Change Detection on Satellite Images using Deep Learning Techniques

MINI PROJECT REPORT submitted in partial fulfillment of the requirements
Submitted by

BACHELOR OF TECHNOLOGY
IN
INFORMATION TECHNOLOGY

by

NAGARAJU AJAY KUMAR VARMA (208W1A12A1)
PALLAPATI LATHA SRI (218W5A1209)

Under the Guidance of

Dr M. SUNEETHA,
PROFESSOR AND HEAD

DEPARTMENT OF INFORMATION TECHNOLOGY V R SIDDHARTHA ENGINEERING COLLEGE
(AUTONOMOUS - AFFILIATED TO JNTU-K, KAKINADA)
Approved by AICTE & Accredited by NBA
KANURU, VIJAYAWADA-7 ACADEMIC YEAR
(2022-23)

V.R.SIDDHARTHA ENGINEERING COLLEGE

(Affiliated to JNTUK: Kakinada, Approved by AICTE, Autonomous)
(An ISO certified and NBA accredited institution)
Kanuru, Vijayawada – 520007

CERTIFICATE

This is to certify that this project report titled "**Change Detection on Satellite Images using Deep Learning Techniques**" is a Bonafide record of work done by **NAGARAJU AJAY KUMAR VARMA (208W1A12A1)** and **PALLAPATI LATHA SRI (218W5A1209)** and under my guidance and supervision is submitted in partial fulfillment of the requirements for the awardof the degree of Bachelor of Technology in Information Technology, **V.R. Siddhartha Engineering College** (Autonomous under JNTUK) during the year **2022-2023**.

(Dr. M. SUNEETHA)	**(Dr. M.SUNEETHA)**
Professor & Head	Professor & Head
Dept. of Information Technology	Dept. of Information Technology

EXTERNAL EXAMINER SIGNATURE

Date of examination: dd-mm-yy

DEPARTMENT OF INFORMATION TECHNOLOGY

V.R.SIDDHARTHA ENGINEERING COLLEGE

PROJECT SUMMARY

S.No	Item	Description
1	**Project Title**	**Change detection on Satellite images using Deep Learning Techniques**
2	**Student Names & Numbers**	**N. AJAY KUMAR VARMA (208W1A12A1)** **P. LATHA SRI (218W5A1209)**
3	**Name of The Guide**	**Dr. M. Suneetha** **Professor and Head**
4	**Name of The Mentor**	
5	**Research Group**	**AI/ML/DL**
6	**Application Area**	**Remote sensing and change detection.**
7	**Aim of the Project**	**Change Detection on Multi-Spectral Satellite Images, in order to detect Changes in Landcover over Time.**
8	**Project Outcomes**	• **A consistent model that accurately detects changes in a given region. Also, shows changes over time in a particular region.** • **Improved urban planning and decision making related to development in a region.**

Student Signatures

1. **Signature of Guide**

2.

ACKNOWLEDGEMENT

First and foremost, I sincerely salute our esteemed institution **V.R SIDDHARTHA ENGINEERING COLLEGE** for giving me this opportunity for fulfilling my project. I am grateful toour principal **Dr. A.V. RATNA PRASAD**, for his encouragement and support all through the way of my project.

On the submission of this Project report, I would like to extend my honor to **Dr.M. Suneetha**, Head of the Department, IT for her constant motivation and support during the course of my work. I feel glad to express my deep sense of gratitude to my project guide **Dr.M. Suneetha, Professor and Head** for her guidance and assistance in completing this project successfully.

I would also like to convey my sincere indebtedness to all faculty members, including supporting staffof the Department, friends and family members who bestowed their great effort and guidance at appropriate times without which it would have been very difficult on my part to finish the project work.

INDEX

TABLE OF CONTENTS:

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

ABSTRACT

It is crucial to understand the changes that have occurred in a particular region between two different points in time. However, it may not always be feasible to physically visit the location to identify these changes. Therefore, satellite imagery is a practical solution to this challenge, which can be obtained from Google Earth Engine for the relevant timestamps. Changes in a specific region are useful for assessing the development that has taken place in that location at a particular point in time, as well as identifying any necessary actions that need to be taken. Gathering high resolution Multi-Spectral Satellite images of a particular region is always challenging. Most of satellites provides imagery with very less resolution it's hard to gather images with high quality and clearness. Most of satellites provides Indian spatial data but with very low resolution. In cities like Mumbai, we can expect somewhat better resolution images. But it's very challenging to get images of Indian villages in order to detect changes over time.

Many researchers have been working on the problem of detecting changes that have taken place between two timestamps. They have built systems that accurately detect these changes using various approaches and different neural network architectures, such as Unet and Cdnet, including upgraded versions designed to detect even the smallest changes with higher accuracy. However, there are some challenges that need to be addressed. Firstly, the usage of compute resources is typically high, so it is important to design neural networks that minimize resource consumption. Additionally, any noise in the detections needs to be properly handled to obtain reliable change maps using the respective models. Moreover, it is preferable for the model to take images as input rather than raster files, as many users may not have access to raster files for change detection. The model should be capable of detecting changes robustly using any combination of bands present in the input image. The selection of the main three bands depends on the specific requirements of the task. For example, if the target is water bodies, the infrared (IR) band would be more useful than the RGB bands for identifying changes.

Change detection involves comparing two satellite images taken at different times to identify any differences that may have occurred in the geographical area of interest. It is implemented with two methods for detecting changes between two satellite images. The primary approach is to use a Fully Convolutional Neural Network, which employs different architectures such as UNet and FresUNet[1]. These models generate a difference image that highlights the areas where changes or developments have taken place. To evaluate the performance of the model, The performance metrics such as Accuracy, Precision, and Recall are used.

From the proposed approach, one can give 2 images of two different timestamps as input and can get change map of two images with more accuracy of changes computed over each pixel of given two images. The model with proposed architecture takes images of 3 or 13 bands as per user's requirement and gives detected changes in the form of a binary change map. The proposed model was trained with OSCD Dataset of Sentinal-2 Satellite images and two images of different timestamps from location called Cumbum which is located in Prakasam District of AP State are used to test the model. The model takes two images as input and detects landcover changes happened in Cumbum region. With validation performed on OSCD Dataset, model achieved 94% accuracy with FresUNet architecture which is a topology of network based on FCNN.

Keywords: Quantum Geographical Information System (QGIS), Multi-Spectral Satellite Images (MSI), Sentinal-2, Fully Convolutional Neural Networks (FCNN), Pixel – Based Change Detection (PBCD).

CHAPTER 1.
INTRODUCTION

This chapter discusses the origin of the problem, the problem description, basic definitions, and remote sensing image applications.

