simulated annealing as an optimization algorithm[11]. Fuzzy is also applied in remote sensing to find urban land cover using hard and fuzzy evaluation technique[12]. Fuzzy classification method estimates the contribution of each class in the pixel. In fuzzy classification, a pixel belongs to a class with a membership degree and the sum of all class degrees will give the classification in class based[13]. From the literature fuzzy gives the better results on remote sensing images in vegetation areas and urban areas. From the above study algorithms SVM, KNN, fuzzy are identified as better classifiers for the classification of remote sensing images. Hence these approaches are taken into the process. For the evaluation of algorithm accuracy thresh holding and accuracy assessment methods like error matrix is used[14].

The research work concentrates on finding out the best classification algorithm for classifying the LANDSAT images and to find the greenery information for the future plan for the Vellore district. This paper organized in the following headings study area, data used for the processing, framework of the entire work, Algorithms (Modified KNN and Modified SVM), Results and comparison, Evaluation of classification algorithms and conclusion.

3. Study Area

The main resource controlling in terrestrial eco system is done based upon the land information like land quality and the characteristics of soil moisture. Vellore district lies between 12° 15’ to 13° 15’ North latitudes and 78° 20’ to 79° 50’ East longitudes, at an altitude of 800 m to 7000 m from mean sea level (msl) in TamilNadu State. Vellore district has 6077 sq. k.m of geographical area. Vellore district is one of the 32 districts in the Tamil Nadu state of India. Vellore City is the headquarters of Vellore district. It had a population of 3,936,331 as of 2013. The average maximum temperature experienced in Vellore district is 39.5°Celsius and the average minimum temperature experienced is 15.6° Celsius. The Vellore district region has an average annual rainfall of 795 mm, out of which North East Monsoon contributes to 535 mm and the South West Monsoon contributed to 442mm. Precipitation of Vellore is 917 millimeters. Average summer temperature 39.5°C (103.1 °F) Average winter temperature 15.6 °C (60.1 °F). Changes which occurred in the land may affect the atmosphere and climate. Now a day’s people are continually changing the land so it is realized that knowing the land cover of the particular region and to do the assessment of the changes could affect in the near future is very important. This is the reason behind to choose study area Vellore District for improving the greenery in future. Vellore District is the hottest region and this forced the environment scientist to concentrate the vegetation growth in this region to reduce the temperature.

Figure 1. Original Landsat Image.

3.1 Data Used

In the present study, the LANDSAT (Land sat Satellite Data) data is used. It is retrieved from LANDSAT satellites. It acquires data in seven spectral bands with the resolution of 250m, 1000m. Spatial resolution measures the smallest object that can be resolved by the sensor, or the area on the ground represented by each pixel. If the resolution is fine then number will be lower. For instance, a spatial resolution of 500 meters is coarser than a spatial resolution of 250 meters. The ground truth values are observed from the ground details and the classes identified are Vegetation area, used land, forest (tree), unused land. Ground truth values taken from national remote sensing center. Table 1 gives the ground truth values of the Vellore district tile which is taken for the processing. LANDSAT image which is used for the Processing is shown in Figure 1.

