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# Accurate identification of complex Land use and Land cover features using IRS (LISS III) multispectral image.

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**Abstract**

Land Use and Land Cover (LULC) is an assortment of activities executed by humans on to the land. The present study was carried out to evaluate supervised classification mechanisms for classification complex Land use and Land cover features using India Remote Sensing System-IRS (Linear Imaging Self-Scanning Sensor 3- LISS III) multispectral data. It showed that Artificial neural networks (ANN) fared better across all the land use and land cover classes with an overall accuracy of 88%. It also revealed that Maximum Likelihood (ML) and Support Vector Machine (SVM) classifier is prone to miss classification of pixels in one or more classes. Outcomes of the present study are comforting the competence of IRS (LISS III) multispectral data for the accurate mapping of complex land use and land cover features. Additionally, the ability of an ANN classifier in the classification of complex features using multispectral data was re-established in the present study.

***Keywords***: *land use and land cover, Multispectral satellite imagery, Artificial neural networks (ANN) , Support vector machine (SVM), Maximum likelihood (ML).*

## 1. Introduction

Land Use and Land Cover (LULC) is a collection of actions performed by humans on to the land, to gain benefits using land resources. Land cover is termed as the vegetation or buildings which take place on the earth. Examples of land covers contain agricultural land, forest, grassland, and wetland while land use refers to the biophysical state of the earth's surface and immediate subsurface, containing soil, topography, surface water, and groundwater, and human structures (Elaalem, Ezlit, Elfghi, & Abushnaf , 2013). Land use is the utilization of the land by humans for economic activities like agriculture, forests, construction, and farming (Waqas et al. 2019).Knowledge of land-use/land-cover (LULC) change is essential in a number of fields based on the use of Earth observations, such as urban and regional planning , environmental vulnerability andimpact assessment , natural disasters and hazards monitoring (Liou, Nguyen, & Li, ,2017), (Nguyen & Liou,,2019),( Talukdar & Pal,2018) Mapping LULC change has been identified as an essential aspect of a wide range of activities and applications, such as in planning for land use or global warming mitigation (Dutta, Rahman, Paul & Kundu, 2019)

Remote Sensing is the science of obtaining data about objects or areas from a distance. With the quick development of remote sensing technologies, its application has been tried in a wide range of fields, for example, land surveying, computer cartography, urban planning, geographic image retrieval, and others (Cheng, Han & Lu,2017), (Xia et al., 2017), (Lu & Weng, 2007), (Richards & Richards, 1999). Remote sensing techniques have also been recognized as a powerful tool to accurately map the LULC pattern of a given landscape. The remote sensing images collected by imaging satellites functioned by governments and businesses around the world. Remote sensing can significantly contribute to providing a timely and accurate image of the agricultural sector, as the convenient and suitable for gathering appropriate information over large areas with high accuracy (Brisco , Brown, Hirose, McNairn, & Staenz , 2014).

Remote Sensing provides the opportunity for rapid acquisition of information on LULC at a much-reduced price compared to the other methods like ground surveys. The satellite images have the advantages of multi-temporal availability as well as large spatial coverage for the LULC mapping (Wittke,Yu, Karjalainen, Hyyppä, & Puttonen,2019), (Viana,,Girão, & Rocha,2019). Multispectral remote sensing images collected by satellite present a massive opportunity for understanding the characteristics of the earth. Land use/land cover (LULC) identification and mapping with remote sensing images have developed great interest among researchers from different disciplines. Land Use/Land Cover refers to the utilization of land through actions like urban planning, natural resource management, water resource monitoring, environmental and agricultural analyses. Remote sensed imagery is the most popular method to capture data on Land Use/Land Cover. Multispectral imaging is one of the most widely used technologies for LULC mapping and monitoring. Image classification is a process where decision rules are developed and used to assign pixels into classes that have similar spectral and information features (Homer, Huang, Yang, Wylie, & Coan, (2004), (L. Fang, He, Li, Ghamisi, & Benediktsson, 2017). The major objective of the present study is to perform supervised classification such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Maximum Likelihood (ML) on the images taken from IRS (LISS III) multispectral platform. Comparison of supervised classification results and identification of best classifier based on percentage accuracy.

