Bibliography

Sr. No	Participation	Title	Organizing Institutions/Industry / University	Month & Year
1	Research Methodology Course (Online/Offline)	Understanding Research Methods	Coursera	Dec – 19
2	Workshop / STTP	Machine Learning And Deep Learning using python	DUIAS AND DSIM&C, GUJCOST, DST	Jan-20
3	FDP (Faculty Development Program)	Structural Equation Modeling	Atmiya University, Rajkot	Dec-19
4	Research Methodology Course (Online/Offline)	Research Methodology	UDEMY	Dec - 19
5	Online Course	computer vision- image basics with OpenCV and Python	Coursera	May - 20
6	Online Course	Computer Vision- Object Detection With Opencv And Python	Coursera	May - 20
7	Online Course	Machine Learning With Python	Cognitive Class	May - 20
8	Workshop / STTP	Basics of Machine Learning	CRSTES, IISER Bhopal, NPTEL, IIT Madras	Apr-20
9	Webinar	Data Science using Machine Learning from Scratch	CESA, Indus University	Dec-19
10	Webinar	Effective Ways to Develop E_Content	SMT.Devkiba Mohansinhji Chauhan College Of Commerce and Science (affiliated to uni. Of Mumbai)	May-20
11	Webinar	Challenges for Research Paper Writing & Publishing	SMT. K.S.N Kansagara Mahila Arts & Commerce College, Rajkot	May-20

12	Webinar	Predictive model using Deep learning, Data science, Importance of cyber security in digital world	V.S.Patel College - Bilimora, BCA department	May-20
13	Webinar	How to Publish high-quality technical journal paper	IEEE	Apr-20
14	Webinar	IEEE Xplore Digital Library: Supporting Every Aspect of YOUR career	IEEE	Apr-20
15	Webinar	IEEE Xplore Digital Library: Supporting Every Aspect of YOUR career	IEEE	Apr-20
16	Webinar	Research Ethics	NPTEL	May-20
17	Webinar	Online onboarding on Turnitin	Atmiya University, Rajkot	Jun-20
18	FDP (Faculty Development Program)	Online Faculty Development Programme On R Language	Auxillium College, Vellore (TN) and Spoken Tutorial IIT Bombay	May-20
19	FDP (Faculty Development Program)	Evolution From Offline to Online Teaching	Satish Pradhan Dhyanasadhna College Thane, Dept. Of IT-Uni. Of Mumbai and Microsoft	Jun-20
20	Online course	Python basics for data science	edX (Atmiya University)	Mar-21
21	FDP (Faculty Development Program)	One week online international FDP on Research Methodology	A.V.Patel ANd Z.S.Shah College of commerce and managenent, Amroli, Surat	Aug-21
22	Refresher Course	Refresher Course in ITGS (Information Technology in Global Society)	HRDC, Ahmedabad.Gujarat University	Sep -21

23	FDP (Faculty Development Program)	NEP - 2020	D-UIAS AND D-SIM&C, Valsad	Jan -23

Appendix A

Plagiarism Report

Ouriginal
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Document Information

Analyzed document	191881001_ComputerScience_NiravDesai_Thesis.pdf (D169100382)
Submitted	2023-05-31 11:58:00
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Sources included in the report

W	URL: https://doi.org/10.17762/ijritcc.v11i3.6329 Fetched: 2023-05-31 12:00:00	8
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SA	2. Nirav Desai.docx Document 2. Nirav Desai.docx (D160714247)	58
SA	rana-9.docx Document rana-9.docx (D54864731)	1
W	URL: https://doi.org/10.1007/978-981-19-8865-3_42 Fetched: 2023-05-31 12:00:00	2
SA	Synopsis 10-05-2019.docx Document Synopsis 10-05-2019.docx (D51818540)	1
W	URL: https://towardsdatascience.com/review-fc-densenet-one-hundred-layer-tiramisu-semantic-segmenta... Fetched: 2023-05-31 11:59:00	2

Entire Document

DESIGN AND DEVELOPMENT OF A MODEL FOR CLASSIFICATION AND MAPPING OF LAND USE/LAND COVER USING MULTI SPECTRAL SPACE BORN REMOTE SENSING
IMAGES A Thesis Submitted to the Atmiya University,
For
the Degree of Doctor of Philosophy in COMPUTER SCIENCE by
Nirav H Desai Enrolment No. 191881001 Under the Guidance of Dr. Parag Shukla Department of Computer Science
ATMIYA UNIVERSITY, Yogidham Gurukul, Kalawad Road, Rajkot–360005, Gujarat (India) June, 2023

Appendix B

Publications

International Journals

[1] Desai, N., & Shukla, P. (2023). Performance of Deep Learning in Land Use Land Cover Classification of Indian Remote Sensing (IRS) LISS – III Multispectral Data. International Journal on Recent and Innovation Trends in Computing and Communication, 11(3), 128–134. https://doi.org/10.17762/ijritcc.v11i3.6329

[2] Desai, N., Shukla, P. (2023). Land Use Land Cover Segmentation of LISS-III Multispectral Space-Born Image Using Deep Learning. In: Chakravarthy, V., Bhateja, V., Flores Fuentes, W., Anguera, J., Vasavi, K.P. (eds) Advances in Signal Processing, Embedded Systems and IoT . Lecture Notes in Electrical Engineering, vol 992. Springer, Singapore. https://doi.org/10.1007/978-981-19-8865-3_42

[3] Desai, N., & Shukla, P. Land Cover Land Use Mapping & Classification Model (Mapping Of Land Cover Land Use Using Multispectral Space Born Image).

[4] Naik, A., Thaker, H., & Desai, N. (2022). Creation and Segmentation of Image Dataset of Mung Bean Plant Leaf. In *Micro-Electronics and Telecommunication Engineering* (pp. 669-683). Springer, Singapore.

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[6] Desai, N., & Shukla, P. (2022). A LAND USE/LAND COVER CLASSIFICATION OF IRS (LISS–III) MULTISPECTRAL DATA USING DECISION TREE AND SVM CLASSIFICATION MECHANISM. *Harbin*

Gongye Daxue Xuebao/Journal of Harbin Institute of Technology, *54*(10), 111-118.

International Conferences

[1] Research paper titled “Land use land cover segmentation of LISS- III multispectral space born image using deep learning” in 7th International Conference on Micro-Electronics, Electromagnetics and Telecommunications ICMEET – 2022, 22-23 July 2022 and will be published in Springer, Lecture Notes in Electrical Engineering.

[2] Won the Best Paper award for presenting a research paper titled “Indian remote sensing (IRS) LISS- III multispectral image semantic segmentation using deep learning(U-Net & Deeplabv3+) ” at the International Conference on Emerging Technologies & Business Intelligence Organized by RK University, Rajkot and Wroclaw University of Science and Technology, Poland.

Under Review

[1] Research paper titled “Indian Remote Sensing (IRS) LISS- III multispectral image semantic segmentation using deep learning (U-Net & Deeplabv3+)” in the journal “Operations Research and Decisions “ Scopus indexed , ISSN 2391-6060 (online version) .

[2] Research paper titled “Multispectral space-born Indian remote sensing image (LISS- III) semantic segmentation using deep learning” in the journal International Journal of Information Technology” (Springer , Scopus indexed).

Performance of deep learning in land use land cover classification of Indian Remote Sensing (IRS) LISS – III Multispectral data

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Abstract—Identification of land use land cover is a very important task. However, methods existing for the above mention purpose are labor incentives, time-consuming, and costly. Remote sensing plays very important role in the mappings. classification of land cover features and offers very noteworthy and sensed information. The present study shows the semantic segmentation of Indian remote sensing (IRS) LISS-III multispectral image and the comparison of three algorithms U-Net, Deeplabv3+and Tiramisu. The deep neural network was used to perform the study. We present total 3 innovative datasets, built on these LISS-III images that has 4 different spectral bands (Band – 2 (Blue), Band-3 (Green), Band-4(Red), and Band-5 (Nearly Infrared), FCC (false color composite) images and the ground truth mask images. Dataset has 13500 labelled images. A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 128 X 128 X 3 and outputs a matrix of shape 128 X 128 X 4 i.e., a one-hot encoded version of the mask. The experiment identifies 4 classes successfully (Water Bodies, Vegetation, Uncultivated Land, and Residential areas). The experiment showed that the U-Net algorithm has a very good capability for the classification of LISS -III images for land use land cover class detection then Tiramisu and Deeplabv3+. U-Net achieved accuracy 84%, Deelabv3+ achieved 29% whereas Tiramisu achieved accuracy 33%.

Keywords- land use land cover, deep learning, FCN, U-Net, Deeplabv3+, Tiramisu

I. INTRODUCTION

In new aeras, satellite images are fetching an immense substance of data for studying the spatial and progressive variability of ecological situations. The beginning of remote sensing with multispectral images in digital format has taken a new dimension in, mapping and monitoring of natural resources of the Earth [9]. Remote sensing is the art of discover and understanding the data or information from a long distance, using sensors without communication with the object being observed [22]. Land use land cover classification anticipates to form space-born images into a precise class, which was reliant on the distribution of predictable land use land cover classes. Land use and land cover mapping are essential errands for preparation and management.

Land use land cover classification using remote sensing images has been applied in several studies, including surveys involving environmental monitoring and change detection [3], research on urbanization effects [24],[10] and disaster mitigation [26]. The spatial resolution of remote-sensing systems is low, so it is probable to recognize the different classes on the Earth's surface [25]. In 2006, Deep learning projected by Hinton et al. [8] and confirmed training complications of a deep neural network can be solved using one-by-one layer initialization. And efficiently applicable to the field of video and image processing, a field of data analysis [5]. The deep learning algorithms gives a new way for remote sensing image explanation and a massive number of deep learning algorithm research in the field of remote sensing image classification. Semantic Segmentation is defined as a pixel-level classification of images where a class is allotted to an individual pixel of the image.

Remotely sensed imagery is an image data with intervallic Earth observation. The appealing benefits of deep neural networks have been presented in many remote-sensing applications.

Deep neural networks (DNNs) refer to end-to-end mappings (i.e., from data to information) by stacking a large number of filters learned from massive samples. In deep learning, mainly Convolutional Neural Networks (CNNs), have been effectively applied for image classification, target detection, and scene understanding [4][7][12][14][28]. A fully convolutional neural network (FCN) was proposed by in 2015[17]. FCN is fully related with layers in CNN with up-convolutional layers and concatenates with a shallow, finer layer to produce end-to-end labels. FCN is more fitting for pixel-based image classification, i.e., labelling all pixel to a separate class. The FCN framework has also revealed excessive potential in remote sensing image classification. The U-Net model projected by [21] is an improved FCN model characterized by balanced U-shaped architecture covering a symmetric contracting path and expansive path. Tiramisu is a polyhedral compiler for dense and sparse deep learning and data-parallel algorithms and points a vast set of loop optimizations and data design variations. Deeplabv3+ is a state-of-the-art semantic segmentation model having encoder-decoder architecture.

The present study accomplished the semantic segmentation on datasets (dataset of 13500 images of different seasons) of LISS -III remote sensing images (South Gujarat Region, INDIA). A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 128 x 128 x 3 and outputs a matrix of shape 128 x 128 x 4 i.e., a one-hot encoded version of the mask. In the study 4 classes have been identified - Water Bodies, Vegetation, Uncultivated Land, and Residential areas. U-Net DeepLabv3+ and Tiramisu were applied to perform land use land cover classification on the LISS - III multispectral remote-sensing image. U-Net gives better performance than DeeplabV3+ and Tiramisu. U-Net achieved very good accuracy 84%, Deelabv3+ achieved 29% whereas Tiramisu achieved accuracy 33%.

I. Literature Review

In the deep learning technique numerous layers of data processing phases in ordered architectures are exploited by unsupervised learning and pattern classification [20]. [16] proposed planned and complete assessment of various groups of applying DL methods. [18] proposed DFS algorithm and compare it with YOLOv2. The dataset derives from Google Earth and detects 6 objects airplanes, boats, warehouses, large ships, bridges, and ports. [13] proposed classification technique for land use land cover classification using neural network with random forest. [9] performs pixel and object-based classification and achieves 87% accuracy from satellite images. [23] used Maximum likelihood to perform classification on images of SPOT, ASTER, and Landsat TM for. And achieved OOA of 85.33%, 86.67%, 88.33%, and 86.38% for the years 1989, 2000, 2010, and 2016 respectively. [19] proposed methods that improved convolutional neural networks for aerial image segmentation.[24] proposed object-based Classification for remote sensing image of Deimos-2 and Cartosat-1 using the Convolution Neural Network.

II. Use Materials and Methods

In the deep learning technique numerous layers of data processing phases in ordered architectures are exploited by unsupervised learning and pattern classification [20]. [16] proposed planned and complete assessment of various groups of applying DL methods. [18] proposed DFS algorithm and compare it with YOLOv2. The dataset derives from Google Earth and detects 6 objects airplanes, boats, warehouses, large ships, bridges, and ports. [13] proposed classification technique for land use land cover classification using neural network with random forest. [9] performs pixel and object-based classification and achieves 87% accuracy from satellite images. [23] used Maximum likelihood to perform classification on images of SPOT, ASTER, and Landsat TM for. And achieved OOA of 85.33%, 86.67%, 88.33%, and 86.38% for the years 1989, 2000, 2010, and 2016 respectively. [19] proposed methods that improved convolutional neural networks for aerial image segmentation.[24] proposed object-based Classification for remote sensing image of Deimos-2 and Cartosat-1 using the Convolution Neural Network.

A. *Data Acquisition*

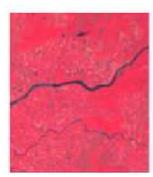
The present study was performed on the South Gujarat Region, State of Gujarat, country INDIA using Indian Remote Sensing (IRS) LISS- III Multispectral remote sensing images. These multispectral images have less than or equal to 10 bands and over 100 nm resolution; have a total of 4 diverse bands in isolated .tiff files and the number of bands is Band – 2,3,4 and 5(Blue, Green, Red, and near Infrared). Quadrats of 30m X 30m size were placed across the study area. Data was acquired from the website of ISRO (https://bhuvan-app3.nrsc.gov.in)

A widespread ground study was accomplished to gather environmental landscapes and circulation forms of dissimilar land use and land cover. The GCPs held in reserve for the individual groups were dependent on the distribution of identified land use land cover classes within the study area. The Latitude, Longitude for the location of the respective class is being verified and recorded which are called Ground Control Points (GCPs). GPS device used to collect GCPs. GPS Garmin – eTrex 30 is used for the study. The GCPs reserved for the respective category were reliant on the allocation of recognized land use classes within the study area.

B. *Pre-Processing*

Indian Remote Sensing (IRS) LISS - III multispectral images have 4 bands. The false color composite (FCC) image was created using combination of these bands. FCCs were designed using stack up these multiband.TIFF image files by the grouping of Band – 4 (Red), Band – 3 (Green), and Band – 2 (Blue). The ground truth masks were designed to train the model after the creation of FCCs for each image. These Masks were created using the maximum likelihood algorithm on the region of interest for each class.

The study was accomplished on a novel dataset that contains the FCC image of different seasons and the Ground Truth Masks. FCCs and their corresponding masks are resized to 1024 * 1024 pixels then after divided into patches of size 128 x 128 pixels with a striding of 64.



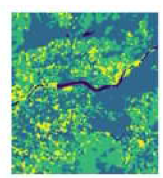


Figure 1. FCC Image Figure 2. Ground Truth Mask

The size of the dataset was 13500 images where 11250 images are used to train the model while 2250 images are reserved for validation and evaluation.

C. *Methods*

The maximum likelihood (ML) classifier was used with IRS LISS- III multispectral image data, where every pixel with the maximum likelihood is classified into the matching class. In maximum likelihood, a pixel is selected for a class based on its chance of fitting. Mean vector and covariance metrics are the main necessities of the ML that can be enhanced from training data [23].