Table 1. Ground truth values for the study area

Map Coordinates				Land cover Details
Latitude	Longitude	Lattitude	Longitude	
N 12°47’21.38”	E78° 41’05.91”	N 12°41’56.11”	E78° 37’59.53”	Vegetation area
N 12°54’47.82”	E79° 07’19.86”	N12° 53’13.85”	E79° 08’40.87”	Used land
N 12°55’00.14”	E78° 37’05.91”	N 12°51’25.98”	E78° 41’11.86”	Forest
N 12°39’44.33”	E79° 18’06.29”	N 12°39’03.17”	E79° 19’13.24”	Unused land
N 12°36’15.53”	E78° 33’00.37”	N 12°36’03.08”	E78° 33’14.31”	Vegetation area
N 12°57’45.36”	E79° 07’53.16”	N 12°56’50.31”	E79° 08’52.04”	Used land
N 12°42’09.93”	E78° 49’32.81”	N 12°32’12.98”	E78° 58’16.67”	Forest
N 12°44’22.55”	E79° 15’03.42”	N 12°43’45.37”	E79° 15’39.28”	Unused land
N 12°31’57.23”	E78° 37’36.54”	N 12°30’51.73”	E78° 38’32.39”	Vegetation area
N 12°47’48.2”	E78° 42’42.61”	N 12°47’14.62”	E78° 43’21.43”	Used land
N 12°30’37.46”	E78° 40’48.52”	N 12°60’30.93”	E78° 41’50.79”	Forest
N 12°44’53.39”	E79° 11’59.26”	N 12°44’55.62”	E79° 10’28.54”	Unused land
N 12°30’17.45”	E78° 37’05.91”	N 12°51’25.98”	E78° 41’11.86”	Vegetation area
N 12°40’35.4”	E78° 30’17.45”	N 12°29’25.55”	E78° 31’15.99”	Used land
N 12°45’04.43”	E78° 56’30.71”	N 12°33’40.01”	E79° 03’31.86”	Forest
N 12°15’43.64”	E78° 47’01.82”	N 12°14’37.88”	E78° 49’02.94”	Unused land
N 12°29’56.30”	E78° 36’30.82”	N 12°29’37.48”	E78° 36’43.99”	Vegetation area
N 12°57’25.46”	E78° 51’53.71”	N 12°56’34.69”	E78° 52’44.01”	Used land
N 13°02’29.00”	E78° 42’33.71”	N 12°57’23.92”	E78° 47’31.65”	Forest
N 12°30’42.98”	E79° 17’28.59”	N 12°29’57.64”	E79° 18’29.31”	Unused land
N 13°02’52.39”	E79° 00’12.52”	N 13°01’01.90”	E79° 01’01.96”	Vegetation area
N 12°54’44.70”	E79° 18’50.89”	N 12°53’50.19”	E79° 19’20.04”	Used land
N 12°49’57.29”	E78° 59’28.02”	N 12°44’05.21”	E79° 03’17.40”	Forest
N 12°37’31.06”	E78° 32’35.77”	N 12°36’57.24”	E78° 33’35.87”	Unused land
N 12°36’27.55”	E78° 37’10.21”	N 12°32’40.40”	E78° 40’27.80 ”	Forest

4. Framework

In this paper various classification algorithms are taken for classifying the LANDSAT image. Input image is taken from the LANDSAT of the Vellore district, This Image is archived in the image database, and will be used for the processing in the later stage. The image is identified with the different features, then algorithms MOKNN and MOSVM applied and classification is done. Classified image is taken and it is compared with the ground truth values which are taken for the particular image. Correctness of the algorithm is tested by using the accuracy metrics. Accuracy of the algorithm is measured using the producer's accuracy, omission error, user's accuracy, commission error and the overall accuracy. These accuracies are calculated and the results are compared to identify the best classification algorithm.

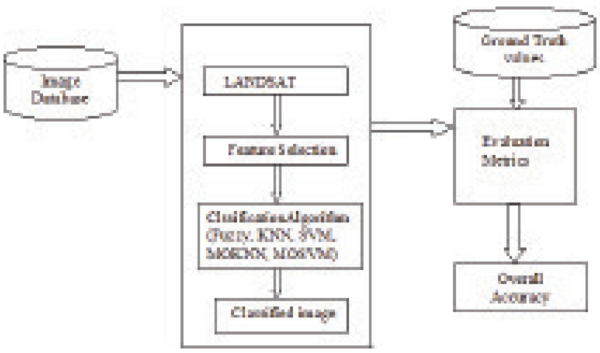

Figure 2. Frame work for the Evaluation of Classification algorithms.