## 2. Objectives

Identification of land use land cover measurement of area under cultivation for a various land cover land use is very important task. Measurement of cultivation area and other land use is costly and time consuming. Remote sensing play important role in mappings and classification of land cover features. However, techniques available for the above mention purpose is labor incentive, time consuming and costly. Images taken with the help of Space born remote sensing platforms (Satellite) can be very helpful for Identification of land cover and land use. Furthermore, this method is cost effective and consumes lesser amount of time for the identification and classification of land use land cover using multi spectral remote sensing images.

## 3. Materials and methods

### 3.1 Model Structure:

Figure 1 shows the model that explains the sequence of adopted methodology for classification of IRS LISS -III multispectral image. The model consists of five stages that includes

Data acquisition: It is a process of gathering information or procedure of collecting related information. An extensive field survey was done to record ecological features and distribution patterns of different land use.

Data Collection and Overlaying GCPS: The Ground Control Points (Ground Control Points, GCPs) is an important baseline data of Remote Sensing Image correction (Chao Yang, 2018). The quantity, distribution, and accuracy of GCPs play an important role in correcting Remote Sensing Images.

Performed supervised classification: To obtain correct as well as quick land cover detail remote sensing classification is very useful and widely applied in the area like a disaster or environment monitoring, Land Cover Land Use, etc. Proposed model designed to work with supervised classification. Supervised classification algorithms include classification methods based on machine learning, including artificial neural network (ANN), support vector machine (SVM) and Maximum Likelihood (ML)

Ground verification validation: The common method for the validation is based on field examination and manual or automatic image interpretation using the original or higher-resolution images. The ground reference, which is often regarded as “ground truth”, however, contains errors, especially when a large amount of such ground references is expected with the speculation of coming era of big geographic data (Sun, Chen &, Zhou, 2017).

Accuracy assessment: Accuracy assessment is an important part of any classification technique. It compares the classified image into another data source that is measured to be accurate or ground truth data.

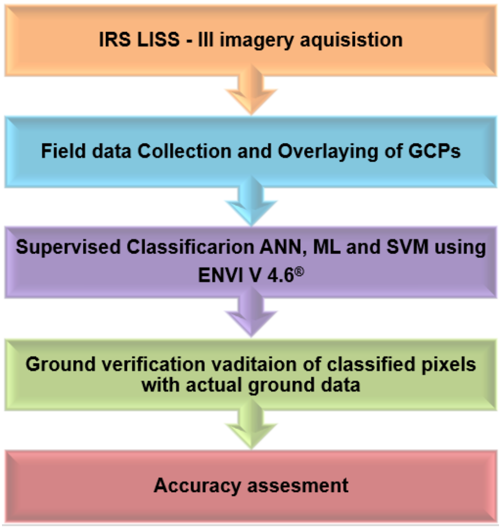


**Figure 1** Model Structure

### 3.2 Study Area:

The study was performed in the South region of Gujarat state, India. Valsad district is located at 20◦ 23" 27' N 73◦ 5" 25' E to 20◦ 18" 7' N 73◦ 11" 20' E (Figure 2). Valsad District of Gujarat state in India. It contains a hilly terrain with hills of moderate altitudes from 110-360 m, an extension of the Sahyadri Range. The landscape of the Valsad district is made up of Agriculture land (chiefly rice cultivars), Orchards of chiefly mango trees, and residential areas (both urban and rural). It chiefly consists of moist deciduous tropical types of forest (Ji, Kumar, Patil,& Soni, 2007). Teak (Tectona grandis L.) and Bamboo (Dendrocalamus strictus Nees.) are the dominant species of the study area. Other tree species growing in the forest area of south Gujarat include Acacia catechu Willd., Terminalia arjuna (Roxb.) Wight & Arn., Butea monosperma (Lamk.), Holarrhena antidysenterica(R.) Br, Mitragyna parviflora (Korth.), Dalbergia latifolia (Roxb.), Anogeissus latifolia (Wall.), Bridelia retusa (L.),Albizia lebbeck (L.), Madhuca indica (Gmel.), Garuga pinnata(Roxb.), Pongamia pinnata (L.) and Ficus racemosa (L.).

