Chapter 1

Introduction

1.1 Digital Image processing

Digital image processing techniques support the handling of digital images by using computers. Digital image processing has a wide variety of applications that cover the areas such as remote sensing, military, geology, etc. A digital image is imagined as a combination of pixels, each designated by a pair of spatial coordinates and its intensity (Gonzalez 2009) Thus any digital image is categorized by two mechanisms namely the size of the image and intensity array (Solomon & Breckon, 2011). The digital images are of sizes 128 * 128, 256 * 256, 512*512, and 1024 * 1024. Digital image processing wants an extensive spectrum of calculations for noise clearing, semantic segmentation, edge detection, feature extraction, classification, analysis, and machine vision.

1.2 Remote Sensing

As we scuffle to recognize the consequence of human movements, on our planet, concerns over global land use and land cover change are rising (Okin et el., 2006). Land use land cover (LULC) classification is very imperative because it offers data for monitoring natural resources in different geographical positions (Chan & Palinckx, 2008). 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 et al., 2013)

Land use land cover (LULC) identification and mapping with remote sensing images have developed great interest among researchers from different disciplines. 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 (Campbell & Wynne, 2008) (Homer et al., 2004) (Fang et al., 2017)

Remote sensing is the art of obtaining data about objects or areas from a distance from airplanes or satellites. Satellite imagery is images of Earth, composed 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).

In the last few years remote sensing has been used as a tool to develop land use land cover maps. Land use land cover refers to the utilization of land through activities like agriculture, different cultivation areas, residential areas, and the physical features on the earth's surface like water bodies, mangroves forests, vegetation cover, and uncultivated land. Space-born remote sensed imagery is the furthermost popular technique to capture data on land use and land cover. Image classification is a significant technique in remote

Remote sensing (RS) is widely used in the military also for example missile early warning, military reconnaissance, and surveying. 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 et al., 2017) (Xia et al., 2017) (Lu & Weng, 2007) (Richards and 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.

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With the help of science and technology, the capability of human beings to grow resources and renovate nature has been continuously boosted. Changes in the world and various human actions are changing the surface landscape and its land use forms every day. The quick growth of the world's population and the nonstop acceleration of urbanization have quicker the speed of this change. Land use land cover change research has become the focus of researchers (Jin et al, 2017) (Lyu et al., 2016) (Polykretis et al., 2020). Features like real-time, fast, wide-coverage, multi-spectral, periodicity, etc. (Zhao et al., 2017) remote sensing technology, has become the main technical means of change detection (Sofina & Ehlers, 2016) (Lopez et al., 2019).

1.3 Satellite Sensor:

The satellite sensors are categorized into two classes: passive sensors and active sensors. The passive sensors calculate the stages for the sources of energy. Passive sensors are the common method for taking a remote sensing image for which, the Sun is the key source of illumination. The active sensors deliver their source of energy from artificial sources. RAdio Detection And Ranging (RADAR) and Light Detection And Ranging (LIDAR) are famous active remote sensing systems.

1.3.1 Passive Sensors Satellites:

Passive sensor satellites provide images in low resolution, moderate resolution, and high resolution.

a) High-Resolution Satellites

- Quickbird

- Orbview
- IKONOS

b) Moderate Resolution Satellite

- IRS (Indian Remote Sensing)
- SPOT
- LANDSAT

c) Low-Resolution satellite

- MODIS

1.3.2 Active Sensors Satellite:

- RADAR
- LIDAR

For the present study, IRS satellites are used.

1.4 IRS (Indian Remote Sensing):

Indian Remote Sensing satellites are a series of earth observation satellites, build, launched, and maintained by Indian Space Research Organisation (ISRO). IRS provides many remote sensing services to INDIA and it is the major group of remote sensing satellites for civilian use in operation today in the globe. IRS data is used for the observation of the country's natural resources applications in land use land cover, agriculture, hydrology, geology, flood monitoring, etc. A continuous source of synoptical, multispectral data of the Earth's land surfaces is obtained. The Indian Space Research Organization (ISRO) presently has 5 satellites of the IRS system. IRS-1C and IRS-1D satellites provide continuous global coverage with the sensors such as IRS-Pan (IRS Panchromatic), and IRS-LISS (Linear Imaging and Self Scanning Sensor).

Data from IRS is available to its users through two resources:

• NRSC (National Remote Sensing Center):

NRSC provides data for Natural resource management, geospatial applications, and information services. It provides data through its purchase process. The major objective of this portal is the dissemination and sharing of geo-spatial information derived from IRS data on land use and land cover in India.

• Bhuvan Geoportal of ISRO

It allows users to explore 2D/3D representations of data. The browser is specifically tailored to view India, offering the highest resolution in this region and providing content in four local languages. Bhuvan made a modest beginning in 2009 with a simple display of satellite data and basic GIS functionality with many thematic maps on display functions. It provides a strong foundation with 1m resolution satellite data for more than 350 cities which is being updated for large areas of the country. It provides data to its users free and in the open domain.