Following is a Discriminant Functions Calculated for Each Pixel:

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

Where i is class, x is n-dimensional data in which n represents the total number of bands. p(ωi) represents the chance that class ωi occurs in the image, |Σi| is the determinant of the covariance matrix, Σi-1 is an inverse matrix the mean vector represents by mi.

Fig.3 shows the basic concepts of maximum likelihood [23]. Ground truth masks were created after the creation of FCC images and used for model training.

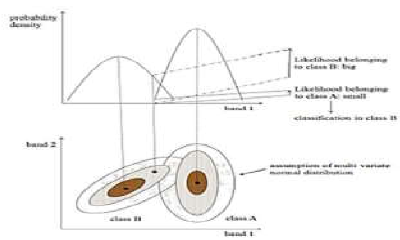


Figure 3: Basic concept of ML [23]

Fully convolutional networks (FCNs) are efficiently applied in the fields like segmentation of an image [1],[9], and medicinal image analysis [6],[15]. FCN is extensively applied in pixel-based classification and used an encoder for feature extraction and a decoder to re-establish the.

A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 128 x 128 x 3 and outputs a matrix of shape 128 x 128 x 4i.e., a one-hot encoded version of the mask. The FCN is a U-Net architecture that contains an encoder part and a decoder part. The encoder part contains 5 blocks and each block is 2 (convolution + batch normalization + relu) layers stacked on top of one another and trailed by a max-pooling except for the last block. The output of this encoder part is then inputted into the decoder containing 4 blocks. Each block in the decoder starts with an upsampling of the input followed by a 1 x 1 convolution operation. A skip connection is also used that concatenates the output of the corresponding encoder block to the output of the upsampling and convolution operation. The concatenated tensor is then again passed to two convolution layers similar to that of the corresponding encoder block. The output of the decoder part is finally fed to a 1 x 1 convolution with the number of filters equivalent to the number of classes which is 4. Fig. 4 shows the U-Net architecture [17]. The arrows denote the various processes, the black containers denote the feature map and the gray containers denote the cropped feature maps from the contracting path.

$$E = \sum w(x)\log(P_{k(x)}(x)) \tag{2}$$

Where pk is the pixel-wise SoftMax function applied over the final feature map.

$$P_k(x) = \frac{e^{ak(x)}}{\sum^{k}_{k!=} eak(x),} \tag{3}$$

And ak (x) denotes the activation in channel k.

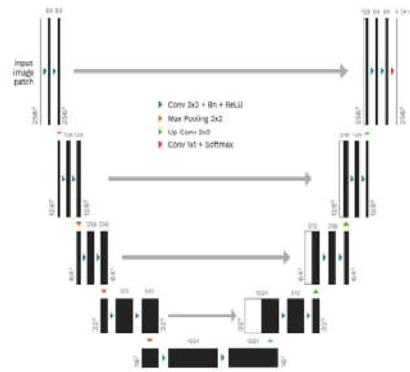


Figure. 4 U-Net architecture

Deeplabv3+ is a state-of-the-art semantic segmentation model having encoder-decoder architecture. The encoder consisting of a pre-trained CNN model is used to get encoded feature maps of the input image, and the decoder reconstructs output from the essential information extracted by the encoder using upsampling. Fig. 5 shows the Deeplabv3+ architecture [2]. DeepLabv3+ extends DeepLabv3 by adding an encoder-decoder structure. The encoder module processes multiscale contextual information by applying dilated convolution at multiple scales, while the decoder module refines the segmentation results of a long object boundary. As go deeper in the network by dilated convolution, can keep the stride constant but with a bigger field-of-view without growing the number of parameters or the amount of calculation. Also, it permits bigger output feature maps, which is useful for semantic segmentation. The purpose of using Dilated Spatial Pyramid Pooling is that it was shown that as the sampling rate becomes bigger, the number of valid filter weights becomes lesser.

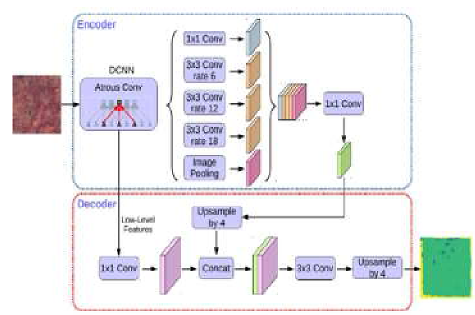


Figure 5: Deeplabv3+

Tiramisu is a polyhedral compiler for dense and sparse deep learning and data-parallel algorithms and directs a huge set of loop optimizations and data design alterations. It is the only open-source DNN compiler that optimizes sparse DNNs and marks distributed architectures. It can perform complex loop transformations and uses dependence investigation to assure the accuracy of optimizations. Tiramisu has also demonstrated its performance on various standards like deep learning operations (Convolution, ReLu, MaxPool, Sparse Neural Networks, etc.) and linear algebra. However, the Tiramisu network, which itself is a modified U-Net, is much larger and took longer to train. Fig. 6 shows the tiramisu architecture.

$$x_l = H_l(x_{l-1}) \quad (4)$$

in standard convolution, xl is computed by applying a non-linear transformation Hl to the output of the previous layer xl-1.

$$x_l = H_l(x_{l-1}) + x_{l-1} \quad (5)$$

ResNet introduces a residual block that sums the identity mapping of the input to the output of a layer

$$x_l = H_l([x_{l-1}, x_{l-2}, \ldots\ldots\ldots, x_0]) \quad (6)$$

DenseNet input concatenates all previous feature outputs in a feedforward fashion for convolution.

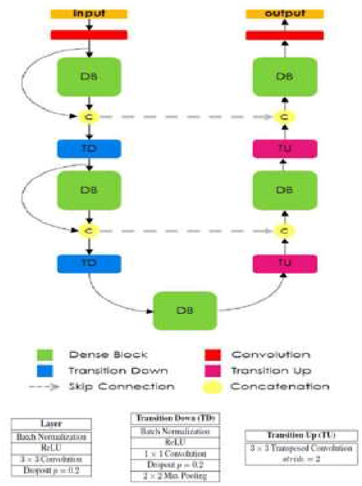
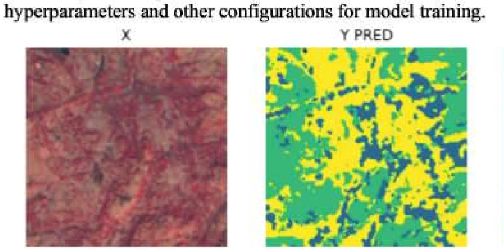


Figure 6. Tiramisu Architecture [29]

A. *Training Configuration*

While data ingestion, standardize the input images by clipping them to [0.0, 255.0] while the masks are one-hot encoded according to the total number of classes. Random augmentations are applied to the bunch of images and masks before passing them to the model for training. This enlarges the dataset and makes the model robust enough to encounter dissimilar orientations than just the training data. And it prevents overfitting when augmentations are done correctly. A custom image data generator is created to fulfill the requirements of this data ingestion pipeline. Table No.1 represents the hyperparameters and other configurations for model training.



(a)

TABLE . 1 HYPERPARAMETERS AND OTHER CONFIGURATIONS USED FOR TRAINING THE MODEL.

Hyperparameters & Configurations	Values
Train Batch Size	16
Validation Batch Size	16
Input Image Shape	128,128,3
Number of classes	4
Epochs	50
Loss	Categorical Focal Loss*
Optimizer	Adam
Metrics	Dice Coefficient*
Class Weights	[1.69941, 0.53043, 1.23977, 1.38949]

II. RESULT

The algorithm for classification developed in U-Net, Deeplabv3+ and Tiramisu was coded with python + OpenCV. The experiment performed the best fine-tuning parameters for U-net, Deeplabv3+ and Tiramisu with RGB bands of the dataset of IRS LISS- III multispectral remote sensing images. The parameters which give very good performance are used to develop the final model. The model also used data augmentation.

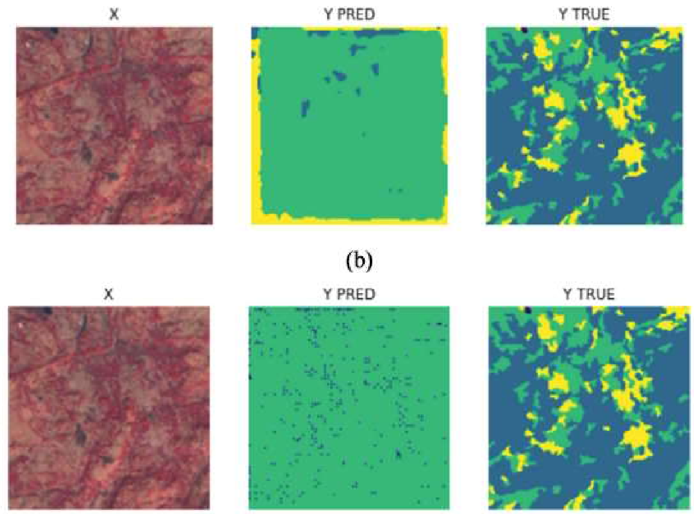
TABLE 2 EXPERIMENT RESULT

Sr.No	Algorithm	Optimizer	EPOCH Trained	Accuracy
a	U-Net	Adam	50	84
b	Deeplabv3+	Adam	50	29
c	Tiramisu	Adam	50	33

Table -2 shows the experiment results and accuracy with different epochs. And from the outcomes, it was noticed that U-net gives healthier results in classifying land use land cover classes. Fig. 7 shows the predicted results.

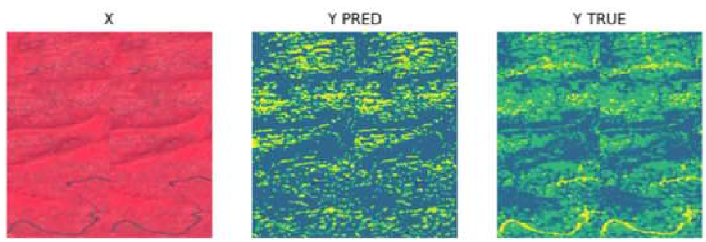
Fig. 7 shows the land use land cover classification by the U-Net model. Fig.7(b) show the classification of land use land cover by Deeplabv3+ and Fig. 7(c) shows the result predicted by the model Tiramisu. Water Bodies are black, Vegetation is light green, Uncultivated Land is light blue, and Residential Areas in yellow.

Fig. 8 shows the quantification for each respective class after classification was performed. The values 0 – represent water, 1 represents vegetation, 2 represents uncultivated land and 3 represents the residential area.



(c)

Figure. 7 Result




```
{0: 1.2038230895996094}
{0: 1.2038230895996094, 1: 83.2174301147461}
{0: 1.2038230895996094, 1: 83.2174301147461, 2: 3.7054061889648438}
{0: 1.2038230895996094, 1: 83.2174301147461, 2: 3.7054061889648438, 3: 11.873340606689453}
```

Figure. 8 Quantification

I. Conclusion

The proposed model achieved very good accuracy in the land use land cover classification using a deep learning approach. Deep learning for LULC classification becoming more evident. It will deliver a cost-effective and time management resolution than the visual understanding The grouping of maximum Likelihood for ground truth masking and U-net for classification gives better results. In the present study, we proposed a land use land cover classification model built on U-Net, Deeplabv3+ and tiramisu algorithms. The models were trained and tested on LISS-III multispectral space-born image dataset. Experiments show that model detected a total of 4 land use land cover classes i.e., Water body, vegetation, uncultivated land, and residential with very good accuracy. Results predicted by the model confirmed that the U-Net classifier holds gigantic potential for accurate detection of land use land cover classes than deeplabv3+ and tiramisu. The U-Net model achieves a very good accuracy of 84 %.

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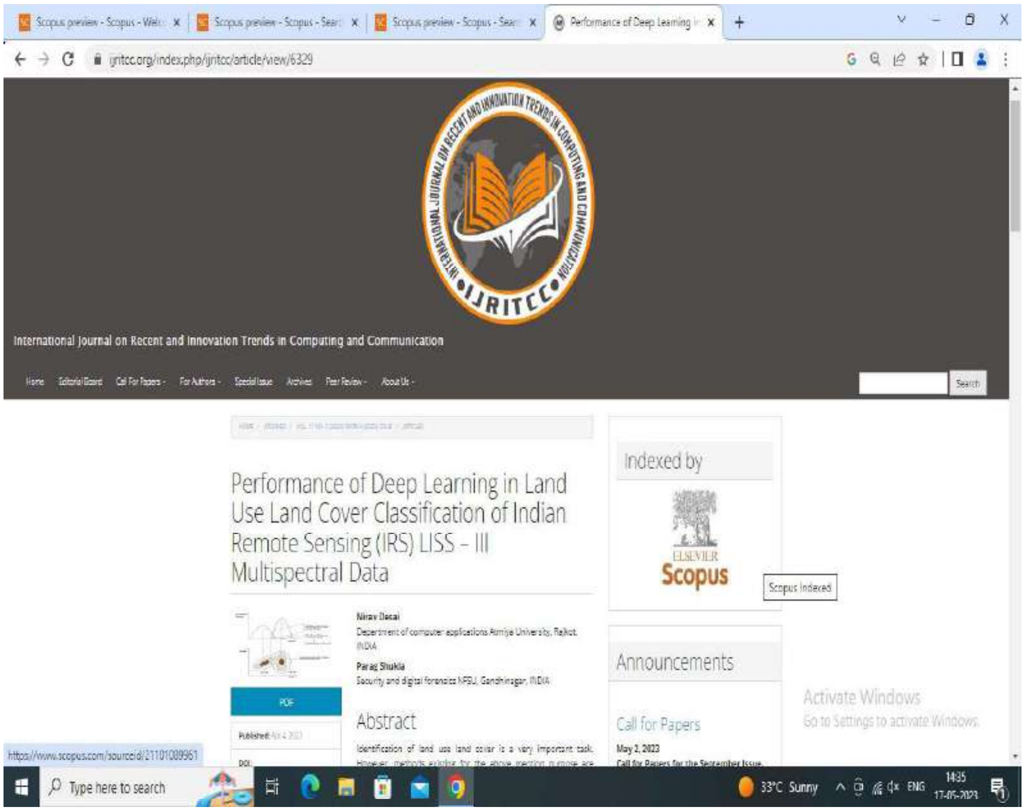
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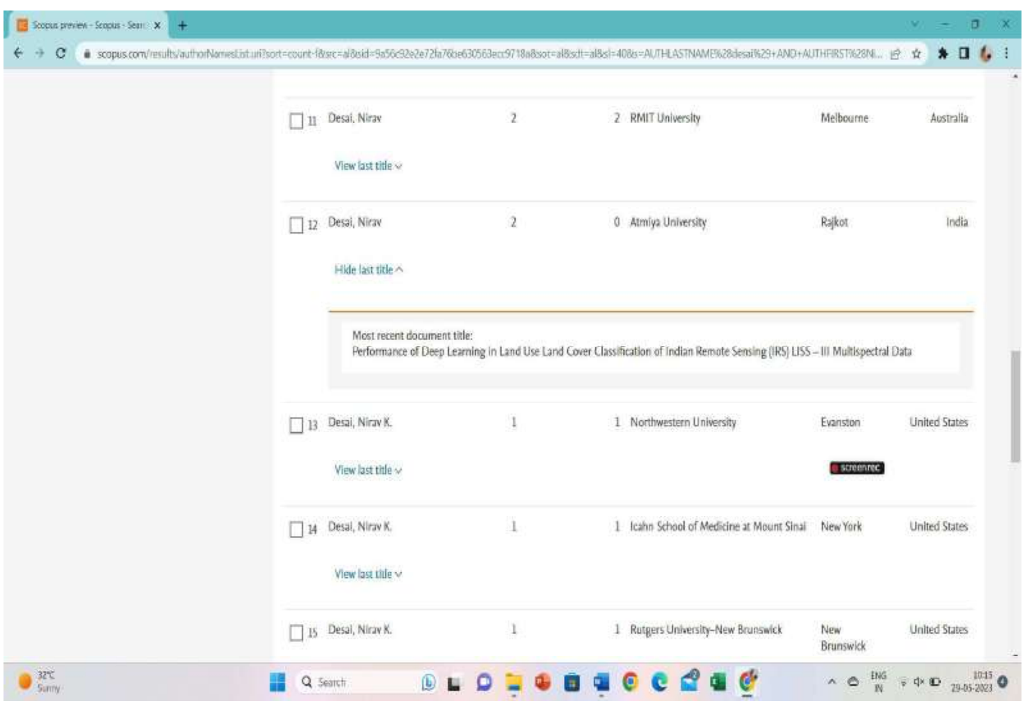
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Performance of Deep Learning in Land Use Land Cover Classification of Indian Remote Sensing (IRS) LISS – III Multispectral Data

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Abstract—Identification of land use land cover is a very important task. However, methods existing for the above mention purpose are labor incentives, time-consuming, and costly. Remote sensing plays very important role in the mappings. classification of land cover features and offers very noteworthy and sensed information. The present study shows the semantic segmentation of Indian remote sensing (IRS) LISS-III multispectral image and the comparison of three algorithms U-Net, Deeplabv3+and Tiramisu. The deep neural network was used to perform the study. We present total 3 innovative datasets, built on these LISS-III images that has 4 different spectral bands (Band – 2 (Blue), Band-3 (Green), Band-4(Red), and Band-5 (Nearly Infrared), FCC (false color composite) images and the ground truth mask images. Dataset has 13500 labelled images. A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 128 X 128 X 3 and outputs a matrix of shape 128 X 128 X 4 i.e., a one-hot encoded version of the mask. The experiment identifies 4 classes successfully (Water Bodies, Vegetation, Uncultivated Land, and Residential areas). The experiment showed that the U-Net algorithm has a very good capability for the classification of LISS -III images for land use land cover class detection then Tiramisu and Deeplabv3+. U-Net achieved accuracy 84%, Deelabv3+ achieved 29% whereas Tiramisu achieved accuracy 33%.