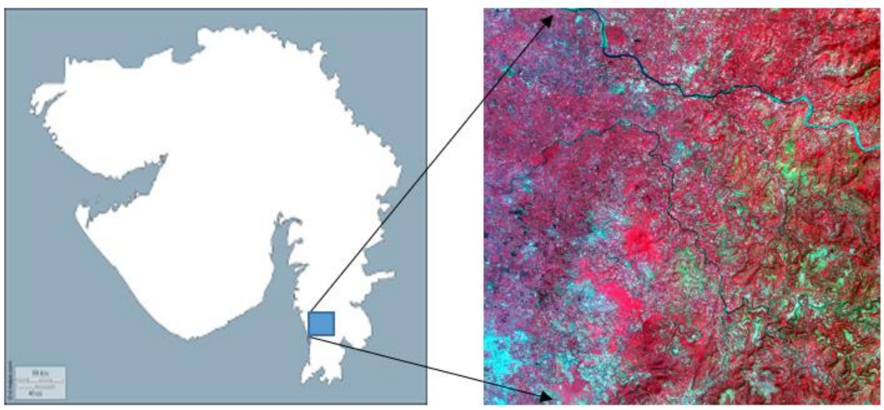

**Figure 2. (a**) Map of Guj.(d-maps.com) **Figue 2(b.)** FCC Image

**Figure 2** Study Area

### 3.3 Field data collection:

An extensive field survey was done to record ecological features and distribution patterns of Land Use Land Cover. Five distinct vegetation classes have been identified in the study area. Of these 5 classes, Agriculture land, Water bodies, Barren land, Forest region, Residential area. A total of 150 (30 for each class) quadrats of 30 × 30 m size (corresponding with a spatial resolution of LISS III data) were laid down across the marked study area. The numbers of Ground Control Points (GCP) taken for each class were dependent on the distribution of identified vegetation classes within the study area. GPS locations of all the quadrats were recorded within an error of ± 4m.

**3.4 Image acquisition and processing:**

IRS LISS III data was obtained on 13th, January 21 at the time of data acquisition, cloud cover was less than 25%. The image was obtained from National Remote Sensing Centre, ISRO (bhuvan-app3.nrsc.gov.in). Image acquisition coincides exactly with the one covered by an extensive field survey. Additional image processing was performed in ENVI V 4.6®. Image processing systems (IPS) are a very important key to support remote sensing applications and have increased in number and capability in the last many years (Elaalem, Ezlit,, Elfghi, Abushnaf, ,2013). Image processing techniques have been developed to support the understanding of remote sensing images and to fetch as much information as possible from the images. The selection of specific techniques or algorithms depends on the areas as per individual requirement

**3.5 Image Classification:**

The image classification procedure works in a organized format where different tasks are to be accomplished in an ordered format to achieve the desired results and classifying the image accurately (Lu, D. & Weng Q. , 2007). Inherent supervised classification mechanism from ENVI V 4.6® was used to cluster pixels in the dataset into classes corresponding to defined training classes. Built-in complex non-linear classification algorithms (ML, ANN, and SVM) from ENVI V.4.6 were used to classify the image. Out of a total of 100 GCP 50 used as training data set while the remaining 50 used as test data set to calculate Over All Accuracy (OAA).

**3.5 Maximum likelihood classification:**

Maximum likelihood (ML) classifier is the commonly used supervised classification technique used with remote sensing image data, in which a pixel with the maximum likelihood is classified into the corresponding class. In ML, a pixel is selected to a class according to its probability of fitting to a particular class. Mean vector and covariance metrics are the main constituent of MLC that can be recovered from training data (Richards, & Richards,1999). ML classification adopts that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than the threshold you specify, the pixel remains unclassified.

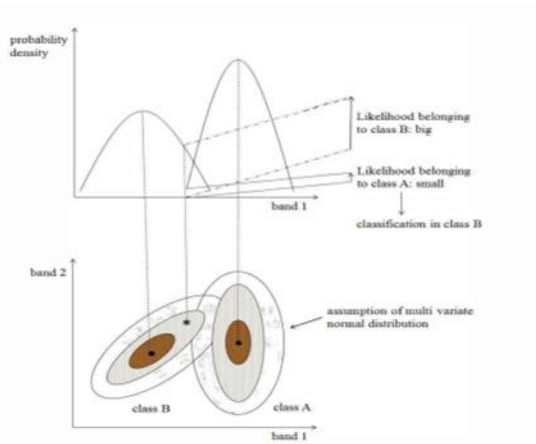


**Figure 3** Bacis concept of ML(JARS,1999)

Following is a Discriminant Functions Calculated for Each Pixel:

$$g_i(\boldsymbol{x}) - \ln\ p(\omega_i) - 1/2\ln|\Sigma_i| - 1/2(\boldsymbol{x} - \boldsymbol{m}_i)^t\Sigma_i^{-1}(\boldsymbol{x} - \boldsymbol{m}_i) \quad (1)$$