Currently, Bhuvan provides the data from

- IRS P6 (Resourcesat-1)
- Resourcesat-2
- AWiFS Oceansat-2
- IMS 1
- IRS P5 (Cartosat 1)
- IRS P6 (Resourcesat -1)

AWiFS Oceansat – 2

It is an Indian satellite constructed mainly for ocean applications. The main purposes of Oceansat-2 are to collect organized data for oceanographic, coastal, and atmospheric applications. The main objectives of this satellite are to observe surface winds and ocean surface strata, observation of chlorophyll concentrations, monitoring of phytoplankton blooms, study atmospheric aerosols and suspended sediments in the water (https://web.archive.org/web/20090419165641/http://www.isro.org/rep2005/EOS.htm)

IMS 1

IMS-1 is an Earth observation satellite in a sun-synchronous orbit. This satellite is the fourteenth satellite in the Indian Remote Sensing (IRS) satellite series that has been built, launched, and managed by the Indian Space Research Organisation (ISRO).

IRS P5 (Cartosat 1)

The aims of the IRS-P5 focused on geo-engineering (mapping) applications, calling for high-resolution panchromatic imagery with high pointing accuracies. The spacecraft has two high-resolution panchromatic cameras that may be used for in-flight stereo imaging.

Resourcesat -1/ Resourcesat- 2

The Resourcesat-1/Resourcesat-2 aims to deliver continued remote sensing data services on an operational basis for integrated land and water resources management. This satellite is the extension of IRS-1C missions with much-improved abilities.

Linear Imaging Self Scanner (LISS) – 4, LISS- III, and Advanced wide Field Sensor were attached with Resourcesat -1.

LISS – III: LISS-III sensor has operating in three spectral bands in Near Infrared Region (NIR) and one in Short Wave Infrared (SWIR) band. It has a spatial resolution of 23.5m and Swath 140km.

LISS- IV: The LISS -IV sensor has operating in three spectral bands in the visible and Near Infrared Region (NIR). It has a spatial resolution: of 5.8m and a Swath of 23.9km.

Advanced Wide Field Sensor (AWiFS): AWiFS operates in three spectral bands in NIR and one band in SWIR. It has a Spatial Resolution of 56m and a Swath of 740km.

1.5 Remote Sensing Images

There are two types of remote-sensing images

1) Multispectral image
2) Hyper spectral image

1.5.1 Multispectral image

Multispectral imaging follows a Low Earth Orbit and is sun-synchronous. Multispectral remote sensing contains the gaining of visible, near-infrared, and short-wave infrared images in frequent extensive wavelength bands. Diverse classes echo and absorb differently, unlike wavelengths. It is possible to separate classes by their spectral reflectance signatures, whereas direct identification is not possible. Multispectral image has 3 to 10 bands and each band has a descriptive title.

In multispectral remote sensing, each pixel has a separate sample spectrum. For example, some bands may have more than 4 to less than 20 data points per pixel. The multispectral image includes red, green, blue, and near-infrared bands. Multispectral imagery is beneficial to classify land use land cover features and patterns. Multispectral remote sensing systems use similar sensor arrays that notice radiation in a minor number of wider wavebands. Multispectral images are taken with special cameras that distinct wavelengths using filters or with instruments that are sensitive to particular wavelengths. Figure 1.1 shows the multispectral images.

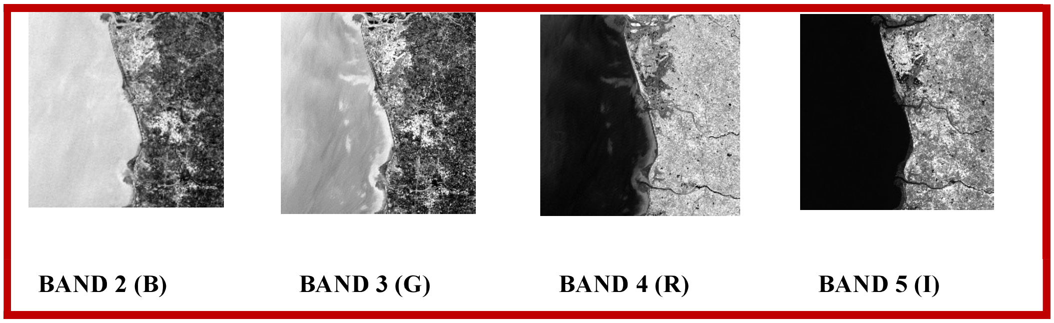

Figure 1.1: LISS – III Multispectral image

1.5.2 Hyper spectral image

Hyperspectral imaging can find more than 100 different bands within the light spectrum. Hyperspectral image contains much finer bands (10-20 nm). In hyperspectral remote sensing, each pixel has a continuous spectrum. A hyperspectral image could have hundreds or thousands of bands. hyperspectral imaging technology is enabled by the vast informational content. It may be difficult to decrease redundancies due to the complexity of many bands in the hyperspectral image. hyperspectral images contain hundreds of points for each band and each band has much more detail to observe. Hyperspectral cameras can notice many diverse wavelengths separately. Hyperspectral imaging collects numerous spectral bands in a single acquisition, this feature has made it exclusive as it required more technological improvement to develop more detailed spectral data.