Figure 2 which gives the overall information of the process which is carried out in this pape, Figure 2 gives the overall framework for the entire process of evaluating different classification algorithms? Image processing will be done based upon the images, processing of the image may differ from image to image. Different time period image is required for the processing, that will be stored in the database for the future reference. Here the required image is taken from the image archive. These images, training set and the Ground truth values are stored in the image database. Required LANDSAT image is given as the input for the processing then the features like used land, vegetation, forest and unused land are extracted from image. Based upon the feature extraction this will be given as input for the proposed classifiers MOKNN, MOSVM. Better performance is analyzed by the metrics of commission error, omission error, producer's accuracy and user's accuracy, finally the overall accuracy is calculated and compared with the existing Classification technique KNN, SVM and fuzzy and MOKNN and MOSVM shows the better performance the existing KNN, SVM and fuzzy.

5. Proposed Algorithm

5.1 Modified KNN

In the modified KNN approach calculating the distance metrics plays an important role. When the existing KNN algorithm is taken it uses the priori technique metric in the predictor space. In the proposed MOKNN it search for a metric in an embedded space. Embedded space represents intrinsic non linearity in multivariate data sets like LANDSAT images. Figure 3 which shows the data transformation from predictor space to the embedded space.

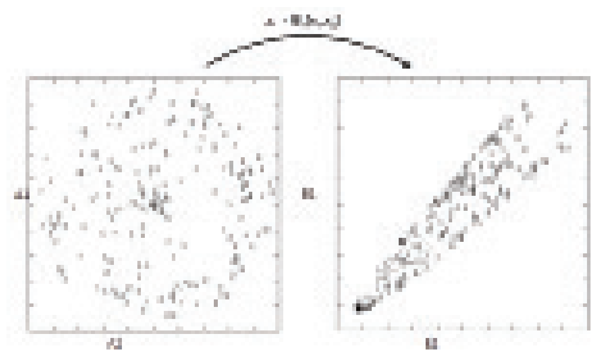

Figure 3. Transformation of information from predictor space to embedding space.

The proposed algorithm for MOKNN is

- Select an attribute denoted as r
- Predict the optimal distance d_r for the binary-classification.
- Perform the binary classification using *K*NN
  Compute K centroid vectors $\{cv_1, cv_2, \ldots\ldots, cv_k\}$;

For each document t in test set Do
Step 1 Search K1 neighboring centroid vectors
$\{cv^t_1, cv^t_2, \ldots\ldots cv^t_{k1}\}$ with respect to categories
$\{C^t_1, C^t_2, \ldots\ldots, C^t_{k1}\}$;
Step 2 Calculate similarities between document t
And all documents in categories $\{C^t_1, C^t_2, \ldots\ldots, C^t_{k1}\}$;
Step 3 Employ KNN decision rule to assign label to t.
End

- and the distance d_r, for the vector A_0 a partial membership vector *{y*y_r*'}*
- Repeat the Steps 1 -3 for each attribute *r*.
- Membership are collected in the final classification y_0
- The class show the highest class membership value is allocated to x_0.

By applying the Modified KNN classified classes in the LANDSAT image is shown in the Figure 4. Class 1 shows the vegetation area, Class 2 shows used land, Class 3 shows Forest and used land is classified in Class 4.

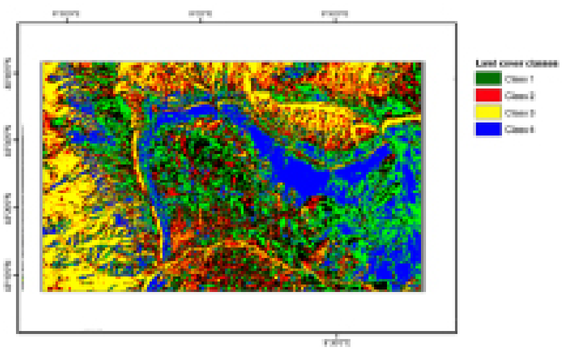

Figure 4. Classified Image by using MOKNN.

5.2 Modified SVM Classifier

Support Vector Machines (SVM) is used when the data has 2 classes (denoted by + and -). It classifies data by finding the hyper plane that classifies the data of one class from that of the other class with maximum distance separating them on[15].