1.1 ORIGIN OF THE PROBLEM

Promoting sustainable development depends on being able to recognize changes in our environment. In order to detect changes in land use, land cover, and urbanization, a technique known as "change detection" is used to examine several dates. Change detection is frequently carried out using remote sensing data in a variety of applications. Observation of changes can be divided into two categories: supervised and unsupervised. The main type of data used is geographic data, which can be either digital (like satellite imagery) or analogue (like aerial photographs) or vector (like feature maps) in nature. The analysis can also use ancillary data, such as historical, economic, and other kinds of data.

1.2 BASIC DEFINITIONS AND BACKGROUND

1.2.1 REMOTE SENSING:

Remote sensing refers to the process of acquiring data from a distance using specialized cameras to capture remotely sensed images, which allows researchers to "see" information about the Earth. The type of remote sensing employed is determined by the energy sources utilized, which can be either active or passive. Active remote sensing involves the use of man-made energy sources to emit signals, while passive remote sensing uses natural energy sources. Remote sensing can capture digital data over large areas, making it a highly effective tool. However, the extraction of data from these images typically requires the expertise of a trained professional[2][3].

Remote sensing systems capture data in the form of images or other measurements from the electromagnetic spectrum, ranging from visible light to microwaves and even beyond. These data can be analyzed and interpreted to extract valuable information about the Earth's features and processes. Change detection is a fundamental application of remote sensing. It involves identifying and analyzing changes that occur in a particular area or feature over time[4]. Change detection techniques compare multiple images or datasets acquired at different times to detect and quantify the changes that have occurred. Change detection in remote sensing can be performed using various methods, including visual interpretation, manual comparison, and digital image processing techniques.

1.2.2 MULTI SPECTRAL IMAGES:

Multi-spectral imaging allows for the capture of light frequencies beyond those visible to the human eye, such as infrared. This can reveal information that cannot be detected by the eye's red, green, and blue receptors alone. The term "multi-spectral" is used to describe the imaging when it includes three to fifteen bands.

Multispectral images, obtained from remote sensing platforms, provide valuable information for change detection in land cover. These images capture data in several spectral bands, allowing for the differentiation of land cover types based on their unique spectral signatures. By comparing multispectral images acquired at different times, changes in land cover such as urban expansion, deforestation, or vegetation dynamics can be identified and analyzed. This information is crucial for land management, environmental monitoring, and land-use planning[2][3].

1.2.3 GOOGLE EARTH ENGINE:

The Earth Engine Explorer (EE Explorer) is a user-friendly tool for viewing geospatial image data, offering access to a vast array of global and regional datasets available in the Earth Engine Data Catalog. It enables fast and easy data viewing, allowing users to zoom in and out, pan across any location on Earth, and customize visualization settings. Additionally, users can layer data to explore changes over time[4].

Google Earth Engine grants access to a vast collection of satellite imagery and geospatial datasets, including historical data from various sensors. It employs cloud computing to handle large-scale data processing, enabling efficient analysis of extensive imagery for change detection. The platform provides built-in preprocessing tools for tasks like image registration, radiometric correction, and cloud masking, ensuring accurate and consistent datasets. Additionally, it offers a diverse range of analytical functions and algorithms tailored for change detection, allowing users to identify and quantify changes in land cover, vegetation, urban areas, and more[6].

1.2.4 QUANTUM GEOGRAPHICAL INFORMATION SYSTEM (QGIS):

QGIS is a popular open-source geographic information system that provides a range of tools and plugins for change detection analysis on satellite imagery. It allows users to import, visualize, and manipulate satellite images from different sources and carry out image differencing to identify changes. QGIS is highly useful for change detection tasks as it offers a comprehensive set of tools for image processing, spatial analysis, and visualization. It allows users to integrate different geospatial data formats, perform image differencing, classification, and enhancement[6].

The software supports spatial analysis techniques for quantifying and evaluating changes, while also providing interactive mapping and visualization capabilities to communicate change detection results effectively. Additionally, QGIS's plugin support enables the integration of specialized tools and functionalities specific to change detection.

1.2.5 SENTINAL-2:

Sentinel-2 is a satellite mission of the European Space Agency that provides high-resolution optical images of Earth's land and coastal areas. It offers a range of spectral bands that can be used for various applications, including land cover mapping and change detection. Sentinel-2 satellite data is highly valuable for change detection tasks due to its high spatial resolution, frequent revisit intervals, and multi-spectral capabilities[1].

The data provides detailed information about land cover and vegetation dynamics, enabling the identification and analysis of changes over time. With its ability to capture images in multiple spectral bands, Sentinel-2 data facilitates the differentiation of land cover types and assists in detecting changes such as deforestation, urban expansion, and agricultural changes.

The frequent revisit intervals allow for the monitoring of temporal changes and the generation of accurate and up-to-date change detection information[7].

1.2.6 FULLY CONVOLUTIONAL NEURAL NETWORKS (FCNN):

Fully Convolutional Neural Networks (FCNNs) have emerged as powerful tools for change detection in satellite images. Unlike traditional convolutional neural networks, FCNNs are designed to preserve spatial information by utilizing convolutional layers throughout the network[11]. FCNNs can take in an entire image as input and produce pixel-level predictions, enabling them to effectively identify and delineate changes in land cover and other features.

By leveraging the hierarchical representations learned from training data, FCNNs can capture complex patterns and variations in satellite imagery, enhancing the accuracy of change detection results. FCNNs have been successfully applied in various domains, including urban monitoring, environmental assessment, and infrastructure monitoring, providing valuable insights for land management and decision-making processes [8].

1.2.7 PIXEL-BASED CHANGE DETECTION:

Pixel-based change detection on satellite images using Fully Convolutional Neural Networks (FCNNs) is a powerful technique that enables the accurate identification of changes at a pixel-level. FCNNs are designed to learn spatial features and capture complex patterns in the data. In this approach, pairs of pre- and post-change satellite images are used as input, and the FCNN is trained to classify each pixel as changed or unchanged. The FCNN's ability to analyze the entire image simultaneously ensures the preservation of spatial context, allowing for more precise change detection[7].

The model learns to differentiate between spectral and textural variations, improving the detection of subtle changes. FCNN-based pixel-level change detection has found applications in various domains, including urban growth monitoring, environmental change analysis, and land cover mapping, aiding in better understanding and decision-making related to land management and resource planning.

1.2.8 OBJECT-BASED CHANGE DETECTION:

Object-based change detection using Fully Convolutional Neural Networks (FCNNs) is an advanced approach that goes beyond pixel-level analysis. FCNNs are employed to segment and classify objects in pre- and post-change satellite images. The network learns to identify and differentiate changed and unchanged objects based on their spatial and spectral characteristics[6].

By considering object-level information, this method provides a more holistic understanding of the changes occurring in the scene. Object-based change detection using FCNNs offers improved accuracy and reduces false alarms compared to pixel-based approaches[13]. It finds applications in urban planning, disaster assessment, and land cover change monitoring, facilitating more precise analysis and decision-making in complex and dynamic environments.