Keywords- land use land cover, deep learning, FCN, U-Net, Deeplabv3+, Tiramisu

I. Introduction

In new aeras, satellite images are fetching an immense substance of data for studying the spatial and progressive variability of ecological situations. The beginning of remote sensing with multispectral images in digital format has taken a new dimension in, mapping and monitoring of natural resources of the Earth [9]. Remote sensing is the art of discover and understanding the data or information from a long distance, using sensors without communication with the object being observed [22]. Land use land cover classification anticipates to form space-born images into a precise class, which was reliant on the distribution of predictable land use land cover classes. Land use and land cover mapping are essential errands for preparation and management.

Land use land cover classification using remote sensing images has been applied in several studies, including surveys involving environmental monitoring and change detection [3], research on urbanization effects [24],[10] and disaster mitigation [26]. The spatial resolution of remote-sensing systems is low, so it is probable to recognize the different classes on the Earth's surface [25]. In 2006, Deep learning projected by Hinton et al. [8] and confirmed training complications of a deep neural network can be solved using one-by-one layer initialization. And efficiently applicable to the field of video and image processing, a field of data analysis [5]. The deep learning algorithms gives a new way for remote sensing image explanation and a massive number of deep learning algorithm research in the field of remote sensing image classification. Semantic Segmentation is defined as a pixel-level classification of images where a class is allotted to an individual pixel of the image.

Remotely sensed imagery is an image data with intervallic Earth observation. The appealing benefits of deep neural networks have been presented in many remote-sensing applications.

Deep neural networks (DNNs) refer to end-to-end mappings (i.e., from data to information) by stacking a large number of filters learned from massive samples. In deep learning, mainly Convolutional Neural Networks (CNNs), have been effectively applied for image classification, target detection, and scene understanding [4][7][12][14][28]. A fully convolutional neural

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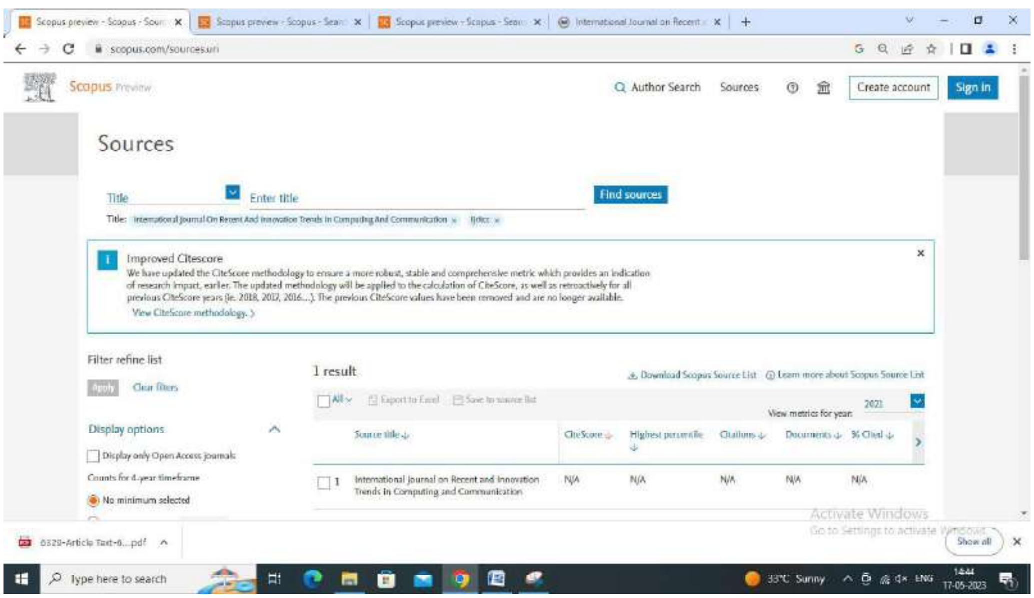

Land use land cover segmentation of LISS- III multispectral space born image using deep learning

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Abstract. Remote sensing information provides important and sensed data. The study represents semantic segmentation using a fully convolutional network (FCN) for semantic segmentation. Semantic Segmentation is a pixel-level classification of images where each pixel is assigned to a respective class. In this present study, 4 classes – Water Bodies, Vegetation, Uncultivated Land, and Residential areas were identified. There are various types of machine learning (ML) models as well as deep learning (DL) models to handle segmentation tasks. In this study deep neural network was used. A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 256 * 256 * 3 and outputs a matrix of shape 256 * 256 * 4 i.e., a one-hot encoded version of the mask. The experiment showed that the FCN classifier has a very good capability for land use land cover class detection. The model identifies 4 classes with 81% of OAA.

Keywords: remote sensing, multispectral image, land use land cover classification, deep learning, Fully Convolutional Network (FCN)

1 Introduction

In recent eras, the consumption of land resources has become a serious problem. Remote sensing (RS) is the art of finding and understanding data from a long distance, using sensors without communication with the object being observed [35]. Land Use land cover classification aims to organize space-born images into an exact class, which were reliant on the distribution of recognized land use land cover classes. In the last few years variety of applications like urban development, monitoring of natural tragedies, and land use land cover analysis[10],[20],[21],[32]. The remote Sensed image consists of residential areas, agricultural land, uncultivated land, water bodies, and other open areas.

Hinton[15], et al. projected deep learning and demonstrated training difficulties of a deep neural network can be solved using one-by-one layer initialization. And effectively applicable to the field of video and image processing, a field of data analysis [9]. In the DL mechanism, the machines learn from the information themselves by growing more layers of a network [33].

Fully-convolutional networks are applied for the classification of the land use land cover of the South Gujarat region, India. The success of the classifier was tested on physical data. In the present study total of 4 classes have been classified - Water Bodies, Vegetation, Uncultivated Land, and Residential areas. Semantic Segmentation is defined as a pixel-level classification of images where a class is allotted to an individual pixel of the image. There are various types of machine learning models and deep learning models to handle segmentation tasks. In this study deep neural network was applied to handle this task. A fully-convolutional network (FCN) with skip connections is trained to take an input image of size 256 x 256 x 3 and outputs a matrix of shape 256 * 256 * 4 i.e., a one-hot encoded version of the mask. The model achieved an OAA of 81%.

2 Literature review

Deep learning (DL) belongs to machine learning techniques, where various layers of data processing phases in ordered architectures are overburdened by unsupervised learning and pattern classification [27].[5] presented hyperspectral image classification with a hybrid framework that contains deep learning, and logistic regression. Zuo et al. applied deep belief networks [41], and the result exposed the success of the model. [25],[30] used CNN for Land use land cover segmentation, where designated training data in each repetition with DL achieved good results. The deficiency of labeled data was managed by applying data augmentation techniques [42]. [40] merging CNN and multi-scale feature fusion on the controlled data. [6] studied Saliency Dual Attention Residual for achieving good performance. [39] projected classification technique includes the neural network with random forest(RF) for land use land cover classification. Alichiri et al. EfficientNet-B3 CNN [1] tested it on six common Land cover land use datasets and showed the efficiency in space-born image scene classification. This resulted in an important enhancement in overfitting and better accuracy. [31] proposed strategies that improved convolutional neural networks for aerial image segmentation.

Semantic segmentation is the job of appointing every pixel in an image to the defined various classes. It identifies which substances are displayed and where they are obtainable [28]. DL and CNN have transformed the image classification part over a long period and now became a central method for image classification [6]. [22] gives an organized and comprehensive evaluation of various groups of applying DL methods. [13] placed diverse stress on the command during training. Many techniques are abridged in [36] and new advances are given detailed in [2],[26].

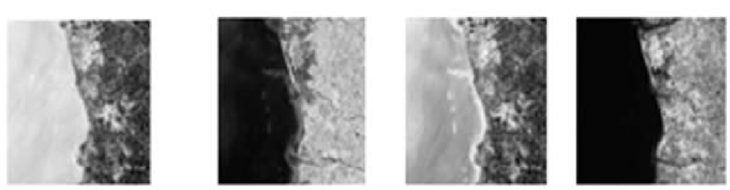
3 Materials and methods

3.1 Data collection

Multispectral space-born image (LISS – III) was used for the study. It has more than 100 nm resolution and less the 10 bands. The LISS_ III image contains a total of 4 bands; the spatial resolution is 30 meters. Quadrats of 30m * 30m size were laid down across the study area. Data was collected from the website https://bhuvan-app3.nrsc.gov.in The data were processed using the software ENVI4.7. A wide field study was completed to collect environmental landscapes and circulation patterns of different land use and land cover. And the Longitude and Latitude of the location for the respective class are recorded (GCPs). To record GCPS, the GPS device Garmin – eTrex 30 is used for GCPs collection. The GCPs reserved for the respective category were reliant on the allocation of recognized land use classes within the study area. A LISS-III multispectral remote sensing image consists of 4 different bands in separate .tiff files and the number of bands is Band – 2,3,4 and 5(Blue, Green, Red, and near Infrared)

3.2 Pre-Processing

For the land use land cover classes inspection in the study, the LISS - III space-born multispectral images were merged into a False Colour Composite (FCC) image. False-color composites (FCC) are created by stacking these multiband.TIFF images are on top of each other and take a stacked grouping of Band - 4, Band - 3, and Band - 2 to generate FCC. After creating FCCs for each image, ground truth masks were created and used to train the deep learning model. These masks are created using the maximum likelihood algorithm on a small region of interest for each class.



(B) (G) (R) (I)

Fig. 1. **FCC Creation**

False color composite (FCC) Image

Both the FCCs and their corresponding masks are resized to 1024 * 1024 pixels and then divided into patches of size 256 * 256 pixels with a striding of 128. This will create 49 patches of size 256 * 256 for each image.

Pre-processing Steps:

1. False-color composites (FCC) are created by stacking these multiband TIFF images on top of each other. Stacked Band - 4, Band - 3, and Band - 2 to generate FCC.

False color composite (FCC) Image

2. After creating FCCs for each image, ground truth masks were generated which were used to train the deep learning model. These masks are created using the maximum likelihood algorithm on a small region of interest for each class.

3. Both the FCCs and their corresponding masks are resized to 1024 * 1024 pixels and then divided into patches of size 256 * 256 pixels with a striding of 128. This will create 49 patches of size 256 * 256 for each image. Thus, the size of our dataset would be 30 * 49 = 1470 images.

4. These images and masks are separated into two subgroups, one for training and another for validation. 1,255 images are used to train the model while 215 images are reserved for validation and evaluation.

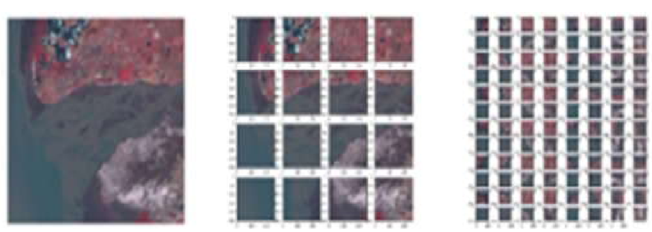


Fig. 2: FCC (1024 X 1024) (256 x 256)

2.3 Methods

A maximum likelihood classifier (MLC) classification is used with space-born image data, in which a pixel with the maximum likelihood is classified into the corresponding class. In MLC, a pixel is selected for a class based on its chance of fitting. Mean vector and covariance metrics are the main constituent of MLC that can be recovered from training data [15].

Following is a Discriminant Functions Calculated for Each Pixel:

$$g_i(x) = \ln p(\omega_i) - 1/2 \ln |\Sigma_i| - 1/2(x - m_i)^t \Sigma_i^{-1}(x - m_i) \qquad (1)$$

Where i is class, x is n-dimensional data in which n represents the total number of bands. $p(\omega_i)$ represents the chance that class ω_i occurs in the image, |Σi| is the determinant of the covariance matrix, Σi-1 is an inverse matrix the mean vector represents by m_i.

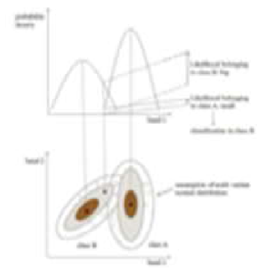


Fig 3: **Basic concept of ML[18]**

After creating FCCs for each image, ground truth masks were created that will be used to train a model. These masks are created using the maximum likelihood algorithm on a small region of interest for each class.

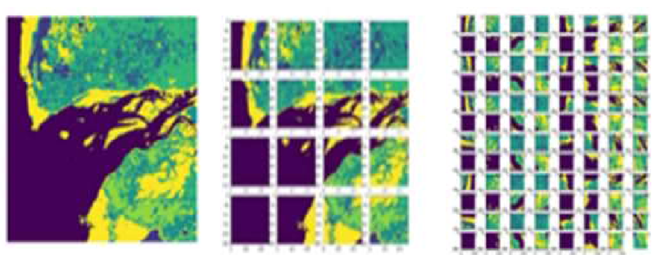


Fig. 4. Ground truth Mask

Fully Convolutional Networks [7] are effectively applied in various fields, such as segmentation of an image[24],[43], and medicinal image analysis [4],[18], character recognition [8]. FCN contains relative within an entirely linked layer in the prior credit for each activation while seen during neural networks[19]. CNN and FCN were applied for the mangrove classification [11],[12],[37]. FCN is broadly applied in pixel-based classification [16]. And used an encoder for feature extraction and a decoder to reestablish the. FCN algorithm used with the RS image gives a satisfactory outcome in mangrove mapping [17].

2.4 Training Configuration

While data ingestion i.e. before passing the images and masks to the model for training, we normalize the input images by clipping them to [0.0, 255.0] while the masks are one-hot encoded according to the total number of classes i.e. 4. In addition, random augmentations are also applied to the batch of images and masks before passing them to the model for training. This expands our dataset and makes the model robust enough to encounter different orientations than just the training data. Data augmentation is a factor that when done correctly, prevents overfitting. A custom image data generator is created to fulfill the requirements of this data ingestion pipeline.

The following is the table of hyperparameters and other configurations used for training the model.

Table 1. hyperparameters and other configurations used for training the model.