5.2.1 Primal Formulation

The data input is a set of points (vectors) x_i along with their class y_i. For some dimension d, the $x_i \in R^d$, and the $y_i = \pm 1$. The equation of a hyper plane is

$$(w, x) + b = 0 \qquad \text{(Eq. 8)}$$

Where $w \in R^d$, (w, x) is the inner (dot) product of w and x, and b is real.

The following problem defines the best separating hyper plane. Find w and b that minimize ||w|| such that for all data points (x_i, y_i),

$$y_i((w,x_i) + b) \geq 1 \qquad \text{(Eq. 9)}$$

The support vectors are the x_i on the boundary, those for which $y_i((w,x_i) + b) = 1$. For mathematical convenience, the problem is usually given as the equivalent problem of minimizing (w, z)/2. This is a quadratic programming problem. The maximum possible optimal solution w, b enables the classification of class (z). a vector z as follows:

$$\text{class}(z) = \text{sign}((w, z) + b) \qquad \text{(Eq. 10)}$$

5.2.2 Dual Formulation

The dual quadratic programming problem is computationally simpler to solve. To obtain the dual, take positive Lagrange multipliers α_i multiplied by each constraint, and subtract from the objective function:

$$L_P = \frac{1}{2}\langle w,w\rangle - \sum_i \alpha_i \left(y_i\left(\langle w,x_i\rangle + b\right) - 1\right), \qquad \text{(Eq.11)}$$

Where you look for a stationary point of L_P over w and b. setting the gradient of L_P to 0, you get

$$w = \sum_i \alpha_i y_i x_i$$
$$0 = \sum_i \alpha_i y_i. \qquad \text{(Eq.12)}$$

Substituting into L_P, you get the dual L_D:

$$L_D = \sum_i \alpha_i - \frac{1}{2}\sum_i \sum_j \alpha_i \alpha_j y_i y_j \langle x_i, x_j\rangle, \qquad \text{(Eq.13)}$$

Which you maximize over $\alpha_i \geq 0$. In general, many α_i are 0 at the maximum. The nonzero α_i in the solution to the dual problem define the hyper plane, as seen in Equation 1-1, which gives was the sum of $\alpha_i y_i x_i$. The data point's x_i corresponding to nonzero α_i is the support vectors.
The derivative of L_D with respect to a nonzero α_i is 0 at an optimum. This gives

$$y_i((w,x_i) + b) - 1 = 0. \qquad \text{(Eq.14)}$$

In particular, this gives the value of b at the solution, by taking any i with nonzero α_i.

SVM Algorithm:
Initialize $y_i = Y_I$ for $i \in I$
REPEAT
compute SVM solution w, *b* for data set with impute labels
compute outputs $f_i = (w, x_{i)} + b$ for all x_i in positive bags
set $y_i = \text{sgn}(f_i)$ for every $i \in I$, $Y_I = 1$
FOR (every positive bag B_I)
IF ($\sum i \in I\ (1 + y_i)/2$ ==0)

compute i^{+} = arg max$_i \in f_i$
set y_i= 1
END
END
WHILE (inputted labels have changed)
OUTPUT (w, *b*)
Steps to be followed to implement the modified SVM.

- Take an input LANDSAT image.
- Group the similar features.
- Apply the Support Vector Machine to train the model.
- Find the Posterior Probability of each and every pixel.
- Find out the optimal threshold value of each and every pixel.
- If (Posterior Probability) is less than or equal to threshold value
- Classify each pixels to connect the components and to combine the regions. Else Classify the interior pixels.

By applying the Modified SVM, classified classes in the LANDSAT image is shown in the Figure 5. Class 1 shows the vegetation area, Class 2 shows used land, Class 3 shows Forest and used land is classified in Class 4.

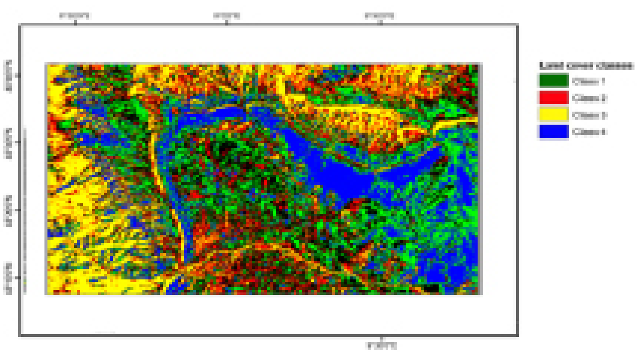

Figure 5. Classified Image after applying MOSVM.