1.3 PROBLEM STATEMENT

Change Detection on Satellite images using deep learning techniques. The main goal of this project is to detect changes in landcover over time. The model should be able to detect changes effectively when two satellite images of two different timestamps is given.

1.4 APPLICATIONS

Satellites have played a vital role in the development of various technologies such as global mapping and GPS. Remote sensing has proven to be a valuable tool in several fields such as Agriculture, Forestry, Weather, Disaster Management, and Biodiversity. Our project aims to detect changes that have occurred in a particular area by utilizing multispectral remote sensing images from two different timestamps.

Change detection analysis can help in monitoring the expansion of urban areas and predicting future growth patterns. This information is useful in urban planning and management. Deep learning-based change detection on satellite images has several important applications. It is used for urban monitoring to track urban growth and infrastructure development. In environmental monitoring, it helps detect deforestation and changes in water bodies. Agriculture and crop monitoring benefit from identifying crop health and land cover changes. Infrastructure monitoring involves assessing structural changes and damage after disasters. Lastly, deep learning aids in accurate land cover and land use mapping for improved land management and decision-making.

CHAPTER 2.
REVIEW OF LITERATURE

This Chapter discusses about the Existing Systems and their Approaches with Summary and Software Requirement Specification.

2.1 DESCRIPTION OF EXISTING SYSTEMS

2.1.1 A Deep Learning Model for Change Detection on Satellite Images

Authors: Elyes Ouerghi, Jean-Michel Morel.

Year of Publishing: 2022

Observation:

They developed a model for detection of changes in satellite images. They used OSCD dataset to train and test their model. They used Convolutional neural networks algorithm. They got 96% Global Accuracy with FC-EF Architecture. The precision and Recall values are 64% and 50% respectively.

2.1.2 A Change Detection Method for Remote Sensing Images Based on Coupled Dictionary and Deep Learning

Authors: Weiwei Yang, Haifeng Song, Lei Du, Songsong Dai and Yingying Xu.

Year of Publishing: 2023

Observation:

They have developed model based on Couple Dictionary Learning. The dictionaries used to sparsely represent difference between images. They used the Couple Dictionary Learning, FC-EF, FCN-PP, FC-Siam-Conc, FC-Siam-Diff , CDNet, CD-UNet++ , and GANs algorithms. They got 98% Accuracy with their proposed methodology [2].

2.1.3 A 3d CNN Approach For Change Detection In Hr Satellite Image Time Series Based On A Pretrained 2d CNN.

Authors: Khatereh Meshkini, Francesca Bovolo, Lorenzo Bruzzone.

Year of Publishing: 2022

Observation:

They developed model for change detection in HR Satellite image time series. Their approach is unsupervised change detection. 3D CNN feature extraction is done. They used Three-Dimensional CNN algorithm. They obtained varying time series of false alarms and missing alarms. That is overall of 14% pixels got false alarms [3].

2.1.4 Single-Temporal Supervised Object Change Detection in Remote Sensing Imagery

Authors: Zhuo Zheng, Ailong Ma, Liangpei Zhang, Yanfei Zhong.

Year of Publishing: 2021

Observation:

They developed model for change detection. They used neural network architecture named Change Star which a segmentation model and Change Mixing module. They used the CNN,Conv Net,Simple Temporal supervised learning (STAR) algorithms. They made comparison between Bi-Temporal and Single temporal supervised learning and obtained 91% IoU with Bitemporal [4].

2.1.5 3M-CDNet-V2: An Efficient Medium-Weight Neural Network for Remote Sensing Image Change Detection

Authors: Bo Zhao, Panpan Tang, Xiaoyan Luo, Dongsheng Liu, And Hui Wang.
Year of Publishing: 2022
Observation:
The authors proposed methodology for change detection using 3M-CDNet-V2 architecture. They used Self-Attention layer which gives output feature map. They used the 3D-CDNet-V2,CNN Algorithms. The model achieved 88% IOU with CDD dataset, 71% IOU with PIESAT-CD dataset and 62% IOU with CD data GZ dataset [5].

2.2 SUMMARY OF LITERATURE STUDY

The table 2.1 shows summary of literature study.

Table 2.1 Summaries of Literature Study

Sno	Paper	Methodology	Year	Algorithm	Observation
1	A Deep Learning Model for Change Detection on Satellite Images	They developed a model for detection of changes in satellite images. They used OSCD dataset to train and test their model.	2022	Convolutional Neural Networks	They got 96% Global Accuracy with FC-EF Architecture. The precision and Recall values are 64% and 50% respectively.
2	A Change Detection Method for Remote Sensing Images Based on Coupled Dictionary and Deep Learning	They have developed model based on Couple Dictionary Learning . The dictionaries used to sparsely represent difference between images.	2023	Couple Dictionary Learning, FC-EF, FCN-PP, FC-Siam-Conc , FC-Siam-Diff , CDNet , CD-UNet ++ , and GANs	They got 98% Accuracy with their proposed methodology.
3	A 3d CNN Approach For Change Detection In Hr Satellite Image Time Series Based On A Pretrained 2d CNN.	They developed model for change detection in HR Satellite image time series. Their approach is unsupervised change detection. 3D CNN feature extraction is done.	2022	Three Dimensional CNN	They obtained varying time series of false alarms and missing alarms. That is overall of 14% pixels got false alarms.
4	Single-Temporal Supervised Object Change Detection in Remote Sensing Imagery	They developed model for change detection. They used neural network architecture named Change Star which a segmentation model and Change Mixing module	2021	CNN , Conv Net , Simple Temporal supervised learning (STAR)	They made comparison between Bi-Temporal and Single temporal supervised learning and obtained 91% IoU With Bitemporal.
5	3M-CDNet-V2: An Efficient Medium-Weight Neural Network for Remote Sensing Image Change Detection	The authors proposed methodology for change detection using 3M-CDNet-V2 architecture. They used Self-Attention layer which gives output feature map.	2022	3D-CDNet-V2,CNN	The model achieved 88% IOU with CDD dataset, 71% IOU with PIESAT-CD dataset and 62% IOU with CD data GZ dataset.

2.3 Software Requirement Specification

2.3.1. Google Colab

Google Colab will be used to implement the deep learning techniques and train the FCNN. Google colab provides GPU which is very useful for image processing. As FCNN involves working with each and every pixel present in an image it is very important to make sure that system has high-end configuration with atleast 8gb of RAM and 2.5 Ghz computational power (GPU also included with minimum 2gb).

2.3.2. Quantum Geographical Information System (QGIS)

QGIS will be used for geospatial analysis and processing of the input images. Raster layer feature present in QGIS helps user to load Tif file of Raster and apply operations on it like extracting, cropping etc.