Hyperparameters & Configurations	Values
Train Batch Size	16
Validation Batch Size	16
Input Image Shape	(256,256,3)
# of classes	4
Epochs	50
Loss	Categorical Focal Loss*
Optimizer	Adam
Metrics	Dice Coefficient*
Class Weights	[1.69941, 0.53043, 1.23977, 1.38949]

2.5 Model Structure

Semantic Segmentation is defined as a pixel-level classification of images where a class is allotted to each pixel of the image. In the present study, there are 4 classes - Water Bodies, Vegetation, Uncultivated Land, and Residential areas. A deep neural network was used to handle this task. A fully-convolutional network (FCN) with skip connections is trained to take an image input of size 256 * 256 * 3 and outputs a matrix of shape 256 * 256 * 4 i.e., a one-hot encoded version of the mask. The FCN is a U-Net architecture that contains an encoder part and a decoder part. The encoder part contains 5 blocks and each block is 2 (convolution + batch normalization + relu) layers stacked on top of one another and trailed by a max-pooling except for the last block. The output of this encoder part is then inputted to the decoder containing 4 blocks. Each block in the decoder starts with an upsampling of the input followed by a 1 * 1 convolution operation. A skip connection is also used that concatenates the output of the corresponding encoder block to the output of the upsampling and convolution operation. The concatenated tensor is then again passed to two convolution layers similar to that of the corresponding encoder block. The output of the decoder part is finally fed to a 1 * 1 convolution with the amount of filters equivalent to the amount of classes which is 4.

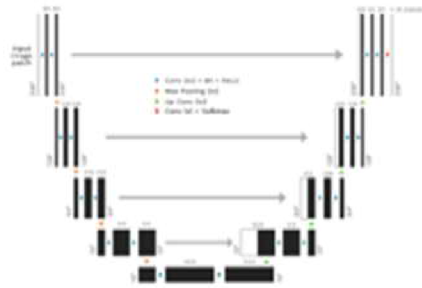


Fig. 5. U-net Architecture

The arrows denote the various processes, the black containers denote the feature map and the gray containers denote the cropped feature maps from the contracting path.

$$E = \sum w(x) \log (P_{k(x)}(x)) \qquad (2)$$

Where p_k is the pixel-wise SoftMax function applied over the final feature map.

$$P_k(x) = \frac{e^{ak(x)}}{\sum_{k'=1}^{k} e^{ak'(x)}} \qquad (3)$$

And a_k (x) denotes the activation in channel k.

2.6 Algorithm steps

The steps of the FCN algorithm are as follows:

(1) The pre-processing steps include remotely sensed image alteration, registration, and the masking of the image. The images containing band- 2 to band - 4

(2) For training and testing, a total of four types of classes were selected, such as Water Bodies, Vegetation, Uncultivated Land, and Residential areas. This study used the ENVI image processing software (ROI Tool) to pick the four types of classes.

(3) Total of four types of classes was used for the building and training of the model. The model structure was shown in fig-5. The model structure and parameters were kept for successive image segmentation or classification after training.

(4) The FCN model which was trained in step -3 was applied for classification.

(5) Find whether all the classifications were finished or not. If all is done then the classification outcome will be displayed and terminate the algorithm.

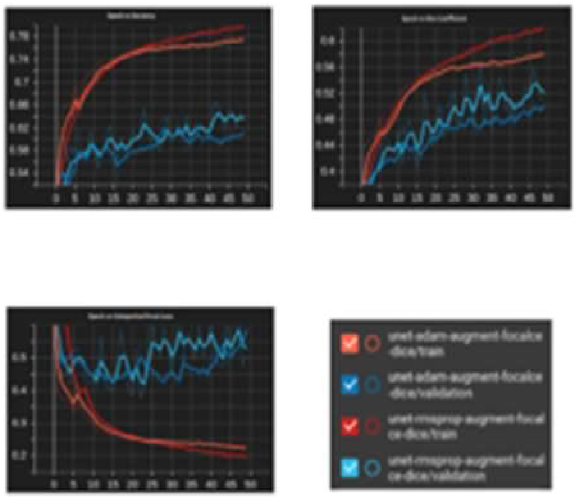


Fig. 6. Training Logs

3. Result and discussion

The environment for the experiment is as follows: Windows 11 operating system and Envi 4.7 is used to process the remote sensing information, such as selection of training sample, generation of masking, etc. The algorithm for classification developed in Fully-Convolutional Network (FCN) was coded with python + OpenCV

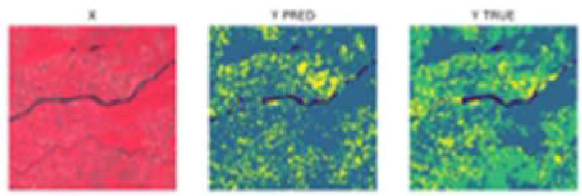
Table – 2: Experiment result

MODEL	Optimizer	EPOCH Trained	Total Time	Accuracy
U-net	adam	25	1 Hr 30 Min	79
U-net	adam	50	2 Hr 45 Min	81

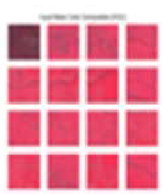
Experiment figured out the best fine-tuning parameters for U-net with RGB bands of the dataset of LISS- III multispectral remote sensing images. The parameters which give vast performance are used to develop the final model. The model also used data augmentation. Table -2 shows the experiment results and accuracy with different epochs. And from the outcomes, it was detected that U-net gives better results in classifying land use land cover classes.

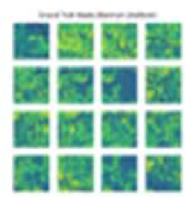
Fig.1. is an FCC image combined by LISS- III multispectral space born image in Band - 4, Band - 3, and Band - 2 using tools of ENVI 4.7, in which the class Water Bodies are in blue, class Vegetation is in red, class Uncultivated Land in light red color, and class Residential Area is in white. Fig.7. (a.) shows the land cover land use classification

Fig.1. is an FCC image combined by LISS- III multispectral space born image in Band - 4, Band - 3, and Band - 2 using tools of ENVI 4.7, in which the class Water Bodies are in blue, class Vegetation is in red, class Uncultivated Land in light red color, and class Residential Area is in white. Fig.7. (a.) shows the land cover land use classification results in the south Gujarat region, India by FCN algorithm respectively. In Fig.7.(a.) Water Bodies are black, Vegetation is in light green, Uncultivated Land is in light blue, and Residential Area is in yellow. Fig.7. (b.) shows the FCC image and Fig.7.(c.) shows the ground truth mask generated via the maximum likelihood classifier. And Fig.7. (d.) shows the model prediction for the 4 specified classes.

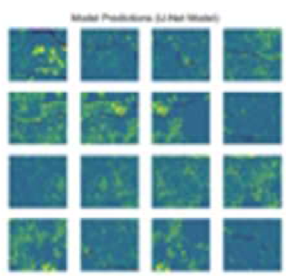


(a.)





(b.) (c.)



(d.)

Fig. 7. Classification of land cover land use in FCN algorithm

The model classified the image into 4 classes i.e. Water Bodies, Vegetation, Uncultivated Land, and Residential areas with an OAA of 81 % accuracy. The combination of maximum Likelihood for ground truth masking and FCN for classification gives better results. Table1 shows the training configuration for the model and Fig.5. shows the training logs. Fig.7. (a) shows the fcc image, predicted, and truth image respectively. Fig.7. (d) shows the classified image which is very near to Fig.7. (c) regarding Ground truth masking. This research work was done on a total of 30 FCC images. FCC images and their matching masks are resized to 1024 * 1024 pixels and then divided into patches of size 256 * 256 pixels with a striding of 128. This will create 49 patches of size 256 * 256 for each image. Thus the size of the dataset would be 30 * 49 = 1470 images. A total of 1,255 images were used for purpose of training the model while 215 images are reserved for validation and evaluation.

4 Conclusion

The advantages of using intelligent systems like deep learning for LULC classification becoming more evident. It will provide a cost-effective and time management solution than the visual interpretation or other machine learning techniques currently obtainable today. In this paper, a land-use land cover classification model is presented, built on an FCN classifier which is trained and tested on land use land cover LISS-III multispectral space born image dataset. Experiments show that model able to detect land use land cover classes. A model can detect different classes with very good accuracy. Outcomes confirmed that the FCN classifier holds massive potential for accurate detection of land use land cover classes. The model identifies 4 classes with very good accuracy.

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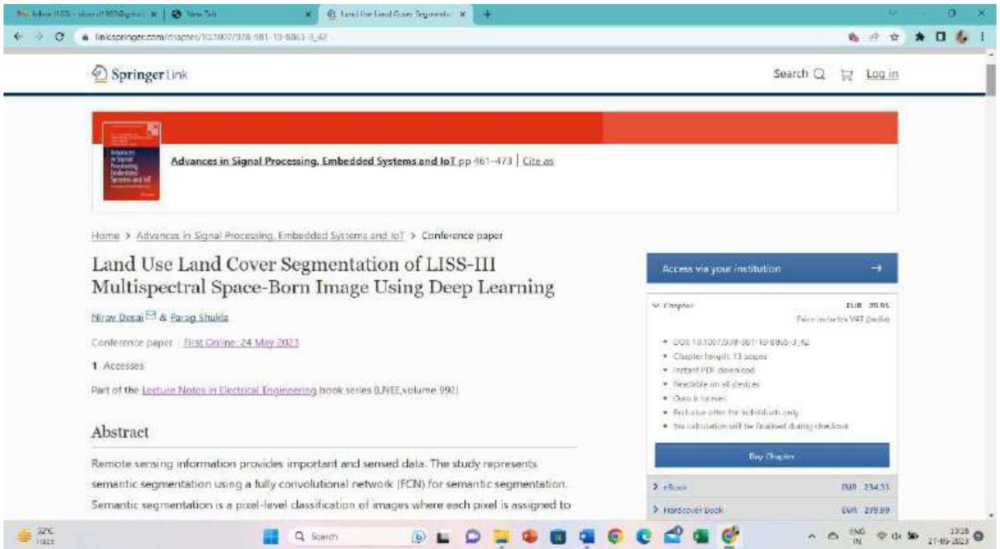
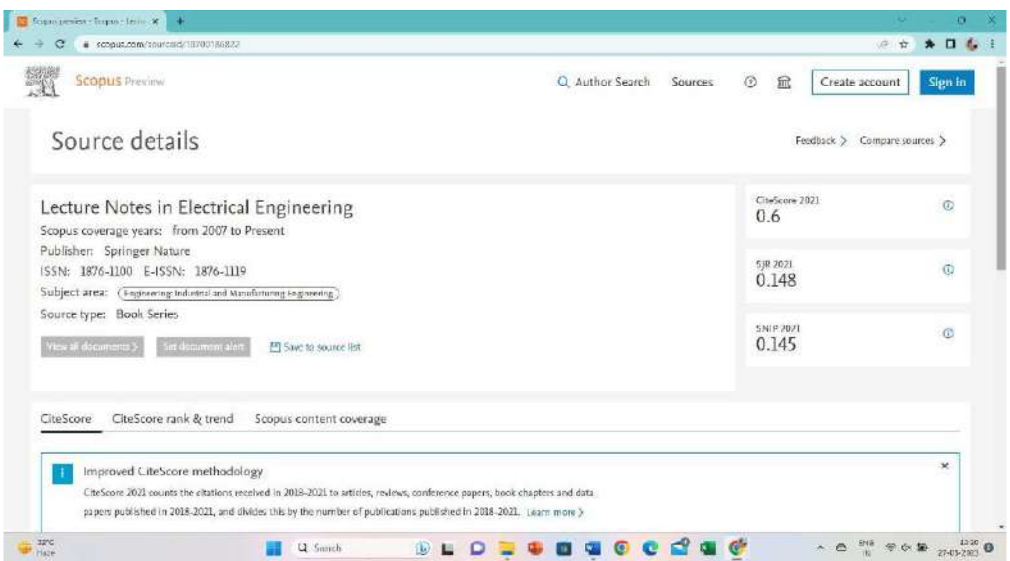


DOI : https://doi.org/10.1007/978-981-19-8865-3_42



3)

LAND COVER LAND USE MAPPING & CLASSIFICATION MODEL

(Mapping of land cover land use using multispectral space born image)

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Abstract

Measurement of land use and land cover is costly and time-consuming by imperial technique. Remote sensing plays important role in the mappings and classification of land cover features. Indigenous space-born images can be used for identification and mapping. Remote sensed imagery is 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.This paper proposes a model which will help to classify and map land cover land use using remote sensing imagery. It also increase accuracy in the mapping and classification of land area land cover.

Keywords: *Classification; Remote Sensing; Land cover land use, Satellite Image;*

INTRODUCTION

Identification of Land cover land use and measurement of land cover land use is a very important task. However, techniques available for the above mention purpose are labor incentives, time-consuming and costly. Images were taken with the help of Space born remote sensing platforms (Satellite) can be very helpful for the Identification and measurement of land cover land. Furthermore, this method is cost-effective and consumes a lesser amount of time. As we struggle to comprehend the influence of anthropological activities on our earth, concerns over global land use and land cover change are rising [1]. For years remote sensing has been used as an instrument to generate land use/land cover maps [2]. Many studies have been carried out to produce land cover maps of several ecosystems using broadband multispectral data [3] – [7]. Landsat TM imagery is predominantly used in the classification studies of forest growth stages [8], [9]. Arroyo-Mora [10] has studied different successional stages of dry deciduous forest with the help of a combined Landsat TM and IKONOS data set. Asner et al. [11] attempted to monitor forest degradation and deforestation over different types.

Remote Sensing plays an important role in providing the land coverage mappings and classification of land cover features. Characteristics of land cover land use, the difference of spectral reflectance of different land use, and difference in feature characteristics such as shape and texture are important parameters that should be considered while working land cover land use areas with remote sensing. Therefore, image classification is an important tool for examine and assessing satellite images.

1. LITERATURE REVIEW

ANN classifier gave the highest OAA values of 81%. The image classification done with the help of SVM showed OAA of 71% and SAM showed the lowest OAA of 66%. SVM showed the highest OAA of 80% in classifying spectra coming from 165 processed bands [12]. Used SVM classification into land cover and land-use sectors. Pre-processing contains Gaussian filtering & RGB to Lab colorspace image translation. Segmentation is done using the fuzzy incorporated hierarchical clustering technique. The cluster centroids are subjected to the trained SVM to obtain the land use and land cover sectors [13]. Correctness and consistency of Support Vector Machine (SVM) classifier and compare its performance with Artificial Neural Network (ANN) classifier for multispectral Landsat- 8 images of Hyderabad region. Overall precisions of Land used and land cover classification approximately 93% for SVM and 89% for ANN According to experiment results SVM has the better classification accuracy [14]. Artificial Neural Network classifier and Principal Components Analysis have been used. After performing the tests, according to the Kappa index, the Artificial Neural Networks are capable of being employed as pattern classifiers in multispectral images [15]. Collected image data from Landsat ETM+ and Terra ASTER images. Maximum Likelihood (ML) and Artificial Neural Network (ANN) classifiers are used. Image band combinations are given to the neural network for training and the success of the classification. According to the results, the ANN classifier yielded more accurate results than the ML classifier [16]. SMA (Spectral Mixture Analysis) to map coconut land-cover. SMA was executed and assessed based on Landsat-8 ETM (Enhanced Thematic Mapper Plus) data [17].

1. Land use/Land cover Mapping & Classification Model

The proposed model for classification and accurate mapping of land use land cover using remote sensing images or space-born images. Indian remote sensing satellite images will be acquired from archives of ISRO and preprocessed. After geometric corrections GCPs will be laid down on images to perform supervised classification. An inherent supervised classification mechanism was used to cluster pixels in the dataset into classes corresponding to defined training classes. Non-linear classifications algorithms (ANN, SAM, and SVM) were used to classify the image. Hits from all correctly classified pixels were used for accuracy assessment. Two measures of classification accuracy (user's and producer's accuracy), overall accuracy (OAA), and kappa coefficient were calculated.

The Model is intended to perform the following task.