6. Results and Comparison

Five classification algorithms were designed and tested on the data set which is taken for the research such as fuzzy based classification, KNN Classifier, Support vector machine, Modified KNN and Modified SVM. Accuracy was calculated based upon the samples taken for the testing. LANDSAT image of Vellore district is taken for the classification, different time series data also taken for the classification. Classes which are identified in the image are

- Vegetation area
- Used land
- Forest
- Unused land.

6.1 Evaluation of Classification Algorithms

The assessment of the classification algorithm is the important work to predict which algorithm is best for the classification. This assessment is made by comparing the classification algorithm with the ground truth values (which is assumed true) to predict the classification accuracy. Evaluation of the classification accuracy is followed Thresh holding and accuracy assessment function. Set of reference pixel is used for identifying the actual data are known. These reference pixel and the real ground truth value is forming the error matrix and this error matrix is equal to the number of classification categories assessed in the accuracy (Lille sand, T.M and Kiefer R.W, 2000). In the classification of LANDSAT image the error matrix is calculated from the diagonal values.

Error Matrix (E) = Diagonal values.

The omission error is the non diagonal values in the column.

Omission Error (O) = Non Diagonal Values in the column.

Non diagonal values in the row represent the commission error.

Commission Error(C) = Non diagonal values in the Row.

Producer's accuracy is calculated by number of correct classified pixel divided by number of training pixels in the training category.

Producers Accuracy (PA) = Number of correct classified pixel / Training Pixel

Commission error which says that user accuracy it is calculated by number of correctly classified pixel divided by total number of pixels in the row category.

Users accuracy (UA) = Number of correct classified pixel / Total no of pixel.

The total accuracy is calculated by number of correctly classified pixel divided by total number of tested pixel [16].

Overall Accuracy (OA) = Number of correct classified pixel / Tested Pixel

Following table describes the information of classification algorithm on the given landsat images. First Fuzzy based classification is applied and this algorithm suits for identifying the used land in the accuracy of 37.50%. The remaining vegetation area is 20.00 % producer accuracy. Forest producer accuracy is 28.57%. This Fuzzy based classification gives more commission error and omission error. The overall accuracy is attained 28.00%. Then the K-nn Classifier is applied and the accuracy is calculated the overall accuracy is 28.00% the commission and omission error are greater than or equal to 57.15 %. When Support vector machine is taken for the implementation and the accuracy is increased to 40.00%. Omission error and commission error were reduced to 37.50. Following table 2, 3, 4, 5, 6 gives the error rate and accuracy rate of fuzzy, KNN, SVM, MOKNN and MOSVM. Figure 9 gives the vegetation area identification for fuzzy, KNN, SVM, MOKNN and MOSVM. MOKNN gives best producers accuracy, MOSVM gives the good users accuracy. Figure 6 shows that the MOKNN has less commission and omission error in used land. Figure 7 shows the less error in MOKNN. Figure 8 shows the less error in KNN algorithm. By grouping all these four classes MOKNN gives less error in almost three classes. MOKNN gives the overall accuracy (68%) for the LANDSAT image shown in Figure 10.