2.3.3. Google Earth Engine

Google Earth Engine will be used for accessing and preprocessing the input satellite images.

2.3.4. Hardware

The system may experience performance issues if the system RAM is less than 8GB.

2.3.5. Data Availability

The system's accuracy may be limited by the availability of labeled training data and high-quality satellite images.

The existing systems able to detect changes very well with small differences in Accuracies between each model which different authors developed. Among all of them, it can be clearly noticeable that models which uses FCNN Algorithm based Architectures are proven to be giving more Accurate changes than any Unsupervised models. By experimenting the models with different layer count, different network topologies and also different approaches like what to perform either concatenation or transpose gives more fluctuations in performance of model. By observing existing works, it is clearly understandable that by using architectures based on FCNN with different approach the Accuracy maybe high than previous models[12].

The paper "A Deep Learning Model for Change Detection on Satellite Images" proposes a deep learning model for change detection on satellite images. The model uses the early fusion technique combined with a U-net architecture and can be used on color or multispectral images. The model was tested on the Onera Satellite Change Detection (OSCD) dataset and achieved state-of-the-art results.

The second method realizes the spatial-temporal modeling and correlation of multitemporal remote sensing images through a coupled dictionary learning module and ensures the transferability of reconstruction coefficients between multisource image blocks[2].

CHAPTER 3.
PROPOSED METHODOLOGY

This chapter discusses the Design methodology, Proposed system architecture and its terms, Description of Algorithm and Description of Dataset along with all requirements.

3.1 DESIGN METHODOLOGY

The Fig 3.1 below shows the design methodology.

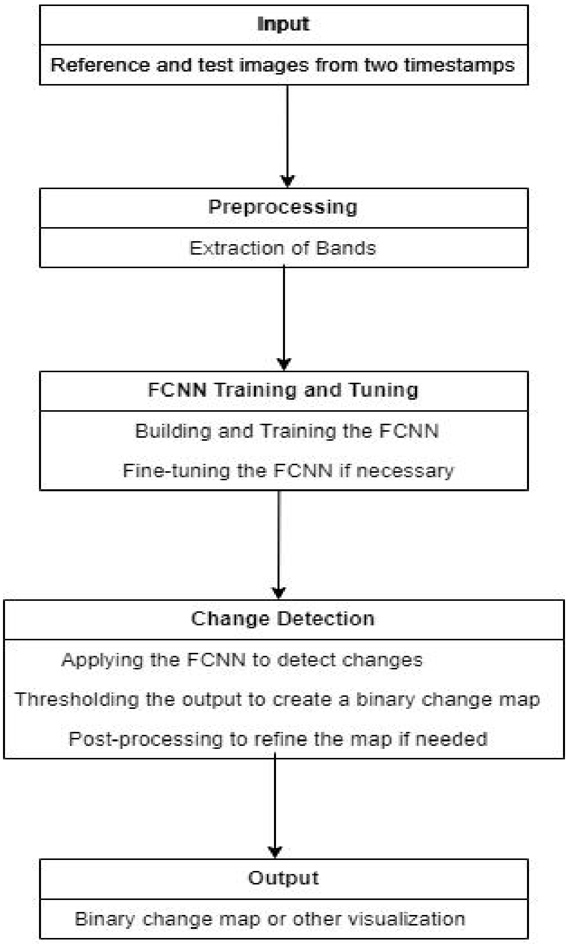

Fig 3.1 The Block Diagram for Design Methodology.

Process Steps:

1) Initially, the images are downloaded or gathered from google earth engine in Tif format. Download them and load them in QGIS.
2) Extract all 13 bands into individual Tif file. At the time of model training the Tif's can be loaded individually based on user's requirement either 3 or 13 bands.
3) Feed two images to model of two different two time stamps and then the model as per specified bands considers the number of channels (here the number of channels is count of number of bands specified by user).
4) The Unet, F-res-Unet, Siamese conc and Siamese diff Architectures anyone among these can be chosen.
5) The images are passed as input to FCNN (any one of above Architectures) so after performing

pixel-based change mapping it will generate a change map.

6) The change map is final detection by the model. It is then compared pixel wise with Original Reference map in order to know what percentage of changes was correctly detected by the developed model.
7) Here, Accuracy, Precision and Recall are used to Judge the model's Performance.

3.2 SYSTEM ARCHITECTURE DIAGRAM

The Architecture diagram of proposed work is displayed in Fig 3.2.

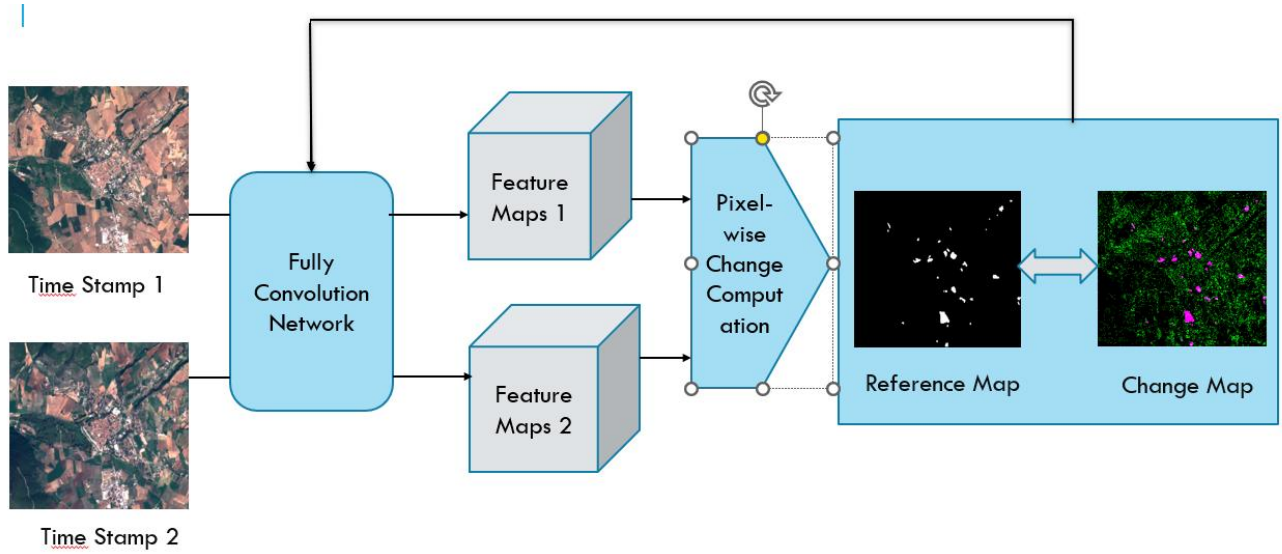

Fig 3.2 Architecture Diagram for Change Detection using FCNN.