1.1 Data Acquisition

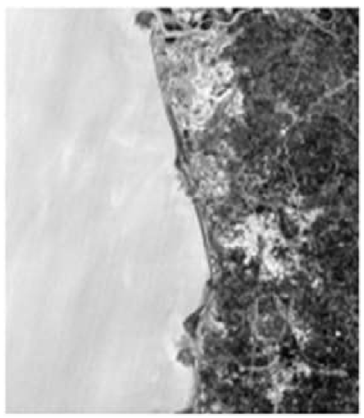
1.2 Data Pre-processing

1.3 Identification and classification

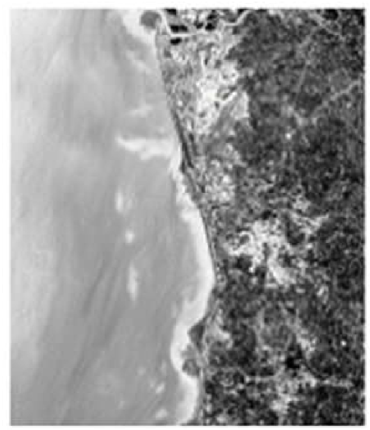
Figure 1 : Land use land covers Mapping & Classification Model

3.1 Data Acquisition

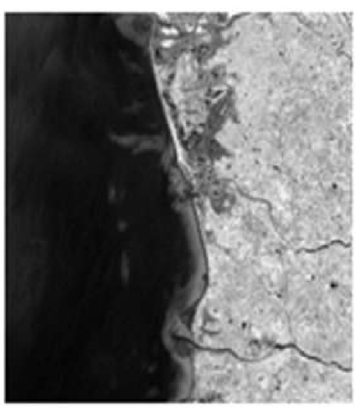
It is a process of gathering information or procedure of collecting related information. An extensive field survey was done to record ecological features and distribution patterns of different land use. Eight distinct land use classes have been identified in the study area. Quadrats of 30m×30m size (corresponding with a spatial resolution of satellite sensor 30m) were laid down across the marked study area. The numbers of points taken for each class were dependent on the distribution of identified land use classes within the study area. Ground control Points (GPS) locations of all the quadrats were recorded within an error of ±4m. Images were taken from IRS (LISS III) platform (Spatial Resolution 30 m). The numbers of points taken for each class were dependent on the distribution of identified land use classes within the study area.



Band 2 (Blue)



Band 3(Green)



Band 4 (Red)

Band 5 (Infrared)

Figure 2: LISS – III Image

3.1 Data Pre-Processing

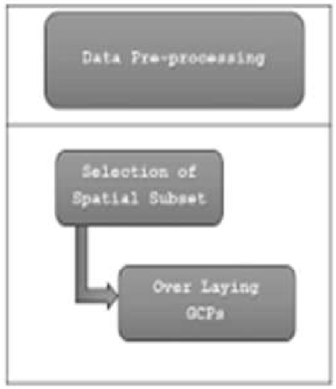


Figure 3: Data Pre-Processing

3.2.1 Selection of Spatial Subset

In this section, the image is processed and converted into a rectangular shape. Input the x and y coordinates of the upper left and lower right. Subset your data into a rectangle that contains the selected ROIs. The rectangle is the smallest rectangle that will fit the ROI. You can mask the pixels in the rectangle that do not fall within the ROI.

3.2.2 Over Laying GCPs (Ground Control Points)

The Ground Control Points (Ground Control Points, GCPs) is an important baseline data of Remote Sensing Image correction [19]. The quantity, distribution, and accuracy of GCPs play an important role in correcting Remote Sensing Images.

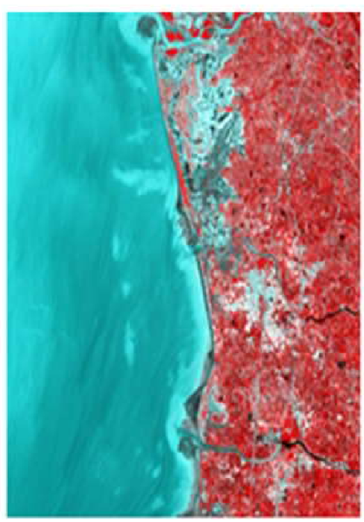


Figure 4 Pre-Processing (False Color Composition (FCC)) Image

3.1 Identification and classification

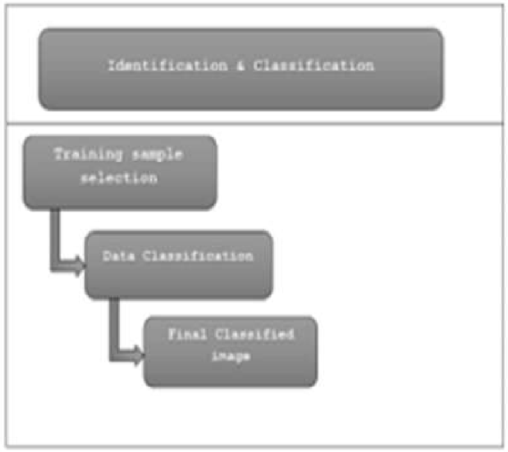


Figure 5 Identification and classification

3.3.1 Training Sample Selection

It is the most important component of remote sensing classification and measuring the quality of the region of interest (ROI). Accurate classification accuracy is dependent upon good training sample selection. . Classification correctness is mainly determined by ROI separability. High-quality classification training samples (with high ROI reparability) determines the classification accuracy to a certain extent [20].

3.3.2 Data 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 decision tree.

3.3.3 Final Classified Image

The final classified image contains different classes of land use/land cover classification. The final image is classified into the classes like water bodies, agricultural land, residential areas, grasslands, mangroves, etc. with different value pixels.

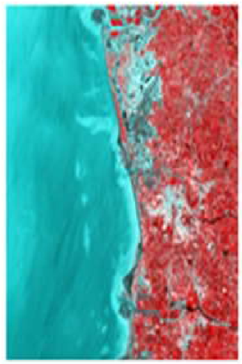
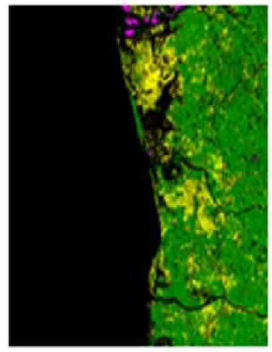


Figure 6 : FCC Image



Final classified image (SVM)

1. CONCLUSION

The proposed model is concerned with the finding of different land cover land use. It helps various government agencies to survey an area and future planning. That will increase accuracy in the mapping and classification of land area land cover.

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Land Cover Land Use Mapping & Classification Model (Mapping Of Land Cover Land Use Using Multispectral Space Born Image)

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Abstract

Measurement of land use and land cover is costly and time-consuming by imperial technique. Remote sensing plays important role in the mappings and classification of land cover features. Indigenous space-born images can be used for identification and mapping. Remote sensed imagery is 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.This paper proposes a model which will help to classify and map land cover land use using remote sensing imagery.It also increase accuracy in the mapping and classification of land area land cover.

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INTRODUCTION

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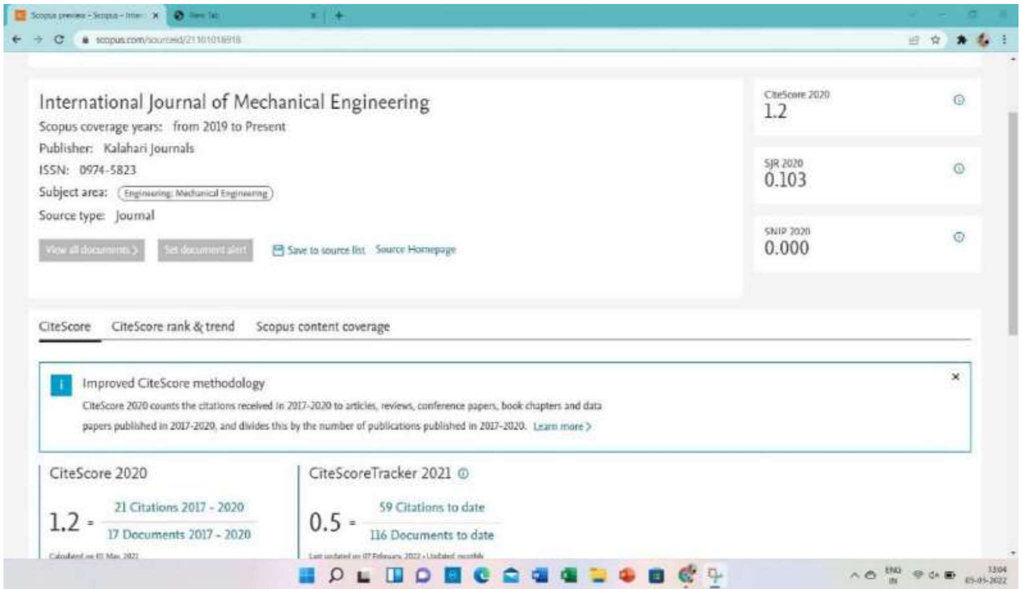
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Subject area: Engineering: Mechanical Engineering
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21 Citations 2017 - 2020
17 Documents 2017 - 2020
CiteScoreTracker 2021
0.5 =
59 Citations to date
116 Documents to date

4)

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 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.

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.

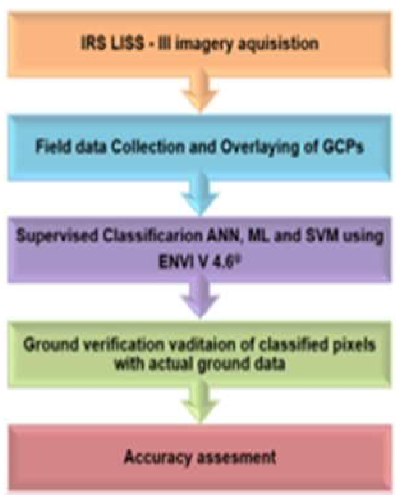

Figure 3 Model Structure

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.).

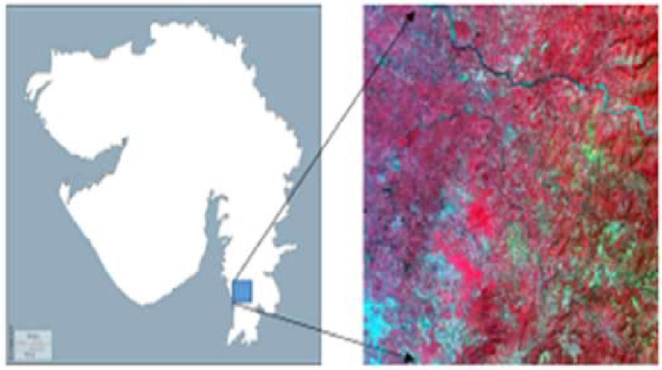

Figure 2. (a) Map of Guj.(d-maps.com) Figue 2(b.) FCC Image

Figure 4 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.

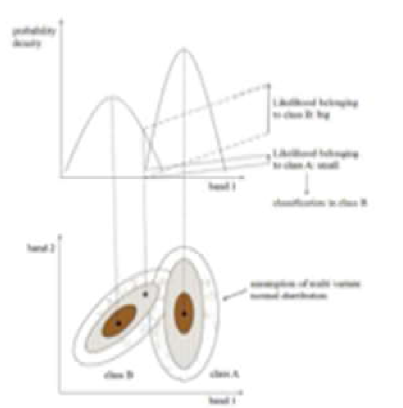

Figure 5 Basic concept of ML(JARS,1999)

Following is a Discriminant Functions Calculated for Each Pixel:

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

Where:

i = class

x = n-dimensional data (where n is the number of bands)

$p(\omega i)$ = probability that class ωi occurs in the image and is assumed the same for all classes

$|\Sigma i|$ = 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).

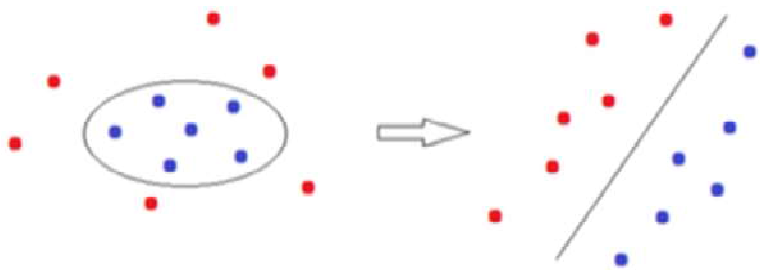

Figure 6 Graphic representation of the SVM method (Naik, Thaker,& Vyas, 2021).

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))

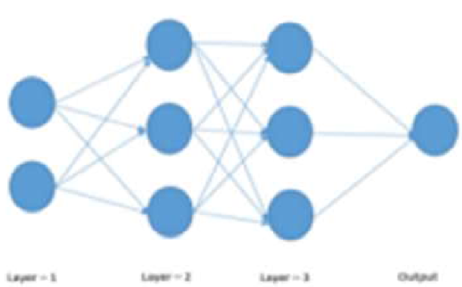

Figure 7 A graphical representation of the Neural Network method (Naik,Thaker & Vyas , 2021).

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%

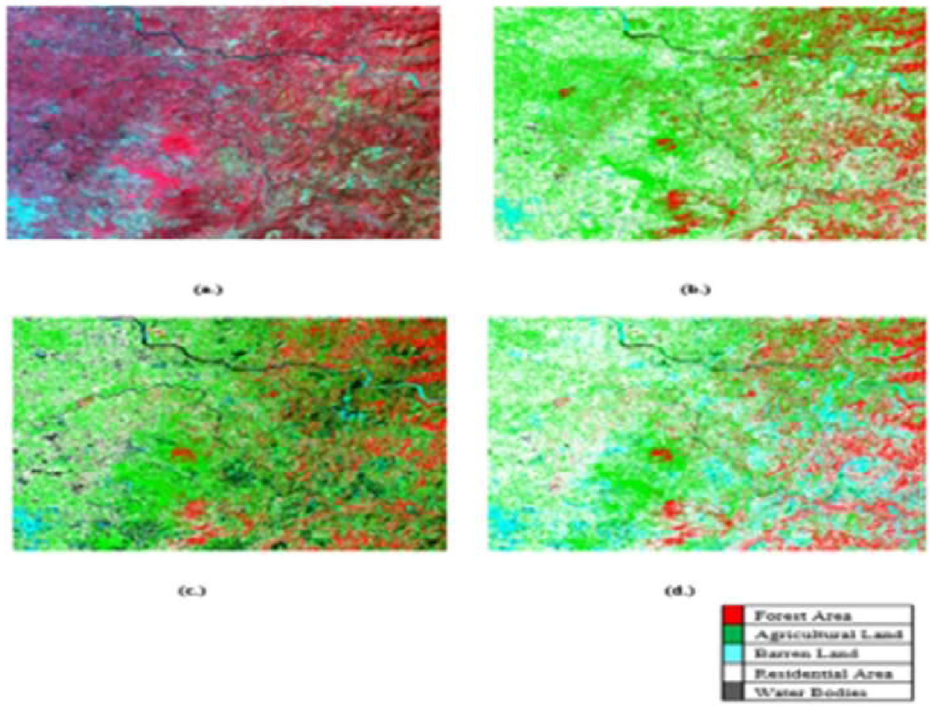

Figure 8 Classified images (a.) FCC (b.) ANN (c.) ML (d.) SVM

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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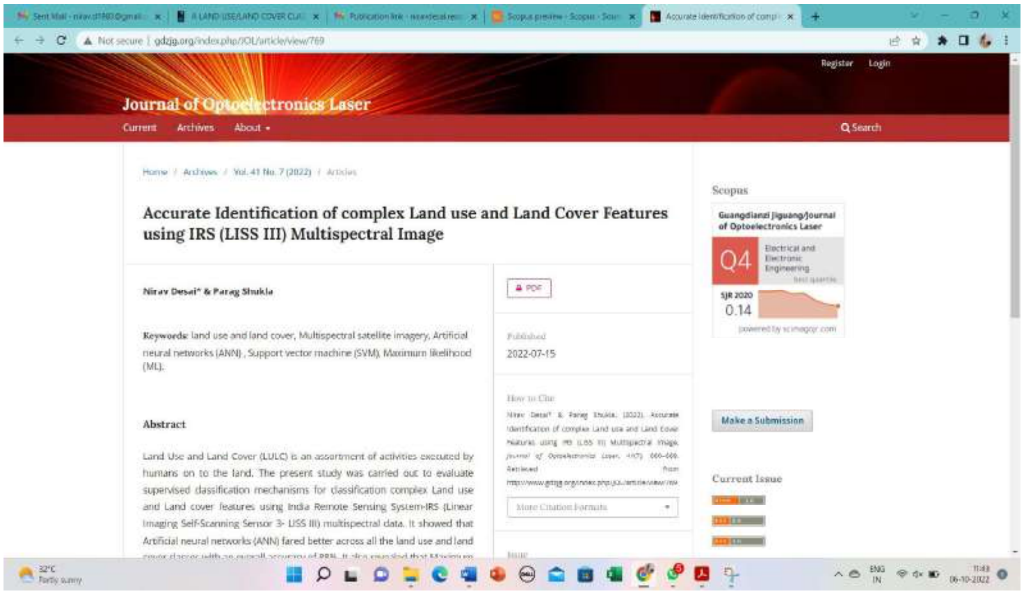

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Accurate Identification of complex Land use and Land Cover Features using IRS (LISS III) Multispectral Image

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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.