Fuzzy Classifier:

Table 2. Fuzzy classification accuracy table

Class name	Vegetation area	Used land	Forest	Unused land	Row total	Producers accuracy	Omission Error	Users Accuracy	Commission Error
Vegetation area	1	2	1	2	6	20.00%	80.00%	16.66%	83.40%
Used land	2	3	1	1	7	37.5%	62.50%	42.85%	57.15%
Forest	1	1	2	1	5	28.57%	71.43%	40.00%	60.00%
Unused land	1	2	3	1	7	20.00%	80.00%	14.28%	85.72%
Column total	5	8	7	5	25				
Overall classification accuray						**28.00%**			

KNN Classifier:

Table 3. KNN classification accuracy table

Class name	Vegetation area	Used land	Forest	Unused land	Row total	Producers accuracy	Omission Error	Users Accuracy	Commission error
Vegetation area	3	2	1	2	7	60.00%	40.00%	42.85%	57.15%
Used land	1	1	2	2	6	20.00%	80.00%	16.67%	83.33%
Forest	1	1	1	1	4	12.50 %	87.50%	25.00%	75.00%
Unused land	1	1	4	2	8	28.57%	71.43%	25.00%	75.00%
Column total	5	5	8	7	25				
Overall classification accuray						**28.00%**			

SVM classifier:

Table 4. SVM classification accuracy table

Class name	Vegetation area	Used land	Forest	Unused land	Row total	Producers accuracy	Omission Error	Users Accuracy	Commission error
Vegetation area	3	1	1	1	6	42.85%	57.15%	50.00%	50.00%
Used land	2	1	0	0	3	25.00%	75.00%	33.33%	66.67%
Forest	1	1	1	2	5	16.67%	83.33%	40.00%	60.00%
Unused land	1	1	4	5	8	62.50%	37.50%	62.50%	37.50%
Column total	7	4	6	8	25				
Overall classification accuracy						**40.00%**			

Modified KNN classifier:

Table 5. Modified KNN classification accuracy table

Class name	Vegetation area	Used land	Forest	Unused land	Row total	Producers accuracy	Omission Error	Users Accuracy	Commission error
Vegetation area	4	0	1	1	6	66.67%	33.33%	66.67%	33.33%
Used land	1	4	1	1	7	80.00%	20.00%	57.14%	42.86%
Forest	0	0	4	1	5	66.67%	33.33%	80.00%	20.00%
Unused land	1	1	0	5	7	62.50%	37.50%	71.43%	28.57%
Column total	*6*	*5*	*6*	*8*	*25*				
Overall classification accuray						**68.00%**			

Modified SVM classifier:

Table 6. Modified SVM classification accuracy table

Class name	Vegetation area	Used land	Forest	Unused land	Row total	Producers accuracy	Omission Error	Users Accuracy	Commission error
Vegetation area	3	1	1	1	6	50.00%	50.00%	50.00%	50.00%
Used land	1	3	2	1	7	60.00%	40.00%	42.86%	57.14%
Forest	0	1	5	1	5	83.33%	16.67%	100.00%	0.00%
Unused land	1	1	0	4	7	50.00%	50.00%	57.14%	42.86%
Column total	*6*	*5*	*6*	*8*	*25*				
Overall classification accuray						**60.00%**			

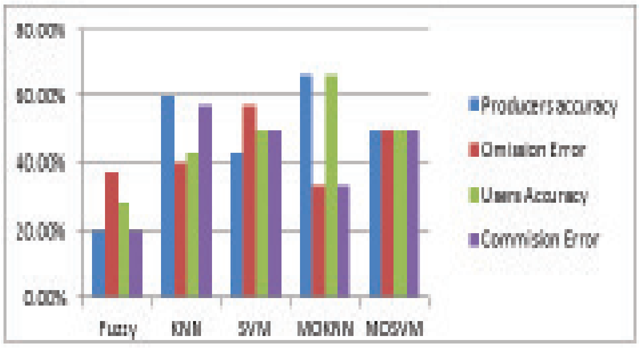

Figure 6. Vegetation Accuracy in Fuzzy, KNN, SVM, MOKNN and MOSVM.