3.2.1 MULTI-SPECTRAL IMAGES:

The model requires two multispectral satellite images as input, which can be obtained from Google Earth Engine (GEE) using selected satellite data. In this case, Sentinal-2 was used, which was collected from GEE[8]. The initial step involves providing the model with Tif and Png files of the two images from different timestamps. The GEE-collected image must first be extracted or cropped into several .tif files. Each .tif file will contain one band specific to that image. The user can choose to select all 13 bands, RGB bands, or only the grayscale band based on their interest. The model will then load the necessary tif files related to the selected bands[2].

3.2.2 FULLY CONVOLUTIONAL NEURAL NETWORK

The FCNN takes as input two satellite images, one from a time period when no change has occurred (reference image) and another from a time when change has occurred (test image). The two images are pre-processed by normalizing pixel values and resizing them to a common resolution. Then, the FCNN learns to identify the changes between the two images by training on a large dataset of labelled satellite images.

The model uses Unet and F-ResUnet Architecture which is based on FCNN. These are Early

Fusion Segmentation networks for Change detection. The main difference between these two specified architectures is the number of hidden convolutional layers used[15].

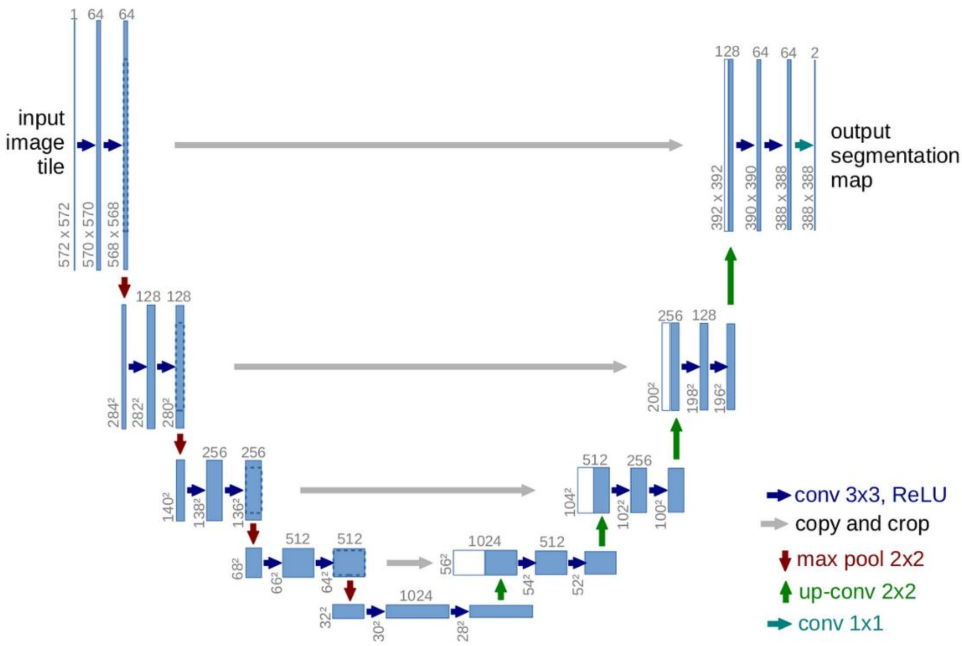

Fig 3.3 Architecture of UNet [1].

The Fig 3.3 shows the Architecture of UNet which is based on FCNN. Here, three kinds of blocks are used: standard residual blocks, subsampling residual blocks and up-sampling residual blocks. Each standard block is composed of three types of layers which are: convolutional layer, batch normalization and ReLU. Because the blocks are residual blocks, the input of a block is added to its output. The precise architecture of the standard block is depicted in Figure 1. Subsampling blocks are based on the standard block architecture but with an additional max pooling layer before the second convolutional layer. Up-sampling blocks are also based on the standard block architecture but with a transposed convolutional layer at the beginning of the block. The output of first block after successful max pooling the output will be passed to next block and as well as opposite block which forms a U-shaped structure called as Unet. The opposite block will receive two inputs in total. The concatenation of features will be done in this Architecture which allows to give change between two images of different time stamps. The number of channels here are number of bands which user wants to use if number of bands is 13 then number of channels is 13[7]. There are approximately 60 hidden layers involved in this architecture including CNN concatenation, max pooling and dropouts.

3.2.3 SIAMESE-UNET (CONC AND DIFF):

The Fig 3.4 and 3.5 shows Architectures of Siamese-UNet Conc and Siamese-UNet Diff.

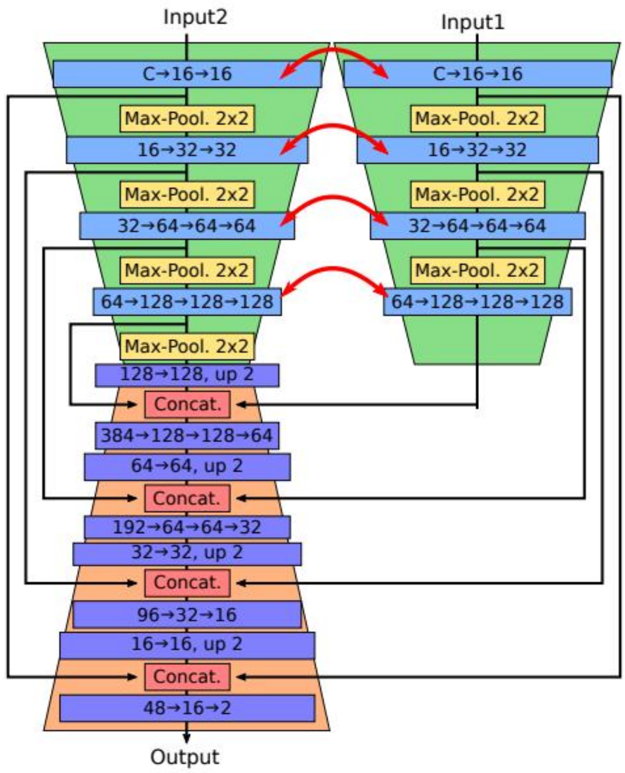

Fig 3.4 Architecture of Siamese-UNet Conc [10].

The Fig 3.4 shows the architecture of Siamese-UNet Conc which is based on FCNN. The model accepts two inputs which are of image format. From both inputs, their respective outputs at each layer are passed to next layer and as well as to the final concatenation block. During Concatenation, the feature present are getting concatenated so that it outputs the changes between two images which are passed as an input.