Where:
i = class
x = n-dimensional data (where n is the number of bands)
p(ωi) = probability that class ωi occurs in the image and is assumed the same for all classes
|Σi| = determinant of the covariance matrix of the data in class ωi
Σi-1 = its inverse matrix
mi = mean vector

**3.6 Support Vector Machine:**

SVM is a non-parametric supervised machine learning technique and initially aimed to solve the binary classification problems (Maxwell, Warner, & Fang, 2018).Support Vector Machine to perform supervised classification on images using a support vector machine (SVM) to identify the class associated with each pixel. SVM is a classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. It can be used for both linear and non-linear purposes (Kamavisdar, Saluja, & Agrawal, 2013). It is simple to identify and show correct results and works accurately even if the training images are noisy (Sanghvi, Aralkar , Sanghvi & Saha, 2020).

The support vector machine (SVM) provides a training approach that depends only on those pixels in the vicinity of the separating hyperplane (called the support pixel vectors). It also leads to a hyperplane position that is in a sense optimal for the available training patterns (Richards & Richards ,1999). The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors (Figure 4). The support vectors are the critical elements of the training set. The classifier tested was SVM has a number of options in kernel selection such as Linear, Polynomial, Sigmoid, and Radial Basis Function (RBF) for SVM. We have classified the Hyperion image with each RBF because the RBF method exploits information about the inner products between data items (Vyas et al., 2011).

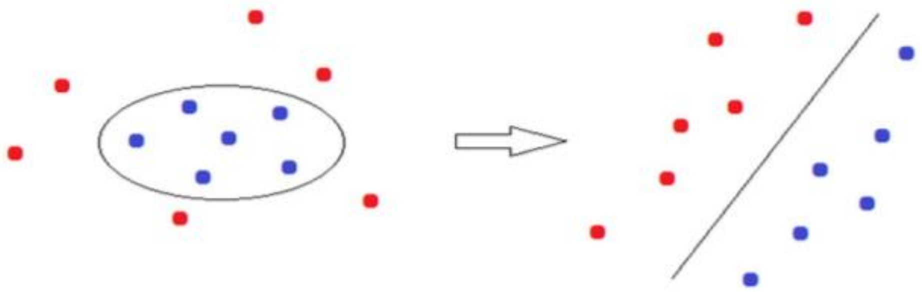

**Figure 4** Graphic representation of the SVM method (Naik, Thaker,& Vyas, 2021).

**3.7 Artificial Neural Network (ANN)**

A neural network classification appears as shown in Figure 5. Being a layered classifier composed of processing elements of the type shown in. It is predictably drawn with an input layer of nodes and an output layer from which the class category information is provided. Amid there may be one or more so-called hidden or other processing layers of nodes. Usually, one hidden layer will be adequate, although the number of nodes to use in the hidden layer is often not readily determined (Richards & Richards ,1999). The ANN is the most widely applied supervised classification, which can be professionally used in non-linear phenomena such as LULC changes with the ability to work on big data analysis. It is currently one of the most used non-parametric classification (Talukdar , Singha Mahato, Pal, Liou , & Rahman, 2020))

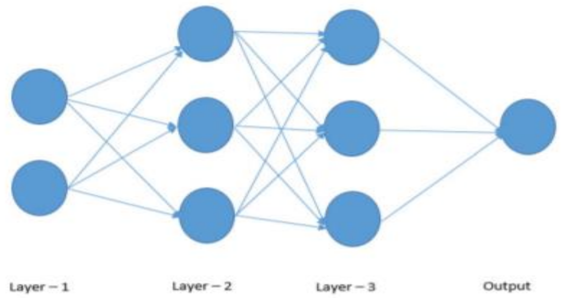


**Figure 5** A graphical representation of the Neural Network method (Naik,Thaker & Vyas , 2021).

## 4. Results and discussion

Ground truthing and validation performed for classification using field survey of study area. Confusion metrics generated about classification as shown in Table1,2 and 3. Tables 1, 2, and 3 show overall accuracy OAA (in the form of confusion matrix) of IRS (LISS III) image classified with the help of ANN, ML, and SVM classifier respectively. Figure 6 shows the IRS (LISS III) image classified with the help of ANN, ML, and SVM classifier respectively. Additionally, overall accuracy of the ANN classifier is more in comparison to ML and SVM.