5)

A land use/land cover classification of IRS (LISS – III) multispectral data using Decision Tree and SVM classification mechanism

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ABSTRACT

Identification of the effect of human activities on our planet concerns over worldwide land use and land cover change is very complex. Land Use and Land Cover refer to the utilization of land through events like agriculture, different types of cultivation areas, residential areas, and the physical features on the earth's surface like the sea, mangroves forest, vegetation cover, and water bodies. However, empirical techniques used for this type of classification are cost-effective and laborious. This paper is focused on remote sensing images and various supervised classifications to identify various Land Use/Land Cover. This research work aims to use images taken from IRS (LISS III) platform to perform supervised classification. The study was performed to compare the performance of Supervised classifiers Decision Tree and SVM to classify different land use land cover classes. The Decision tree classifier gives better results than SVM for the study area. The decision tree classifier achieved 89.97 %. and SVM 81.90 %. It revealed that Decision Tree did better across different levels of occupancy of Land use/Land Cover.

***Keywords**: remote sensing, multispectral satellite image, classification, Decision Tree, SVM*

1. INTRODUCTION

Remote Sensing is a science of obtaining information about objects or areas from a distance, typically from aircraft or satellites. Satellite imagery is images of Earth collected by imaging satellites functioned by governments and businesses around the world. A multispectral image captures image data within specific wavelength ranges across the electromagnetic spectrum (EM). More than 100-nanometer resolution. Less the 10 bands.

Land use is defined as a sequence of actions performed on to the land to carry out by humans, with the purpose to gain products and/or benefits using land resources. Land cover is defined as the vegetation or buildings which take place on the earth. Examples of land covers include agricultural land, forest, grassland, and wetland. And 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 et al., 2013) Land use specifies how persons are using the land, whereas land cover specifies the physical land type. Both the types of data are obtained from analysis of the satellite images

As we struggle to recognize the effect of human actions on our planet, concerns over global land use and land cover change are rising. (Okin et al.) Land Use/Land Cover (LULC) classification is very important because it offers data for the monitoring of natural resources in different geographical positions. For eras, remote sensing has been used as a tool to produce Land Use/Land Cover maps. (Chan et al, 2008). Actions prevalent in an area can be obtained from Land Use / Land Cover (LULC) classification. Land Use/Land Cover refers to the utilization of land through activities like agriculture, different types of cultivation areas, residential areas, and the physical features on the earth's surface like the sea, mangroves forest, vegetation cover, and water bodies. However, empirical techniques used for this type of classification are cost-effective and laborious. Furthermore, practically it is impossible to obtain real-time data by manual human resource-based techniques. Remote sensed imagery is the most popular method to capture data on Land Use/Land Cover. Remote sensing imagery when used for Land Use/Land Cover classification one can get rid of all the above-mentioned problems Image classification is an important technique in remote sensing for image analysis and pattern recognition. Image classification is a process where decision rules are developed and used to assign pixels into classes that have similar spectral and information features (Campbell et al,.2008)(homer et al,.2004)(lu et al,.2007).

This paper is focused on various supervised classifications. The main goal of this research work is to use images taken from IRS (LISS III) platform to perform supervised classification. We will use supervised classification mechanisms such as SVM and Decision Tree and compare the result.

2. MATERIALS AND METHOD

2.1 Study area

The research was performed in Navsari and Valsad district situated in the South region of Gujarat state, India. Navsari district is located at 21° 07' N and 73° 40' E whereas Valsad district is located at 21° 36' N and 72° 59' E (Figure 1).

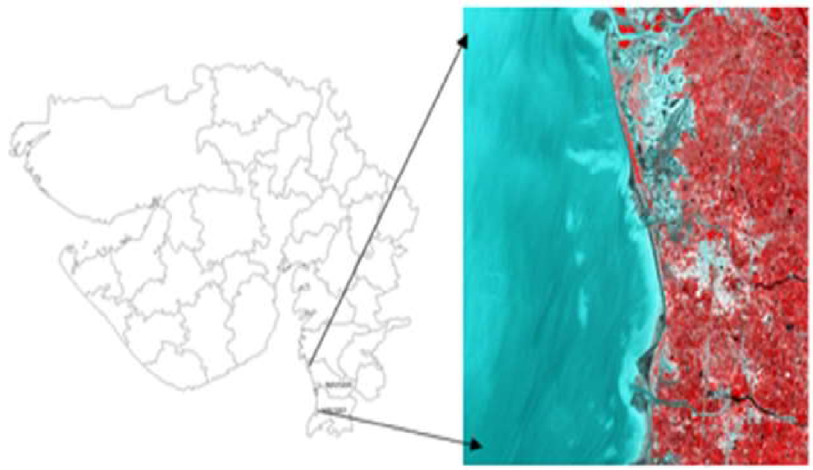

Figure 9. study area

2.2 Land Use Land Cover Definition

Land use is described as a sequence of activities performed on the land to carry out by humans, with the purpose to acquire products and/or benefits using land resources. Land cover is characterized as the vegetation or constructions which take place on the earth. Examples of land covers contain agricultural land, forest, grassland, and wetland. And land-use refers to the biophysical state of the earth's surface and immediate subsurface, containing soil, geography, surface water and groundwater, and human structures. (Elaalem et al., 2013) Land use denotes how persons are using the land, whereas land cover identifies the physical land type. Both types of data are found from the analysis of the satellite images.

2.3 Image acquisition and processing

LISS- III data was obtained on 18th, January 2018. 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 significant key to help remote sensing applications and have grown in number and capability in the last many years. (Elaalem et al., 2013. Image processing techniques have been built to support the understanding of remote sensing images and to retrieve as much info as possible from the images. The selection of specific techniques or algorithms depends on the areas as per particular necessities.

2.4 Image Classification

There are various image classification methods for land use and land cover. The classification technique can be "supervised" or "unsupervised". Different land use and land cover types can be split from an image using several image classification algorithms using spectral features, i.e. the "brightness" and "color" value contained in each pixel. The supervised classification contains classifications like SVM, ANN, and Decision Tree. Each pixel in the entire image is then classified as appropriate in one of the classes depending on how it is closed to its spectral features in the training areas. In unsupervised classification, the algorithms group the pixels in the image into separate clusters, depending on their spectral features. Each cluster will then be allocated a land use and land cover type by the analyst. All classifications were performed using an inbuilt function of ENVI 4.6® image analysis software.

2.4.1 Decision Tree Classifier: A decision tree is built top-down from a root node and contains separate.20ing the data into subsets that contain instances with parallel values (homogenous). The decision tree classifiers are effective than single-stage classifiers. With this classifier, decisions are made at several levels. Decision tree classifiers are also labeled multi-level classifiers. In constructing a decision tree classifier, it is necessary to construct an optimum tree to achieve the highest possible classification accuracy with the minimum number of calculations (Kulkarni,.2001)

2.4.2 SVM :

SVM is a great classification technique that has been largely used in the field of pattern recognition. The support vector machine optimization problem tries to discover a good quality splitting hyperplane amongst two classes in the higher dimensional space.

A supervised classification method was used to cluster pixels in the dataset into classes parallel to defined training classes. Built-in complex non-linear classifications algorithm SVM was applied to classify an image. Decisions for the classification and partition of all the land use classes were made by manual observation of reflectance patterns of all land use classes. A cluster of (n) numbers of reflectance patterns of all land use classes was plotted as a graph to identify decisive Digital Numbers of respective bands.

SVM has many alternatives in kernel selection such as Linear, Polynomial, Sigmoid, and Radial Basis Functions (RBF) for SVM. We have classified the LISS- III image with each of these kernels. Kernel methods exploit information about the inner products between data items. RBF was chosen for its accuracy in classification (Vyas et al., 2011).

Model structure for image processing and classification is given in Figure 2.

3. MODEL STRUCTURE

Figure 10 Model Structure

4. RESULT AND DISCUSSION

A supervised classification mechanism like Decision Tree and SVM was applied to classify land use and land cover in the study area. The results confirmed that the study area was classified into Agriculture land, Mangrove Forest, Residential Area, Water Bodies, and Beach Land.

Figure 3. shows classified images coming from these classifiers respectively. The image classified with decision tree showed OAA (89%) and SVM gave OAA (82%). Tables show confusion matrices pre-pared for the image classified with the two classifiers (Decision Tree and SVM). Accuracy values were highest for classes with standardized distribution such as residential areas and water bodies. Both the tested classifiers showed relatively lesser accuracies for vegetation classes (Mangrove and Agriculture land) with the non-homogenous distribution. However, it is remarkable that in the present study both the selected classifiers were able to disguise between two vegetation variable classes agriculture land and mangrove forest.

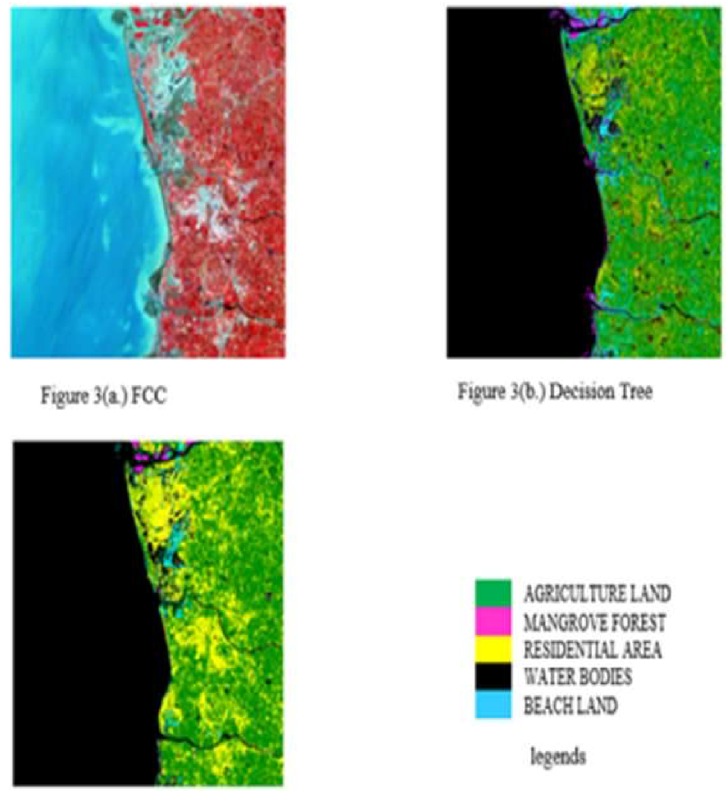

Figure 3(a.) FCC

Figure 3(b.) Decision Tree

Figure 3(c.) SVM

Figure 11 Result Image

Figure 4. shows the algorithm for the decision tree of all the land use classes. Earlier, (Keshtkar et al.,2013) achieved an accuracy of 79 % for the classification of land use and land cover patterns with the help of a decision tree classifier for multispectral data set. Classification accuracy achieved in the present study is far better than mentioned above. Previously, (Punia et al.,2011) concluded that the decision tree classification gave better accuracy in comparison to earlier studies. Results in the present study are in agreement with this conclusion.

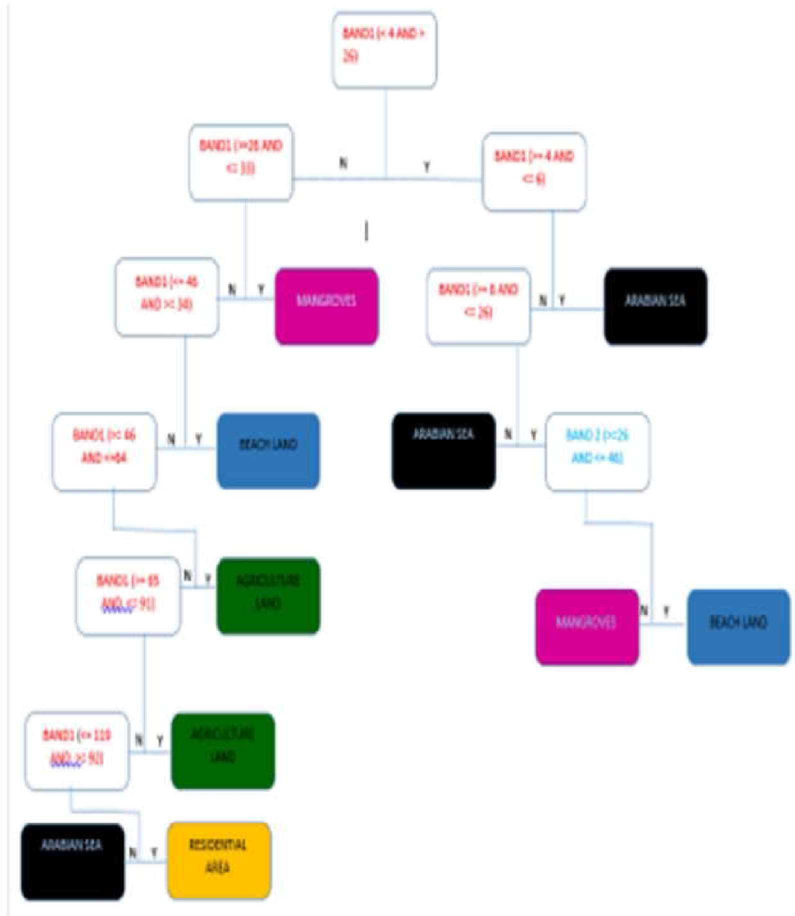

Figure 12 Decision Tree

SVM classifier in the present study achieved a reasonable accuracy number of 81% lesser than Decision Tree. Earlier,(Prasad et al., 2017) accomplished a higher accuracy of 93 % for the IRS LISS III data set. Furthermore, (Macintyre et al.,2020) and (Venkatalakshmi et al., 2005) achieved an accuracy of 73% and 90% for various kinds of multispectral data set. The present study was unable to attain a higher accuracy percentage for SVM.