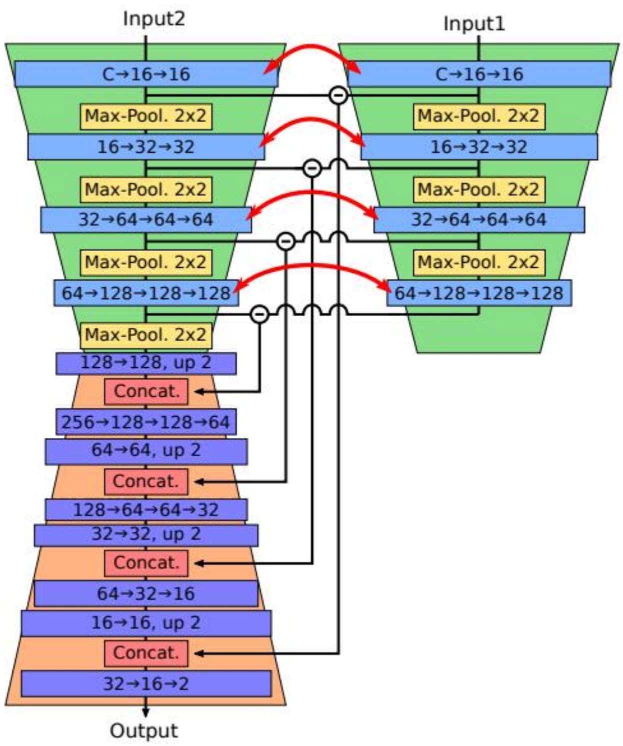

Fig 3.5 Architecture of Siamese-UNet Diff [10].

The Fig 3.5 shows the Architecture of Siamese-UNet Diff. Similar to the Siamese-UNet Conc it also accepts two inputs of same size and processes over its layers. Unlike Concatenation in Siamese-UNet Conc, the Diff approach feeds its output towards below layers as well as to final concatenation blocks. Here the difference is that the feature maps of both inputs are getting subtracted and then the resulting map will get concatenated with up-sampling blocks[7].

3.2.4 REFERENCE AND CHANGE MAPS:

The FCNN model extracts features from the input images. This is done by applying a series of convolutional and pooling layers that learn to identify patterns in the image data. The output of the feature extraction stage is a low-resolution image that represents the features of the input images. This image is then up-sampled using transposed convolutional layers to create a high-resolution map of the features. The up-sampled feature map is then classified on a pixel-wise basis to determine if each pixel in the image represents a change or not. This is typically done using a sigmoid activation function, which produces a probability value between 0 and 1 for each pixel this is called as pixel wise classification. The pixel-wise probability values are then thresholded to produce a binary change map. Pixels with values above a certain threshold are classified as changes, while pixels with values below the threshold are classified as no-change.

3.2.5 SLOW FEATURE ANALYSIS:

Slow Feature Analysis (SFA) is an effective method for change detection on multispectral images. It involves processing a sequence of images captured at different time points. The image sequence undergoes temporal filtering, such as low-pass filtering, to suppress noise and short-term variations. The filtered images are then used to extract slow features, which capture the long-term changes in the scene. By comparing the slow features across different time points, significant changes can be identified while mitigating the influence of temporary variations. SFA enables the detection of persistent changes in multispectral imagery, making it a valuable tool for change detection applications[16].

Mathematically, Slow Feature Analysis (SFA) for change detection on multispectral images can be explained as follows:

Let's denote the sequence of multispectral images as $X(t)$, where t represents the time index. Each image $X(t)$ is a matrix with dimensions $M \times N$, where M and N are the spatial dimensions of the image.

First, a temporal filter is applied to the image sequence $X(t)$. This filter can be represented by a function $f(X(t))$ that operates on the image sequence and emphasizes slow changes while attenuating fast variations. Typically, this is achieved by a low-pass filtering operation that removes high-frequency components.

Next, the filtered image sequence is used to extract slow features. Let's denote the slow features as $Y(t)$, which also have dimensions $M \times N$. The extraction process involves finding a mapping function $g(f(X(t)))$ that captures the slow variations in the filtered images.

The goal of SFA is to find a set of weight vectors w that minimize the derivative of the slow features with respect to time, i.e., $\partial Y(t)/\partial t$. This can be formulated as an optimization problem:

$$\text{minimize } \Sigma\_t \; \|\partial Y(t)/\partial t - w^\wedge T \; \nabla f(X(t))\|^\wedge 2,$$

subject to the constraint $\|w\| = 1$, where ∇ denotes the spatial gradient operator.

The optimization problem aims to find the weight vector w that maximizes the correlation between the spatial gradients of the filtered images and the time derivative of the slow features. Finally, by comparing the slow features Y(t) across different time points, significant changes in the multispectral images can be detected. The slow features capture the persistent variations over time, while reducing the impact of noise and short-term variations. In summary, SFA mathematically formulates the extraction of slow features from a temporally filtered image sequence, allowing for effective change detection in multispectral imagery[16].

3.2.6 VALIDATION:

The performance of our model is assessed using the validation metrics. The common metrics than can be used for assessing change detection model's performance is Accuracy, Precision and Recall. The Accuracy can be calculated by using total number of pixels in which there is change or there is no change. Based on number of pixels having changes and number of pixels which are correctly classified as change exists based on this the Accuracy can be computed.

These performance metrics can be calculated by formulas below:

Accuracy = (TP+TN) / (TP+TN+FP+FN)
Precision = (TP) / (TP+FP)
Recall = (TP) / (TP+FN)

The calculation of these 3 performance measures is carried out with the help of reference map. By comparing the obtained change map and original reference map, by checking whether a pixel in which there is change has correctly detected as there is change in that pixel then that is a true positive case. If there is no change and model haven't detected any change in that particular pixel then its true negative case. Similarly, the false positives and false negatives are calculated in the same way[11].

3.3 DESCRIPTION OF ALGORITHM

Algorithm: **Fully Convolutional Neural Networks (FCNN)**
Input: Two satellite images, I1 and I2, of size H x W x C
Output: A binary change map, M, of size H x W

Method:
1.Define the network architecture:

a. Input layer with H x W x C dimensions
b. Several convolutional layers with ReLU activation
c. Max-pooling layers
d. Up-Sampling layers
e. Output layer with sigmoid activation.

$$F=\sigma1[(W_f^T\times f+b_f)+(W_g^T\times g+b_g)] \quad (1)$$

$$\alpha=\sigma2(W_\theta^T\times F+b_\theta) \quad (2)$$

$$\mathrm{Softmax}(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (3)$$

Where σ1 is Relu Activation, σ2 is Softmax Activation function, F is features obtained after applying Relu. α is value obtained by applying Softmax activation. W_θ represents weights after performing convolution operation and b_θ represents results obtained after applying batch normalization on new results.