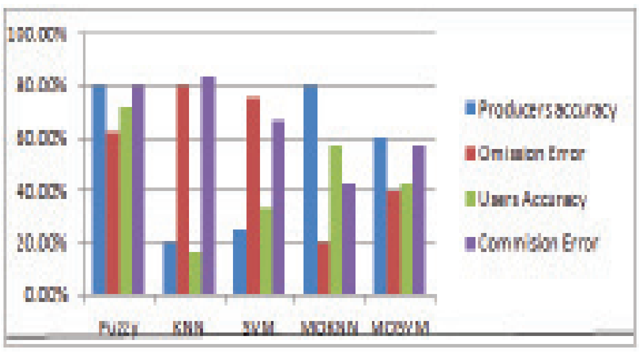

Figure 7. Used lands accuracy in Fuzzy, KNN, SVM, MOKNN and MOSVM.

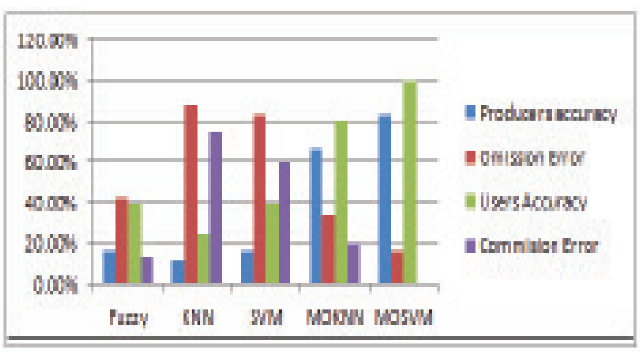

Figure 8. Forest accuracy in Fuzzy, KNN, SVM, MOKNN and MOSVM.

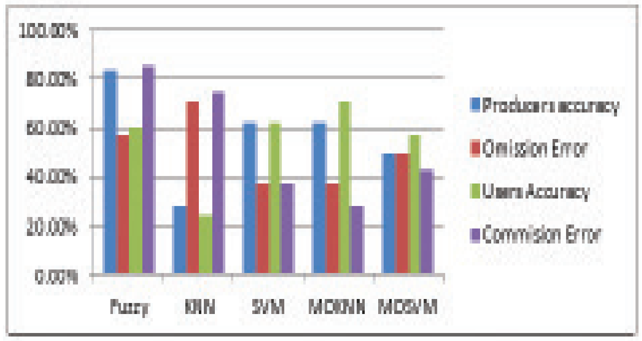

Figure 9. Unused land accuracy in Fuzzy, KNN, SVM, MOKNN and MOSVM.

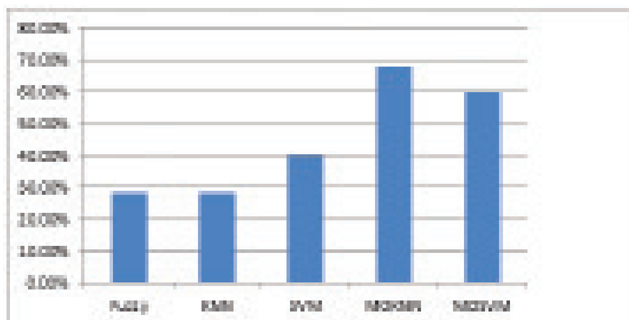

Figure 10. Overall accuracy of Fuzzy, KNN, SVM, MOKNN and MOSVM.

7. Conclusion

In this work different classes predicted by utilizing remote sensing LANDSAT image in Vellore, Tamilnadu, India. Classification of LANDSAT is applied with Five classification algorithms like Fuzzy, SVM, KNN, Modified KNN and Modified SVM. After developing the classified LANDSAT image the accuracy is developed by different methods of assessment. This development has partly been driven by the need for higher accuracies in the classified result. In this study, an object/region based approach for doing image classification is presented. This method was tested on LANDSAT image. The classification results on these LANDSAT image says that the algorithm KNN, Fuzzy based classification are giving the less accuracy for the LANDSAT image. The Modified KNN and modified SVM algorithms gives the better results on the LANDSAT images. If the image source is very large and hybrid algorithm is going to be applied then more accurate results may be derived. This research work may be extended to different types of remote sensing images like MODIS, TM Images. This work suggests the information of applying the hybrid algorithm for better results. This work gives the information of vegetation, unused land, used land and forest, this information will help in planning of vegetation and forest to improvise the usage of unused land.

8. References

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