**Table 1** Confusion matrix obtained using ANN classifier

| | Agriculture Land | Forest | Residential Area | Water Bodies | Barren Land | Total | % Accuracy |
|---|---|---|---|---|---|---|---|
| Agriculture Land | 13 | 2 | 0 | 0 | 0 | 15 | 86.66 |
| Forest | 1 | 13 | 0 | 1 | 0 | 15 | 86.66 |
| Residential Area | 1 | 0 | 13 | 0 | 1 | 15 | 86.66 |
| Water Bodies | 0 | 0 | 0 | 14 | 1 | 15 | 93.33 |
| Barren Land | 1 | 0 | 1 | 0 | 13 | 15 | 86.66 |
| Total | 16 | 15 | 14 | 15 | 15 | 75 | |
| % Accuracy | 81.25 | 86.66 | 92.85 | 93.33 | 86.66 | | |

OAA = 87.99 %

**Table 2** Confusion matrix obtained using ML classifier.

| | Agriculture Land | Forest | Residential Area | Water Bodies | Barren Land | Total | % Accuracy |
|---|---|---|---|---|---|---|---|
| Agriculture Land | 11 | 2 | 0 | 0 | 1 | 15 | 73.33 |
| Forest | 1 | 12 | 1 | 0 | 1 | 15 | 80.00 |
| Residential Area | 1 | 0 | 11 | 1 | 2 | 15 | 73.33 |
| Water Bodies | 1 | 1 | 1 | 10 | 2 | 15 | 66.66 |
| Barren Land | 1 | 1 | 0 | 1 | 12 | 15 | 80.00 |
| Total | 15 | 16 | 13 | 12 | 18 | 75 | |
| % Accuracy | 73.33 | 75.00 | 84.61 | 83.33 | 66.66 | | |

OAA = 74.66 %

**Table 3** Confusion matrix obtained using SVM classifier.

| | Agriculture Land | Forest | Residential Area | Water Bodies | Barren Land | Total | % Accuracy |
|---|---|---|---|---|---|---|---|
| Agriculture Land | 13 | 1 | 0 | 0 | 1 | 15 | 86.66 |
| Forest | 1 | 12 | 1 | 1 | 0 | 15 | 80.00 |
| Residential Area | 1 | 1 | 11 | 1 | 1 | 15 | 73.33 |
| Water Bodies | 0 | 1 | 1 | 12 | 1 | 15 | 80.00 |
| Barren Land | 1 | 1 | 0 | 0 | 13 | 15 | 86.66 |
| Total | 16 | 16 | 13 | 14 | 16 | 75 | |
| % Accuracy | 81.25 | 75.00 | 84.61 | 85.71 | 81.25 | | |