2. Initialize the weights of the network randomly.
3. Define a loss function, L, to measure the difference between the predicted change map and the ground truth change map:

L = -1/N * sum_i (y_i*log(p_i) + (1-y_i)*log(1-p_i)) (4)

where N is the number of pixels in the change map, y_i is the ground truth label (0 or 1), and p_i is the predicted probability of change. Sum represents summation.
4. Train the network:
   a. Feed the two input images, I1 and I2, to the network
   b. Calculate the output change map, M, using the sigmoid activation function
   c. Compute the loss, L, using the predicted change map, M, and the ground truth change map

   d. Backpropagate the error through the network to update the weights using gradient descent or another optimizer
   e. Repeat steps b-d for multiple epochs until the loss converges
5. Evaluate the network:
   a. Feed the two input images, I1 and I2, to the network
   b. Calculate the output change map, M, using the sigmoid activation function
   c. Threshold the change map, M, to obtain a binary map, B, using a threshold value, t
   d. Compare the binary map, B, with the ground truth change map to evaluate the performance of the network using metrics such as accuracy, precision, and recall.
6. Use the trained network to detect changes in new satellite images by repeating step 5 with the new images.

7. End

Note: This algorithm assumes that the two input images, I1 and I2, are pre-processed to have the same spatial resolution and that the ground truth change map is available for training and evaluation.

3.4 DESCRIPTION OF DATASET, REQUIREMENT SPECIFICATION

The OSCD dataset is used to train and test network architectures for change detection. The dataset includes 24 pairs of Sentinel-2 images captured between 2015 and 2018, which have already been co-registered and are of the same size. Each Sentinel-2 image consists of 13 bands, with spatial resolutions varying between 10 m, 20 m, and 60 m. Notably, bands 2, 3, and 4, which are located in the visible spectrum, have a spatial resolution of 10 m.

The provided training set contains 14 pairs of images, which have been manually annotated for changes. The changes primarily consist of urban changes, such as new buildings and roads, but also include changes in agricultural land, as seen in the images from Saclay, France[10].

Fig 3.6 Montpellier, France in 2015 and in 2018

Images from Cumbum location are taken and used for detection of change in land cover.

Tools Required: Google Colab, QGIS , Google Earth Engine, System with 8gb RAM in order to process high resolution images and GPU.

CHAPTER 4.

RESULTS AND OBSERVATIONS

This Chapters discusses about Stepwise Description of Results, Test ase Result Analysis and observations from Work.

4.1 STEPWISE DESCRIPTION OF RESULTS

Initially, after downloading required images in Tif format from google earth engine,

The Tif files are loaded in QGIS in order to extract Tif file for each of band and make them as a separate file. The output of that is displayed below:

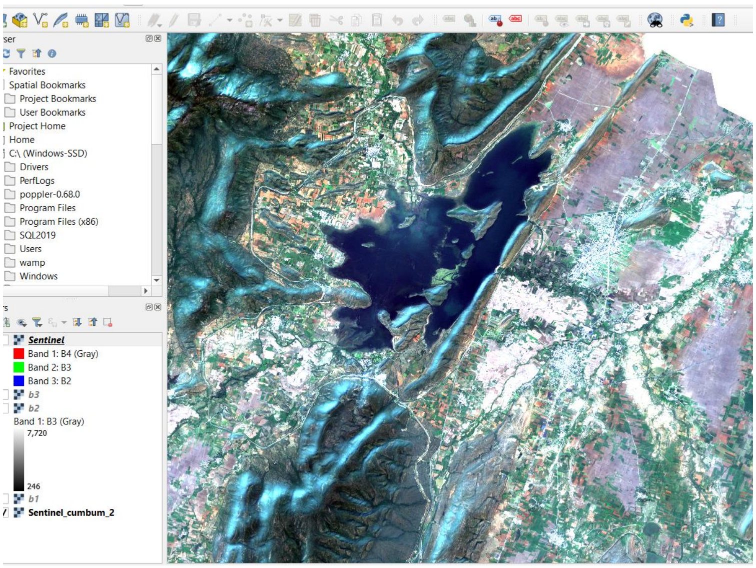

Fig 4.1 Extracting required bands from Tif file.

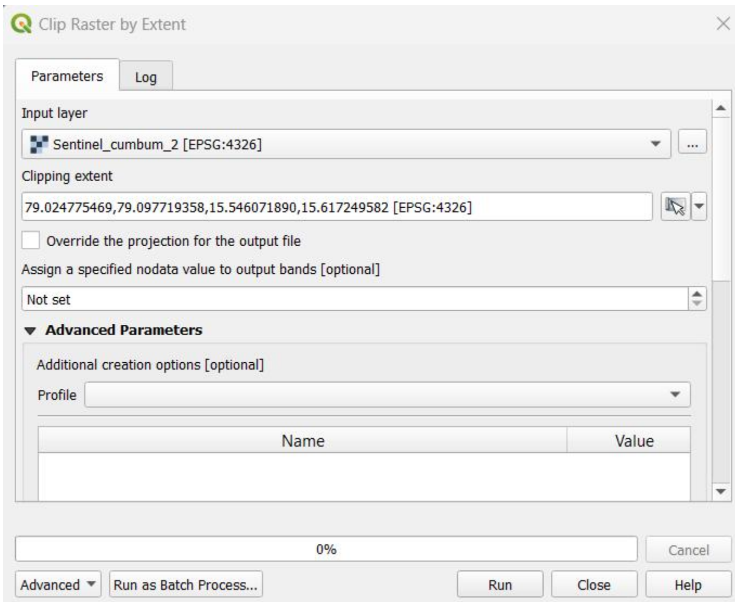

Fig 4.2 Setting up the clipping extent to extract to Tif.

The Results obtained after performing steps from Fig 4.1 and 4.2 is shown below:

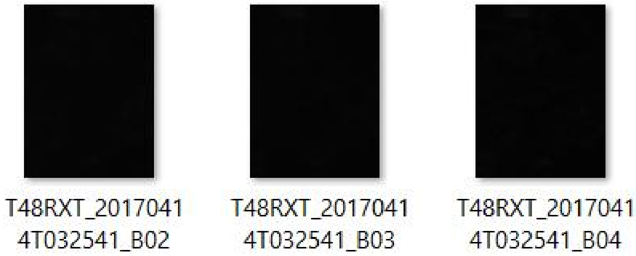

Fig 4.3 Tif obtained by extracting RGB bands.

Now, In QGIS by selecting different we can get stacked image of that respective image which we consider.
The below is output obtained after stacking it.

Fig 4.4 Stacked image of image from Cumbum location.

Now, after getting this the two images of different time stamps are passed as input to model and hence, one can get change map of that particular images as a result and they are discussed in below sections.

4.2 RESULT ANALYSIS AND TEST CASE RESULT

Below figure demonstrates our outputs produced by model from testing dataset.