Knowledge-based Decision Tree classification increased the outcomes as compared to the other supervised classification methods. The Decision Tree classification method is simple and does not depend on the understood hypothesis concerning the association between the spectral information and class proportions. The outcomes of this study prove that the Decision Tree can find the complex relationships amongst spectral bands and classes. And also can identify the most appropriate mixture of bands in increasing the class separability. Also, the structure of the Decision Tree is interpretable and shows the hierarchical relations among bands and class proportions. The results of classifications LISS-III image along with ancillary data demonstrate that Decision Tree

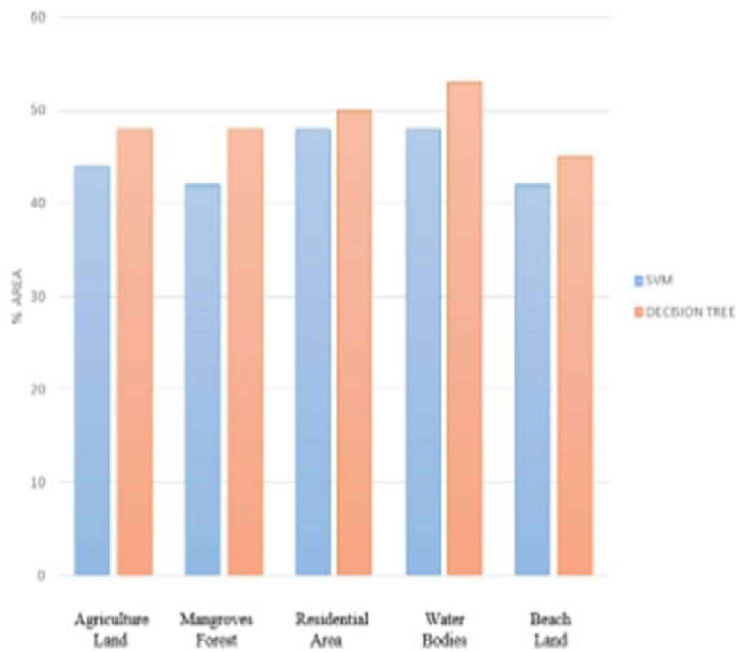

Figure 13. Percentage area occupied by 5 classes in the image subset classified with different classifiers

Table – I: Confusion matrix obtained using Decision Tree classifier.

	Agriculture Land	Mangrove Forest	Residential Area	Water Bodies	Beach Land	Total	% Accuracy
Agriculture Land	48	5	1	0	0	54	88.88
Mangrove Forest	3	48	0	3	0	54	88.88
Residential Area	2	0	50	0	2	54	92.59
Water Bodies	0	2	0	53	1	56	94.64
Beach Land	0	2	3	3	45	53	84.90
Total	53	57	54	59	48	271	
% Accuracy	82.75	84.21	92.59	89.30	93.75		

OAA = 89.97 % , Kappa Coefficient = 0.83.

Table II: Confusion matrix obtained using SVM classifier.

	Agriculture Land	Mangrove Forest	Residential Area	Water Bodies	Beach Land	Total	% Accuracy
Agriculture Land	44	7	3	0	0	54	81.48
Mangrove Forest	6	42	0	6	0	54	77.77
Residential Area	4	0	48	0	2	54	88.88
Water Bodies	0	4	0	48	4	56	85.71
Beach Land	0	3	4	4	42	53	79.24
Total	56	56	52	58	49	271	
% Accuracy	78.27	75.00	86.53	82.75	85.71		

OAA = % 82.61, Kappa Coefficient = 0.76.

The image classified with Decision Tree showed the highest OAA 89% and SVM showed 82% OAA. Tables I and II display confusion matrices prepared for the image classified with the two classifiers. Accuracy values were highest for residential areas and water bodies. Both the tested classifiers showed relatively lesser accuracies for beach land. The decision tree showed higher accuracy in water bodies and residential areas. And showed the same accuracy in agricultural land and mangrove forest, where SVM showed higher accuracy in residential areas and water bodies. Among the two classifiers tested, the Decision tree fared better for all land use land cover classes while SVM showed lesser performance. Figure 5. shows percentage area classified as each land use land cover class in the two classifiers

5. CONCLUSION

The study was carried out to compare the performance of classifiers (Decision Tree and SVM). Among both the classifiers, the Decision tree gives a better result than SVM for the study area. The decision tree achieved 89.97 % and SVM achieved 81.90 %. It revealed that Decision Tree did better across different levels of occupancy of Land use/Land Cover. The findings of the present study are encouraging for Land use and land cover using spaceborne multispectral data.

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A LAND USE/LAND COVER CLASSIFICATION OF IRS (LISS – III) MULTISPECTRAL DATA USING DECISION TREE AND SVM CLASSIFICATION MECHANISM

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ABSTRACT

Identification of the effect of human activities on our planet concerns over worldwide land use and land cover change is very complex. Land Use and Land Cover refer to the utilization of land through events like agriculture, different types of cultivation areas, residential areas, and the physical features on the earth's surface like the sea, mangroves forest, vegetation cover, and water bodies. However, empirical techniques used for this type of classification are cost-effective and laborious. This paper is focused on remote sensing images and various supervised classifications to identify various Land Use/Land Cover. This research work aims to use images taken from IRS (LISS III) platform to perform supervised classification. The study was performed to compare the performance of Supervised classifiers Decision Tree and SVM to classify different land use land cover classes. The Decision tree classifier gives better results than SVM for the study area. The decision tree classifier achieved 89.97 %, and SVM 81.90 %. It revealed that Decision Tree did better across different levels of occupancy of Land use/Land Cover.

Keywords: remote sensing, multispectral satellite image, classification, Decision Tree, SVM.

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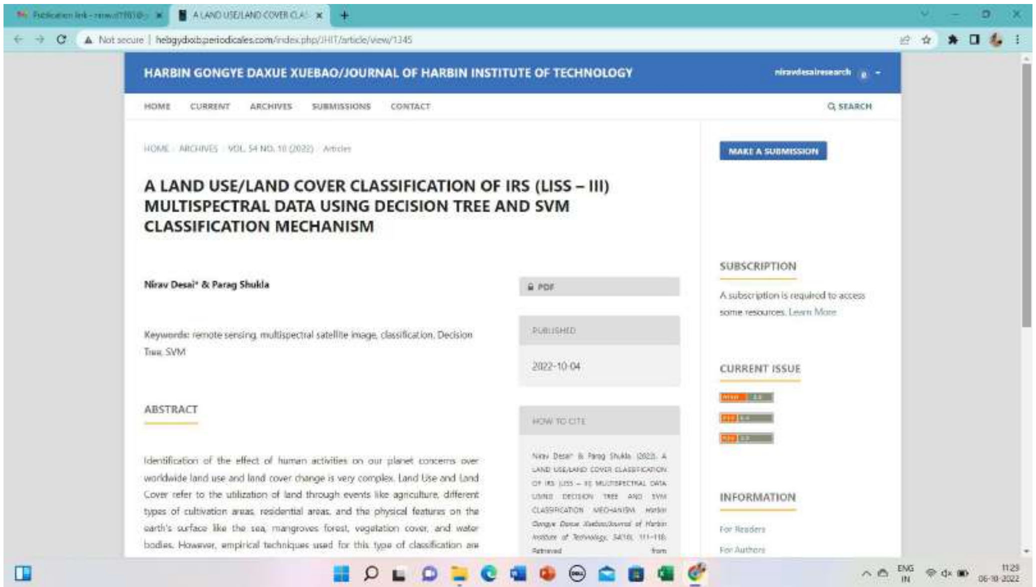
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INFORMATION
For Readers
For Authors

6)

Creation and Segmentation of image dataset of Mung bean plant leaf

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Abstract. Automated plant disease identification is an enduring research subject. Leaves are available for most of the season and they have a flat (2d) surface that's why practically it is physible to detect disease symptoms using image analysis. Data collection and pre-processing are the most significant and crucial stages to obtain the data that can be taken as accurate and appropriate for further processing. Machine learning techniques require a large amount of data for training. The present paper focuses on process standardization for the creation of an image dataset of Mung bean plant leaves and pre-processing steps to enhanced captured images. The diseases in leaves result in loss of economic, and production status in the agricultural industry worldwide. The identification of disease in leaves using image processing, reduce the reliance on the farmers for the safeguard of agricultural crops. In this paper creation and segmentation process of Mung bean plant leaf, performed. Present Dataset will be available to be used by researchers to save their time, efforts, and cost related to dataset creation. Segmentation of images will intensify the accuracy of the identification of various diseases.

Keywords: Mung bean, Leaf, Image analysis, Image Dataset, Disease Identification, Pre-processing, Segmentation.

Introduction

Pulses play important role in nutritional requirements. Pulses help to reduce inanition among the poor masses. They provide minerals, vitamins, energy, dietary fiber, the protein required for the health condition. Pulses contain substantial amounts of essential nutrients like calcium, iron, and lysine (Gowda et al 2013). Latest research studies suggested that consumption of pulses may have likely health benefits as well as reduced risk of hypertension, gastrointestinal disorders, cardiovascular diseases, cancer, diabetes, and osteoporosis (Jacobs and Gallaher 2004).

(Gaston & O'Neill, 2004) projected possibility of plant species identification using artificial intelligence and digital image processing techniques. Ever since many studies have proposed various methods for automated plant and plant disease identification. (Rzanny, Seeland, Wäldchen, & Mäder, 2017a) explored many approaches for image acquisition and pre-processing to improve the quality of plant organ images to train classifiers for the classification process.

This paper proposes an image dataset of Mung bean plant leaves to carry out an image-based plant disease identification and classification. There are no standard plant leaves image dataset for Mung bean leaves is available. The database is created manually by capturing mung leaves images using various smart mobile phones in a controlled environment. How leaf images are acquired and pre-processed does have a substantial effect on the accuracy of the classifier trained on them.

Literature Review

Various effective and novel methods have been projected in recent times for the automatic identification of plant and plant organ diseases. Methods are exploring visual cues present in almost all of those parts, like fruits (Aleixos N, 2002) (Corkidi G, 2005) (López-García F, 2010), stems, roots (Smith SE, 1991), kernels (Ahmad IS, 1999), and leaves. (Amruta Ambatkar et al., 2017) proposed a method for rose diseases detection using an 8-connected boundary detection algorithm for edge detection. (Sannakki et al., 2012) compared binary morphology and Sobel edge detector algorithms that detect edges and proved that morphology is more effective compared to others. (Sabu, Sreekumar & Nair, 2017) used HoG (Histogram of oriented Gradients) and SURF (Speeded Up Robust Features) together with a k-NN classifier to identify plants. (Wang et al. 2013) aimed at a new algorithm that segments a single leaf from real-time video and achieved clear and accurate edges. (Kumar, Surya & Gopi, 2017), conducted the research that considered both front and backside of leaves with fresh and dried leaves and extracts features and test them using Support Vector Machine (SVM) and Multi-Layered Perceptron (MLP) classifiers. (Dahigaonkar & Kalyane, 2018) done related work by extracting various features including geometric, texture, shape, and color using SVM Classifier. (Nisale et al. 2011) achieve 93% accuracy by extracting geometric features of a leaf for detecting various stages and deficiencies in the plant. (Arivazhagan et al. 2013) proposed an algorithm that detects and classify an unhealthy region of leaves and segmented only diseased region with the help of an SVM classifier and obtained 94.74% accuracy. (Venkataraman & Mangayarkarasi, 2017) performs classification and identification of plants using various statistical parameters, texture features, and SVM. (Aitwadkar, Deshpande & Savant, 2018) used Artificial Neural Network (ANN) for automatic identification of plants. (Batvia, Patel & Vasant, 2017) used Convolution Neural Network (CNN) for automatic identification of plants.

Table 1. Summarizes the researches carried out in recent times

Researchers	Culture	Primary Feature	No. of Images Considered	Plant Organ	Classifier / Techniques	Image Acquisition / Dataset	Accuracy
(R. P. Narmadha & G.Arulvadivu)	Paddy	Shape, Color	NA	Leaf	K-means	Custom (Smartphones or digital camera)	NA
(Hidayatuloh et al., 2018)	Tomato	Color	1400	Leaf	CNN	Custom (Smart Phone)	86.92%
(Kawacher Ahmed et al., 2019)	Rice	Color	480	Leaf	Decision Tree	Existing ("Rice leaf diseases data set." https://archive.ics.uci.edu/ml/datasets/Rice+Leaf+Diseases.)	97.91%
(V. N. T. Le et al., 2019)	Canola radish & Barley	Texture	30000	Leaf	SVM	Custom (On-Semi VITA 2000 camera sensor)	91.85%
(Sridhathan C. et al., 2018)	Multi-Species	Color	NA	Leaf	K-mean	Custom (Digital camera or Mobile Phone)	98.27%
(G. Dhingra et al., 2019)	Basil	Color	400	Leaf	SVM	Custom (EOS 5D Mark III, 22.3 megapixel CMOS sensor)	98%
(G. Saleem et al., 2019)	Multi-Species	Color	1600 625	Leaf	KNN	Existing (Flavia) Custom	97.6% 96.1%
(Y. Sun, 2019)	Tea Plant	Texture	1308	Leaf	SVM	Custom (digital SLR camera)	98.5%
(S. Sivasakthi, 2020)	Greenhouse Crop	Color, Texture	NA	Leaf	SVM, ANN	Custom (Camera)	92% 87%
(Majid et al., 2013)	Rice	Color	NA	Leaf	PNN	Custom	91.46%
(Arvind et al., 2018)	Maize	Texture	2000	Leaf	Multiclass SVM	Existing (Plant Village)	83.7%
(Suryawati et al., 2018)	Tomato	Color	18160	Leaf	CNN	Existing (Plant Village)	94%
(Suresha et al., 2017)	Rice	Color	NA	Leaf	kNN	Custom (Digital Camera)	76.59%
(Saradhambal. G et al., 2018)	Multi-Species	Color	75	Leaf	k-means	Custom	NA

(Tucker et al., 1997)	Sunflower & Oat	Shape	40	Leaf	Thresholding	Custom (TMC-76 color CCD)	NA
(Zhang et al., 2011)	Citrus	Color, Texture	500	Leaf	AdaBoost	Custom (DigitalCamera)	88%
(Wang et al., 2012)	Wheat & Grape	Color, Texture & Shape	185	Leaf	PNN	Custom (Digital Camera)	94.29%
(Zhang et al., 2016)	Cucumber	Color	100	Leaf	SVM	Custom	92% Approx.
(Quin et al., 2016)	Alfalfa	Color, Texture & Shape	899	Leaf	SVM	Custom (Digital Camera)	80% Approx.
(Dey et al., 2016)	Betel Vine	Color	12	Leaf	Otsu	Custom	NA
(Youssef et al., 2016)	Vegetable Crop	Color, Texture & Shape	284	Leaf	SVM	Custom (Digital Camera)	87.805
(Ali et al., 2017)	Citrus	Color & Texture	199	Leaf	Bagged Tree Classifier	Custom (DSLR Camera)	99.9%
(Tippannavar et al., 2017)	Multi Species	Color	500	Leaf	KNN, PNN	Custom (Digital Camera)	75.04% 71.24%
(Kaur et al., 2017)	Multi-Species	GLCM Features	NA	Leaf	SVM	NA	95.16 – 98.38%
(Mondal et al., 2017)	Okra & Bitter gourd	Texture	79(Okra) 75(Bitter gourd)	Leaf	Naives Bayes Classifier	Custom (Digital Camera)	NA
(Ma et al., 2017)	Cucumber	Color	93	Leaf	Color map	Custom (Digital Camera)	NA
(Al-Otaibi et al., 2017)	Basil & Parsley	Statistical Feature	30	Leaf	NN	Custom (Digital Camera)	80%
(Manimegalai et al., 2017)	Apple	GLCM Features	NA	Leaf	SVM	NA	98.46%
(Chouhan et al., 2018)	Plant Leaf	Region Growing	276	Leaf	NN	Existing (Plant Village)	86.21%
(Zhang et al., 2018)	Apple & Cucumber	Color	150 (Apple) 150 (Cucumber)	Leaf	k-means	Custom	90.43% (Apple) 92.15% (Cucumber)
(Picon et al., 2018)	Wheat	Color	8178	Leaf	Deep Convolution	Custom (Mobile Phones)	>98%
(Junior et al., 2018)	Multi-Species	Shape	600	Leaf	RNN	NA	88.92%
(Sunny et al., 2018)	Citrus	Texture	100	Leaf	SVM	Custom (Digital Camera)	NA
(Nababa et al., 2018)	Oil Palm	Probability Function	NA	Leaf	Naïve Bayes	NA	80%
(Fuentes et al., 2018)	Tomato	Color	5000	Leaf	NN	Custom (Digital Camera)	96%
(Sabu et al., 2017)	Multi-Species	SURF, HOG	200	Leaf	kNN	Custom	NA
(Vijayashree & Gopal, 2017)	Multi-Species	Texture	127	Leaf	Dissimilarity	Custom	NA
(Pushpa, Anand & Nambiar, 2016)	Multi-Species	Shape & Edge	208	Leaf	NA	Custom	93.75%

Nambiar, 2016)							
(Kumar & Talasila, 2014)	Multi-Species	Shape, Texture & Color	500	Leaf	Unique ID	Custom	NA
(Kumar, Surya & Gopi, 2017)	Multi-Species	Color & Texture	1200	Leaf	SVM	Custom (Scanned Images)	94%
(Dahigaonkar & Kalyane, 2018)	Multi-Species	Color, Texture & Shape	128	Leaf	SVM	Custom	96.66%
(Venkataraman & Mangayarkarasi, 2017)	Multi-Species	Texture	260	Leaf	SVM	Custom	NA
(Airwadkar, Deshpande & Savant, 2018)	Multi-Species	Edge, Color	50	Leaf	ANN	Custom	75%
(Batvia, Patel & Vasant, 2017)	Multi-Species	Shape	4000 approx.	Leaf	CNN	Custom	NA
(Venkataraman & Mangayarkarasi, 2016)	NA	Shape	5	Leaf	ANN, SVM	Custom	NA
(Arun & Christopher Durairaj, 2017)	Multi Species	Color & Texture	250	Leaf	SVM	Custom (Digital camera)	98.7%

Used Abbreviations; SVM: Support Vector Machine, ANN: Artificial Neural Networks, PNN: Probabilistic Neural Networks, KNN: k-nearest neighbors, CNN: convolutional neural network.