OAA = 81.33%

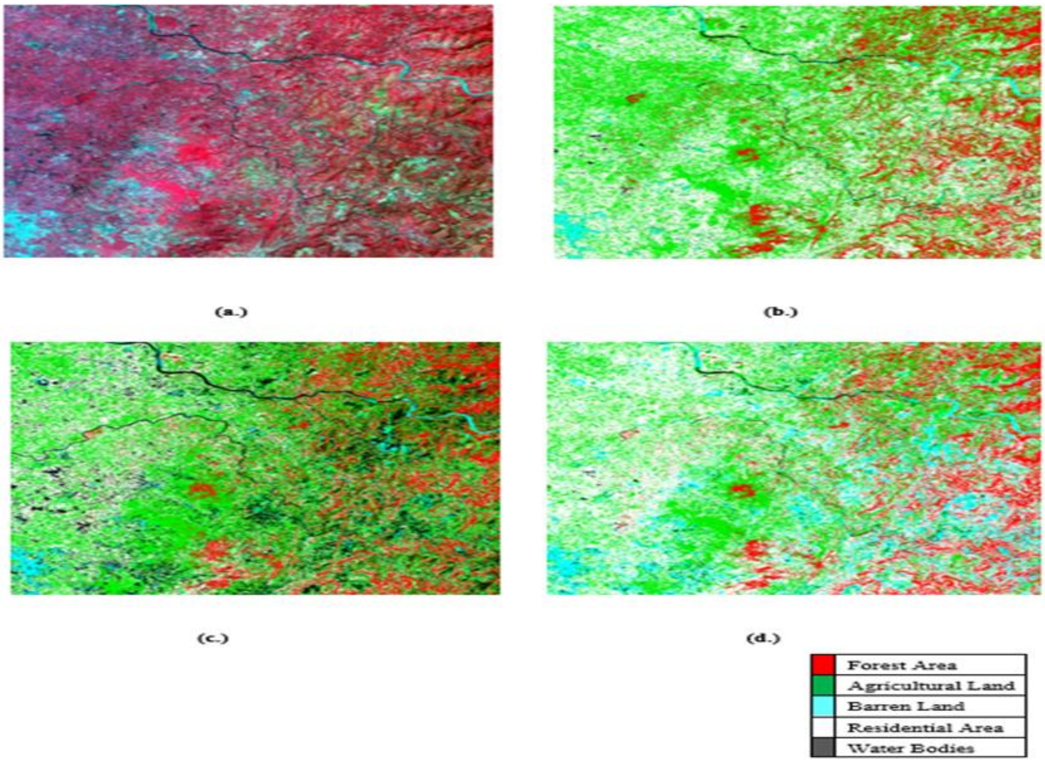


**Figure 6** Classified images (a.) FCC (b.) ANN (c.) ML (d.) SVM

Thoughtful observation of Figure 6 (b) reveals that IRS (LISS III) image classified with ANN classifier is comparable with FCC image. ANN classifier is able to classify minor features such as shadowed forest region (forest patches existing on the mountain slopes that are situated against the sunlight). It is noteworthy that the ANN classifier is also able to classify water bodies more precisely in comparison to the ML / SVM classifier (Table 1). Complex features such as shadowed forest patches and trivial water bodies are accurately classified by ANN. ANN classifier is well known for its ability to separate complex land use classes with higher accuracy. It is noteworthy, that (Nurwauziyah, Umroh Dian,Putra, & Firdaus, 2018), (Pathak & Dikshit, 2005), (Macintyre, Niekerk & Mucina, 2020) achieved an accuracy greater than 70 % for various kinds of multispectral data set. Earlier, (Prasad, Savithri, & Krishna , 2017) accomplished an OAA of 89 % in land cover classification. Previously, (Madhubala, Mohan Rao & Ravindra Babu ,2010) succeeded to attain an accuracy of 56 % with IRS LISS III data. Similarly, (Kontoes , Raptis , Lautner & Oberstadler, ,2000) attained a moderate accuracy of 72 and 74 % respectively using a similar dataset for land use land cover classification. Table 4 represents the suitability of classifiers in land use land cover classification in previous work performed by the various authors.

**Table 4** Suitability of classifier in LULC classification as per the previous works

| Sr. No | Methods used | Best Method | Authors |
|---|---|---|---|
| 1 | Random fores (RF)t, K-nearest neighbors (KNN), Support vector machine (SVM) | SVM | (Noi & kappas,2018) |
| 2 | RF, SVM | SVM | (Ma, Li, Ma, Cheng, Du& Liu,2017) |
| 3 | SVM, ANN, Classification and regression tree (CART) | SVM | (Pal &Ziaul,2017) |
| 4 | SVM, RF, ANN | ANN | (Raczko & Zagajewski,2017) |
| 5 | ANN, SVM | ANN | (Abbas, Ahmad, Shah & Saeed, 2017) |
| 6 | Maximum likelihood (ML), SVM, ANN | ANN | (Srivastava, Han,Rico-Ramirez, Bray & Islam,2012) |
| 7 | RF, Ml | ML | Abbas, Ahmad, Shah & Saeed,2017) |

The present study also ANN achieved a decent OAA of 88 %,SVM achieved 81% and ML classifier achieved a moderate accuracy of 75 %. However, hyper-classification of water bodies is clearly visible in IRS (LISS III) image classified with ML. Furthermore, the shadowed forest region is miss classified as water bodies in most of the regions of the IRS LISS III image by ML classifier. However, ML classifiers accurately disguise between agricultural land and residential area. Earlier, (Navin, & Agilandeeswari, 2019) achieved an accuracy of more than 90 % for IRS (LISS III) images for a fewer number of classes. (Sisodia, Tiwari & Kumar ,2014) accomplished an accuracy of greater than 90% for Landsat ETM+ imagery.