1.6 False Color Composite (FCC)

When dissimilar bands of a multispectral data set are screened, the images in various bands are shown by image planes is defined as False Color Composite (FCC). Color components need an advanced spectral resolution when they are shaped. For an exact color combination, the image processor (RGB) will have bits of memory buffer in the frame buffer allotted to a portion of image information used in the red, blue, and green spectral regions. In the present study, False-color composites (FCC) are created by stacking these multiband TIFF images on top of each other. A stacked combination of Band 4, Band 3, and Band 2 is used to create FCC. Figure 1.2 represents the FCC image.

Figure 1.2: False Color Composite (FCC) image

1.7 Deep Learning

Deep learning (DL) has been measured as one of the most efficient methods for remote sensing image classification (Liu & Shi, 2020) (Zhu et al., 2017) (Guo et al., 2020) (Wang et al., 2019) (Dou & Zeng, 2020). It uses brain imitations to build deep structures with multiple layers to extract high-level features gradually and cracks complex classification problems. DL has the advantage to study the features automatically and classify those using deep networks to improve accuracy (Guo et al., 2020) (Dou & Zeng, 2020). Techniques like deep belief networks (DBN), recurrent neural networks (RNN), and convolutional neural networks (CNN), have been widely used for LULC mapping (Zhong et al., 2017) (Huang et al., 2018) (Lyu et al., 2018). Various DL techniques have dissimilar features when they solve dissimilar classification issues. Some Deep learning techniques, such as CNN, are focused on the powerful capability of feature learning [36], [38]. DL networks to improve classification performance (Dede et al, 2018) (Chen et al., 2018).

(Hinton et al., 2006) projected deep learning for the first time and proved that the training difficult problems of a deep neural network can be solved through initialization layer by layer. Deep learning algorithm has been effectively applied to the field of image processing, video processing, and field of data analysis (Wen-bo et al., 2018). Its core idea of deep learning is to let machines learn from data automatically by increasing the number of layers of the network (Richards & Richards, 1999).

Due to the remarkable feature illustration power of Convolutional Neural Networks (CNN), it has been widely applied to semantic segmentation, image classification, and object detection. The rapid expansion of deep learning technologies quickens the progress in remote sensing image classification.

Deep learning allows researchers in remote sensing to move beyond typical methods and handle several difficulties with accurate outcomes. Implementation of deep learning needs to familiarize with different frameworks such as Caffe, Torch, Theano, and TensorFlow, but applying new techniques needs a skilled programming background and deep learning knowledge. Many studies rely completely on pre-processed, tightly annotated public datasets because data extraction needs information on geospatial standards and tools like Geographic Information Systems and remote sensing image processing software.

In this study, the FCN and CNN classifier was used for land use land cover classification for the South Gujarat region, India. The effectiveness of the classifier was tested by applying it to real continuous data. 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 into 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 number of filters equivalent to the number of classes which is 4.

The experiment showed that the FCN classifier has a very good capability for land use land cover class detection. The classification of remote sensing images using U-Net performs better then DeepLabv3+.

1.8 Contribution of the research work toward the problem domain

- Identification of land use and land cover is a very important task.
- However, techniques available for the above mention purpose are labor incentives, time-consuming and costly.
- Remote sensing plays an important role in mappings and classification of land cover features.
- Images taken with the help of Space born remote sensing platforms (Satellites) can be very helpful for the Identification of land cover and land use.
- Furthermore, this method is cost-effective and consumes a lesser amount of time.
- The research results can provide some meaningful scientific help to government agencies for planning land use in the south Gujarat region.

1.9 Objectives of the Research

- Identification of land cover land use using IRS LISS- III multispectral remote sensing images.
- Classification of land cover land use using Multispectral remote sensing images.
- Classify different classes of land cover land use like water bodies, residential area, vegetation, uncultivated land.
- Creation of novel dataset

- Development of models for classification
- Performance analysis of different models

1.10 Organization of the Thesis

Researcher has distributed complete work into total 4 diverse chapters. Summary of the chapters from chapter 2 to chapter 4 is as follow.

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 clasiification 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.

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