A detailed study of the research work done during the last few years on leaf images are summarized in Table 1. From the information presented in Table 1 main point noticeable is, researches in the field of plant disease identification mostly focuses on a single plant organ leaf. Also, the researchers are forming a custom dataset for their research work as there is no standard dataset available for Mung bean plant organs. The abbreviations used are summarized in the last row of Table 1. Below mentioned Table 2 contains a list of some existing plant image datasets.

Table 2. Existing plant image datasets

Dataset	Organ	No. of Species	Culture	No. of Images
Flavia	Leaf	32	Multi-Species	1907
Plantvillage	Leaf	3	Bell Paper, Potato, Tomato	15442
Oxford_flower102	Flower	102	Flowers	7000+
Swedish	Leaf	15	15 tree classes	1125
New Plant Disease	Leaf	14	Fruits & Vegetables	87000
Coffee-dataset	Leaf	1	Coffee	1747

The main point to note in Table 2 is that none of the above plant organ image datasets are dedicated to the Mung bean plant leaf organ. This research addresses the need for a benchmark dataset for Mung bean plant organs.

MATERIALS AND METHODS

Dataset Collection

The crucial necessity for accurate plant disease identification is a standard dataset of plant organ images. The dataset creation consists of stages as follows:

- Plant Selection
- Capturing Images
- Dataset Creation.

For this research, the Mung bean plant is under consideration as it is a local crop of the South Gujarat Region. In the present work, the leaf dataset consists of four types of healthy and diseased Mung bean leaf images; these are Cercospora Leaf Spot, Yellow Mosaic Virus, and Powdery Mildew. These were collected from The Navsari Agriculture University at Navsari, Gujarat, India for reflective study. A pictorial assessment of the above-mentioned study site is shown in Fig. 1.

Fig. 1. Study Site of Mung bean Plants

Leaf samples are acquired indoor to minimize the effect of lighting conditions. Leaves were digitally captured in a controlled environment using Oppo A5 13MP and MI Note 8 Pro 64MP smartphones.

The Database consists of 1500+ images which include 400+ healthy and 1000+ diseased leaves. The diseases considered are Cercospora Leaf Spot, Powdery Mildew, and Yellow Mosaic Virus. Fig. 2 represents the healthy and diseased Mung bean leaves.

Fig. 2. Healthy & Diseased Mung Bean Leaves

System Model and Discussion

The system model is consist of four crucial steps as follows:

1) Pre-processing: Pre-processing helps to bring out useful information from an image.

2) Segmentation: Segmentation is used for locating objects in the image and to detect bounding lines of the image, background subtraction.

3) Feature extraction: In this phase, unique characteristics of an object or group of objects are collected.

4) Classification: Classification is the phase where training and testing take place. It is where the decision takes place using features extracted from the previous phase.

From the above four phases first, two phases have been discussed in detail in the following sub-sections and the remaining two phases will be implemented in the future. For implementation, OpenCV an open-source computer vision library with Python is used.

1.1.1 **a) Pre-processing**:. Afterimage acquisition the pre-processing phase takes place. In this phase, image enhancement will be done. For this various operations are carried out in a series: RGB image Acquisition and color transformation, normalization/ resize of image size, Augmentation, masking green pixels, Segmentation. This phase makes changes in the image and makes it appropriate for segmentation.

Resize an image

. Resizing refers to the scaling of an image. It helps to reduce or increase no of pixels from an image. Fig. 3 represents the image resize phase.

(a) (b)

Augmentation

. Augmentation encompasses a wide range of techniques used to generate new training samples from the original ones. It helps us to increase the size of the Dataset for training. Image augmentation artificially creates training images through a combination of multiple transformations. The result of image augmentation is displayed in Fig. 4.

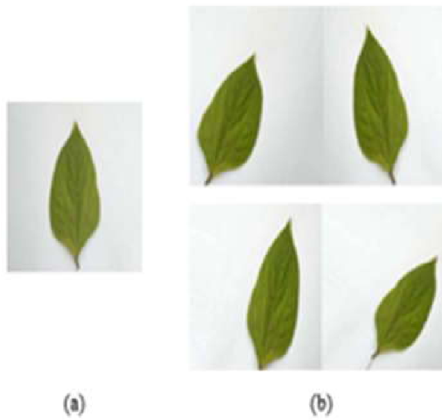


Fig. 4. (a) Original Image, (b) Augmented images

1.1.2 b) Segmentation:. Image segmentation is the first step in image analysis and pattern recognition it is a critical and essential step and is one of the most difficult tasks in image processing, as it determines the quality of the final result of the analysis (Jagtap et al., 2014). During the segmentation phase, the image will be divided into several segments so that the analysis process becomes easy. In this study, edge detection is performed using the canny() edge detector and Interactive foreground extraction is performed using Grebcut() algorithm. Fig. 5 depicts the edge detection and Fig. 6 depicts the Foreground extraction process.

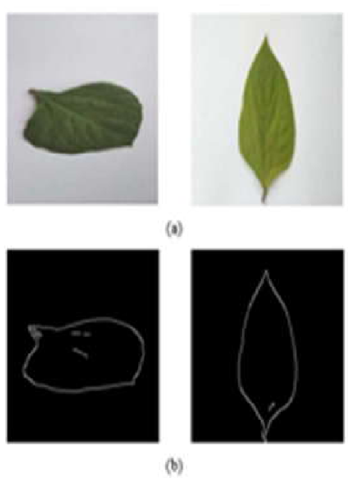


Fig. 5. (a) Original images, (b) Extraction of Boundary

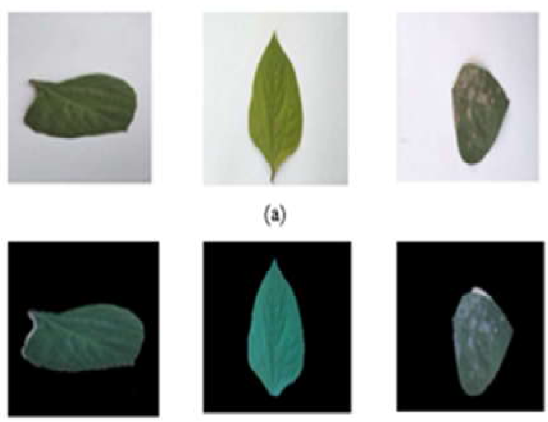
Fig. 5. (a) Original images, (b) Extraction of Boundary

Steps for segmentation

(a) Input Image (b) Simple masked image (c) Separate foreground and background (d) Final mask image (e) Output image after masking

Fig. 6. Segmentation Process

The GrabCut algorithm segments object from the background in an image. The user has to mark a rectangular area as the primary input. The outer part of this rectangle is considered as background and pixels in the outside area are considered as known background and inside are unknown background. A model is then created using this data, to find out whether the unknown pixels are foreground or background. Fig. 7 represents some of the segmented images.



(a)

(b)

Fig. 7. (a) Original Images, (b) Segmented Images

GrabCut is one of the extensively used algorithms for removing background in images. The automatic GrabCut technique was experimentally tested using a dataset of Mung bean leaf images as shown in Fig. 7. This work can be used in regions like plant leaf image classification, plant leaf disease detection from plant leaf images.

CONCLUSION

We considered the creation of the Mung bean plant organ image dataset. Dataset will be released to be used by researchers to save their time, efforts, and cost associated with dataset creation. Segmentation of the image will increase the accuracy of identification of healthy and diseased pixels.

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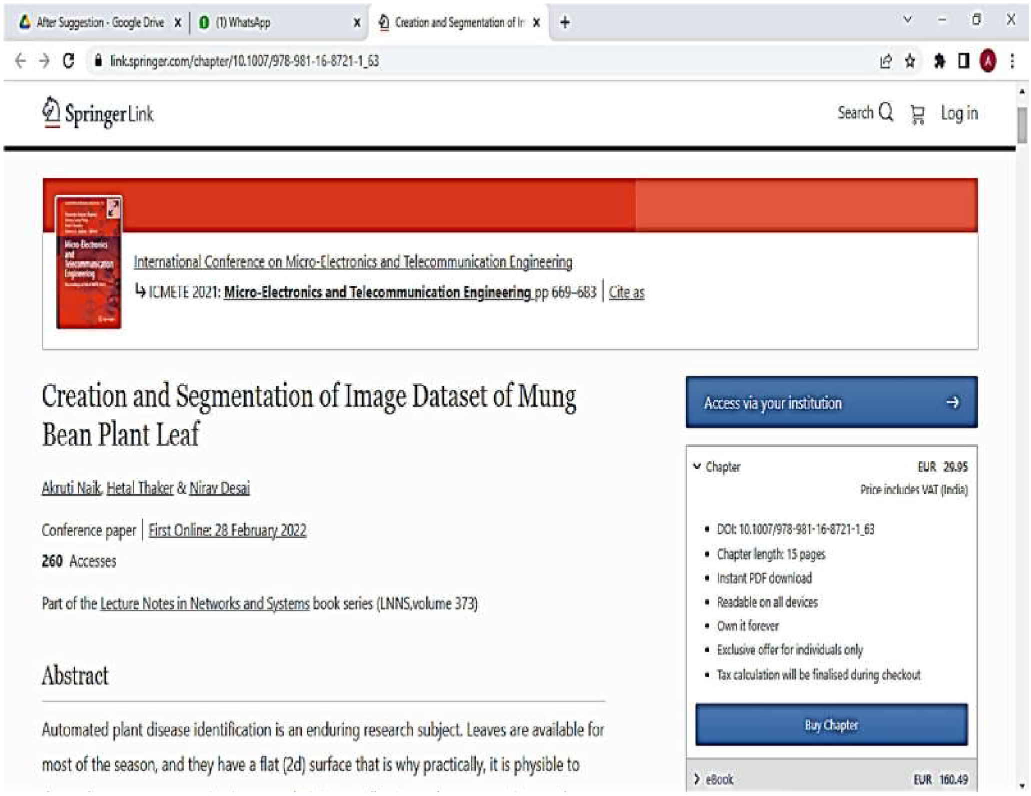

Figure: Journal Link

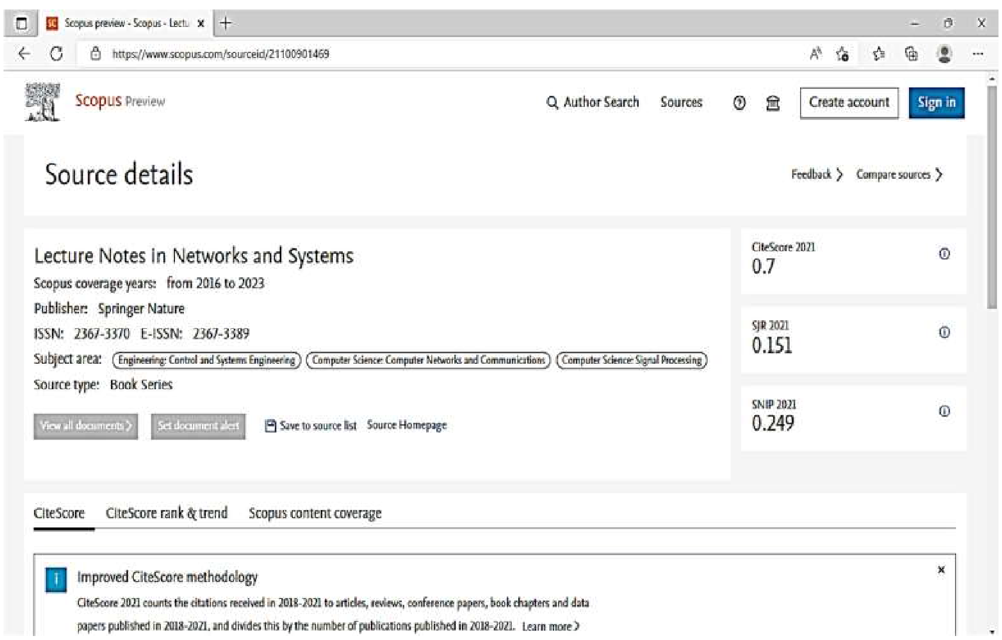

Figure: Scopus Coverage

7th International Conference on Micro-Electronics, Electromagnetics and Telecommunications (ICMEET 2022)
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Department of Electronics and Communication Engineering, Shri Vishnu Engineering College for Women (Autonomous), Bhimavaram, Andhra Pradesh, India.

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CERTIFICATE OF APPRECIATION

This is to certify that Mr/Ms/Dr Nirav Desai of Atmiya University, Rajkot, Gujarat, India has/have contributed a paper titled Land use land cover segmentation of LISS- III multispectral space born image using deep learning in ICMEET 2022 held at Shri Vishnu Engineering College for Women (A), India. The paper has been selected for publication in the ICMEET-2022 conference proceedings by Springer Lecture Notes in Electrical Engineering (LNEE) Series subject to fulfilment of the guidelines issued by Springer. We wish the authors all the very best for future endeavors.

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This is to certify that
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Indian Remote Sensing (IRS) LISS- III multispectral image semantic segmentation using deep learning (U-Net & Deeplabv3
which was adjudged the Best Presented Paper in the International Conference on Emerging Technologies & Business Intelligence organized by School of Management, RK University in association with the Department of Operations Research& Business Intelligence, Wroclaw Tech, Poland at RK University on February 17, 2023

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Summary

Introduction

Remote sensing (RS) is the method of discovers and understanding the information from an extensive distance, using sensors deprived of communication with the object. Satellite imagery is pictures of Earth composed by imaging satellites operated by governments and businesses around the world. Land use refers to the biophysical state of the earth's surface where land covers contain grassland, agriculture land and forest. This study perform classification techniques to identify 4 land use land cover classes (Water bodies, Agriculture land, Residential area, Uncultivated land) using deep learning techniques.

Chapter 1 Introduction

This chapter gives overview of the research work, its scope, objectives, need etc. in detail. Also chapter covers remote sensing, types of sensors and different types of remote sensing images. False composite color (FCC) images and image processing techniques and are also covered in this chapter. The summary of the overall thesis is also discussed.

Chapter 2 Literature Review

Study of the previously done work up to now in the area of land use land cover classification and mapping is discussed in this chapter. It contains research articles, electronic documents. conference articles and web resources.

Chapter 3 Methodology

In this chapter land use land cover classification model is discussed in detail. Components and subcomponents of model are explained in detail in this chapter. This chapter also describes development of the model.

Chapter 4 Results and Conclusion

This chapter contains outcomes of the projected model applied on IRS LISS- III multispectral image dataset. Furthermore this chapter presents conclusion of projected study work.

Conclusion

Results and conclusion are deliberated in detail in chapter 4 built on various parameters. This chapter presented the outcomes related to the numerous proposed models.