However, the current complex landscape OAA achieved in the present study is comparable. SVM classifier achieved a reasonable OAA of 81 %. Earlier, (Macintyre Van Niekerk & Mucina, 2020) achieved an accuracy of 74% with the help of Sentinel-2 multispectral imagery. (Lowe & Kulkarni ,2015) accomplished an accuracy of 87 %. (Nurwauziyah, Umroh Dian, Putra & Firdaus,2018) achieved an accuracy of 87 % using multispectral satellite imagery. OAA attained for SVM in the present study is comparable to the above-mentioned studies. However, it is apparent that over and miss classification of residential area is clearly evident in IRS (LISS III) image classified with SVM. Critical observation reveals the miss classification of Agriculture land into a residential area in IRS (LISS III) image classified with SVM.

## 5. Conclusion

The study was carried out to compare the performance of three different classifiers (ML, ANN, and SVM) over a complex landscape of the Valsad district of the South Gujarat region with IRS (LISS III) imagery. It showed that ANN fared better across all the land use and land cover classes. It also revealed that ML and SVM classifier is prone to miss classification of pixels in one or more classes. IRS (LISS III) classified imagery from ANN are quite similar in showing the distribution of five land use and land cover classes. The findings of the present study are reassuring the capability of IRS (LISS III) multispectral data for the accurate mapping of complex land use and land cover features. Furthermore, proficiency of ANN classifier in the classification of complex features using multispectral data was re-established in the present study**.**

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# Accurate Identification of complex Land use and Land Cover Features using IRS (LISS III) Multispectral Image

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**ABSTRACT** Land Use and Land Cover (LULC) is an assortment of activities executed by humans on to the land. The present study was carried out to evaluate supervised classification mechanisms for classification complex Land use and Land cover features using India Remote Sensing System-IRS (Linear Imaging Self-Scanning Sensor 3- LISS III) multispectral data. It showed that Artificial neural networks (ANN) fared better across all the land use and land cover classes with an overall accuracy of 88%. It also revealed that Maximum Likelihood (ML) and Support Vector Machine (SVM) classifier is prone to miss classification of pixels in one or more classes. Outcomes of the present study are comforting the competence of IRS (LISS III) multispectral data for the accurate mapping of complex land use and land cover features. Additionally, the ability of an ANN classifier in the classification of complex features using multispectral data was re-established in the present study.

**Keywords**: land use and land cover, Multispectral satellite imagery, Artificial neural networks (ANN) , Support vector machine (SVM), Maximum likelihood (ML).

## I. INTRODUCTION

Land Use and Land Cover (LULC) is a collection of actions performed by humans on to the land, to gain benefits using land resources. Land cover is termed as the vegetation or buildings which take place on the earth. Examples of land covers contain agricultural land, forest, grassland, and wetland while land use refers to the biophysical state of the earth's surface and immediate subsurface, containing soil, topography, surface water, and groundwater, and human structures (Elaalem, Ezlit, Elfghi, & Abushnaf , 2013). Land use is the utilization of the land by humans for economic activities like agriculture, forests, construction, and farming (Waqas et al. 2019).Knowledge of land-use/land-cover (LULC) change is essential in a number of fields based on the use of Earth observations, such as urban and regional planning , environmental vulnerability andimpact assessment , natural disasters and hazards monitoring (Liou, Nguyen, & Li, ,2017), (Nguyen & Liou,,2019),( Talukdar & Pal,2018) Mapping LULC change has been identified as an essential aspect of a wide range of activities and applications, such as in planning for land use or global warming mitigation (Dutta, Rahman, Paul & Kundu, 2019)

Remote Sensing is the science of obtaining data about objects or areas from a distance. With the quick development of remote sensing technologies, its application has been tried in a wide range of fields, for example, land surveying, computer cartography, urban planning, geographic image retrieval, and others (Cheng, Han & Lu,2017), (Xia et al., 2017), (Lu & Weng, 2007), (Richards & Richards, 1999). Remote sensing techniques have also been recognized as a powerful tool to accurately map the LULC pattern of a given landscape. The remote sensing images collected by imaging satellites functioned by governments and businesses around the world. Remote sensing can significantly contribute to providing a timely and accurate image of the agricultural sector, as the convenient and suitable for gathering appropriate information over large areas with high accuracy (Brisco , Brown, Hirose, McNairn, & Staenz , 2014).

Remote Sensing provides the opportunity for rapid acquisition of information on LULC at a much-reduced price compared to the other methods like ground surveys. The satellite images have the advantages of multi-temporal availability as well as large spatial coverage for the LULC mapping (Wittke,Yu, Karjalainen, Hyyppä, & Puttonen,2019), (Viana,,Girão, & Rocha,2019). Multispectral remote sensing images collected by satellite present a massive opportunity for understanding the characteristics of the earth. Land use/land cover (LULC) identification and mapping with remote sensing images have developed great interest among researchers from different disciplines. Land Use/Land Cover refers to the utilization of land through actions like urban planning, natural resource management, water resource monitoring, environmental and agricultural analyses. Remote sensed imagery is the most popular method to capture data on Land Use/Land Cover. Multispectral imaging is one of the most widely used technologies for LULC mapping and monitoring. Image classification is a process where decision rules are developed and used to assign pixels into classes that have similar spectral and information features (Homer, Huang, Yang, Wylie, & Coan, (2004), (L. Fang, He, Li, Ghamisi, & Benediktsson, 2017). The major objective of the present study is to pe rform supervised classification such as Artificial Neural Network (ANN), Support Vector Machine (SVM), and Maximum Likelihood (ML) on the images taken from IRS (LISS III) multispectral platform. Comparison of supervised classification results and identification of best classifier based on percentage accuracy.

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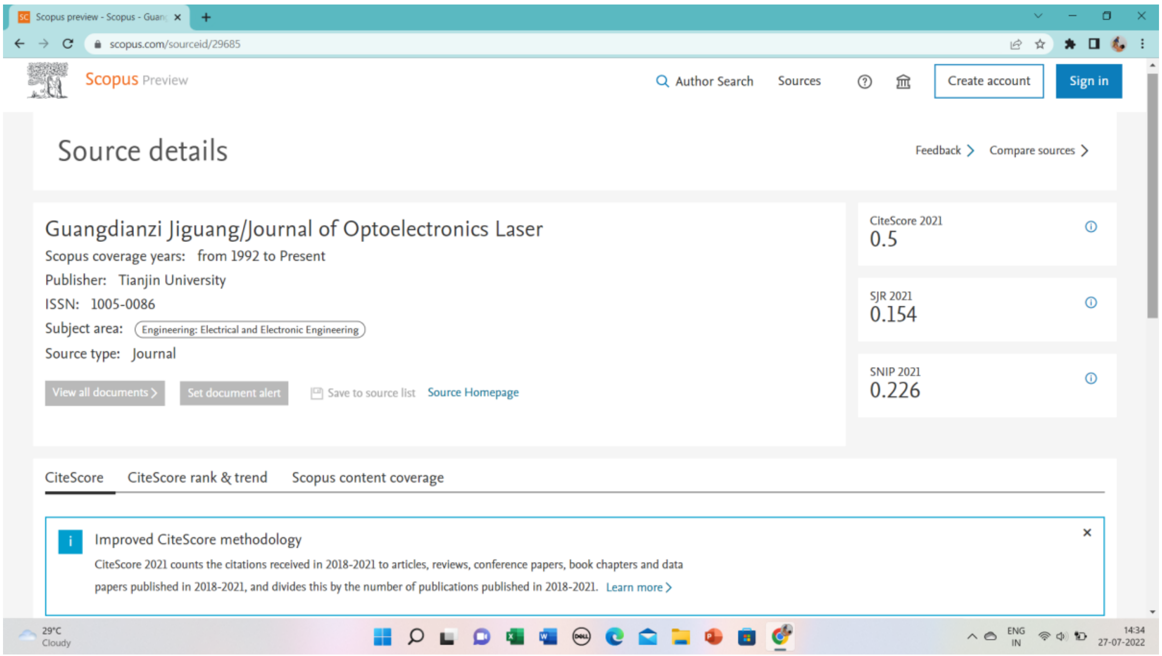
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