Fig 4.5 Sample test set image of 2018 and 2021 time-stamp

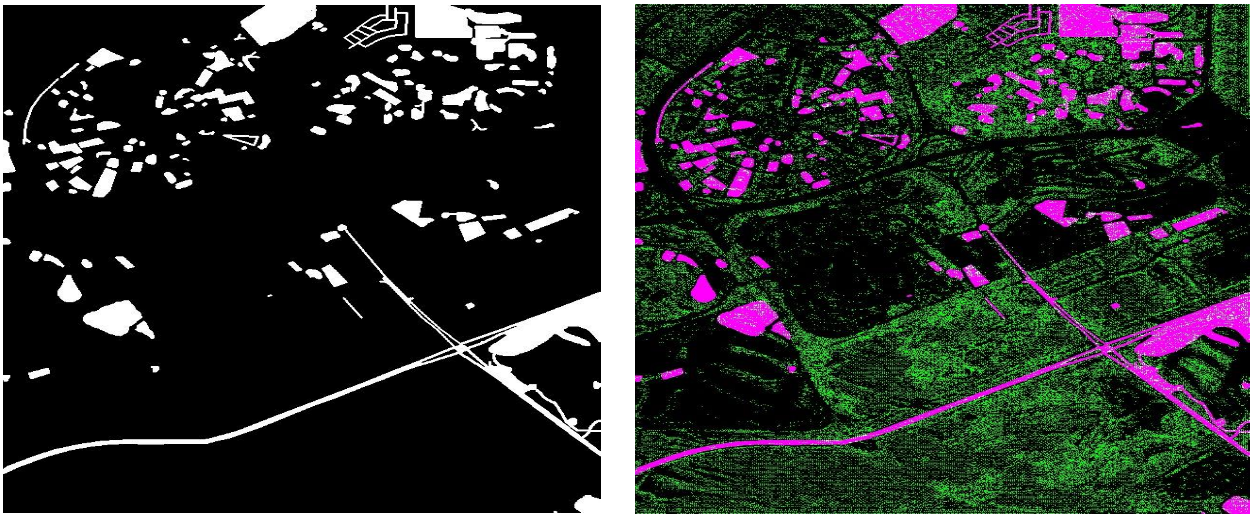

Fig: 4.6 Reference map and final change map given by model.

When two images from Fig 4.5 are given as input to FCNN model either Unet or FresUNet or Siamese conc or Siamese Diff Architecture produces the results which can be seen in Fig 4.6. The Fig 4.6 shows Original Reference map in 1st part and the 2nd part shows what are changes detected by the model in form of a segment. By considering Reference map and change map we can calculate performance of the model by computing changes in each pixel whether change in particular pixel was detected correctly or not.

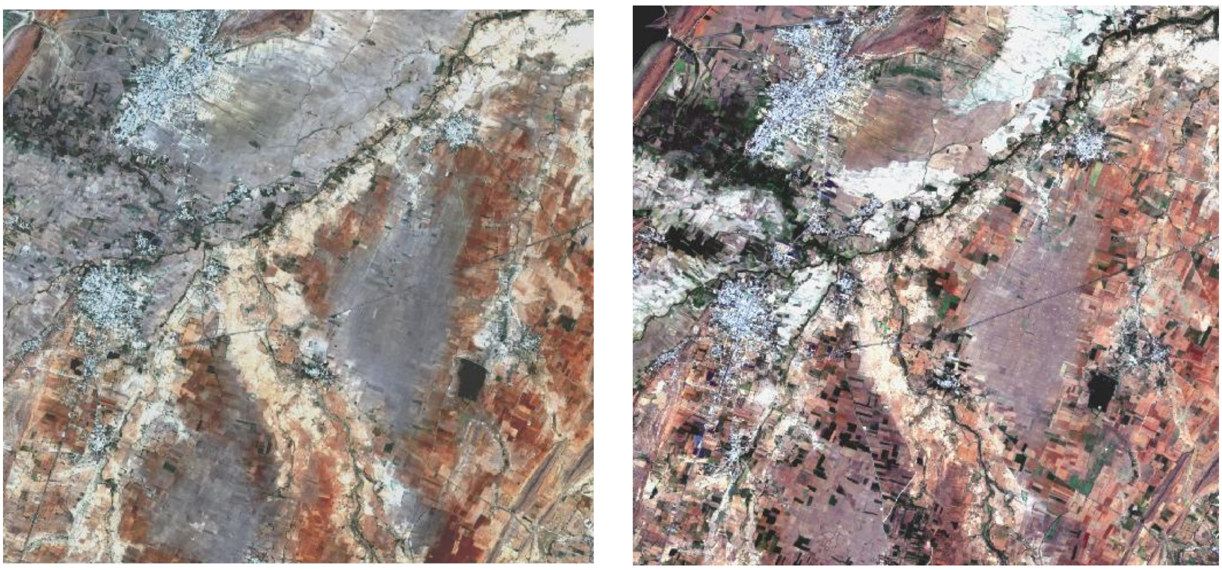

Fig 4.7 Test case images of Cumbum in 2019 and 2022

The above two images are of Cumbum located in Prakasam District in the state of Andhra Pradesh. The above images present in Fig 4.7 are of timestamps 2019 and 2022. These two images are given to model as input which is completely new data which model haven't seen or learnt from training data. The image raster file contains 13 bands and it was processed in QGIS.

The below Fig 4.8 the change map of changes which are detected by the model (FresUNet was used). The images present in Fig 4.7 are directly collected from Google Earth Engine and done required preprocessing and converted raster layer into Png format containing 3 bands of B8, B4, B3.

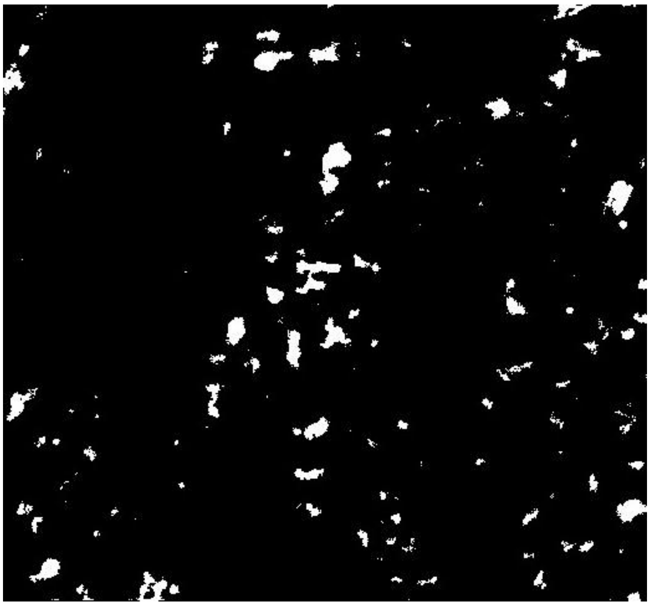

Fig 4.8 Change Map predicted by model for Cumbum images.

The Fig 4.8 shows the change map given by model when images present in Fig 4.7 are passed as input to the FresUNet Architecture of FCNN.

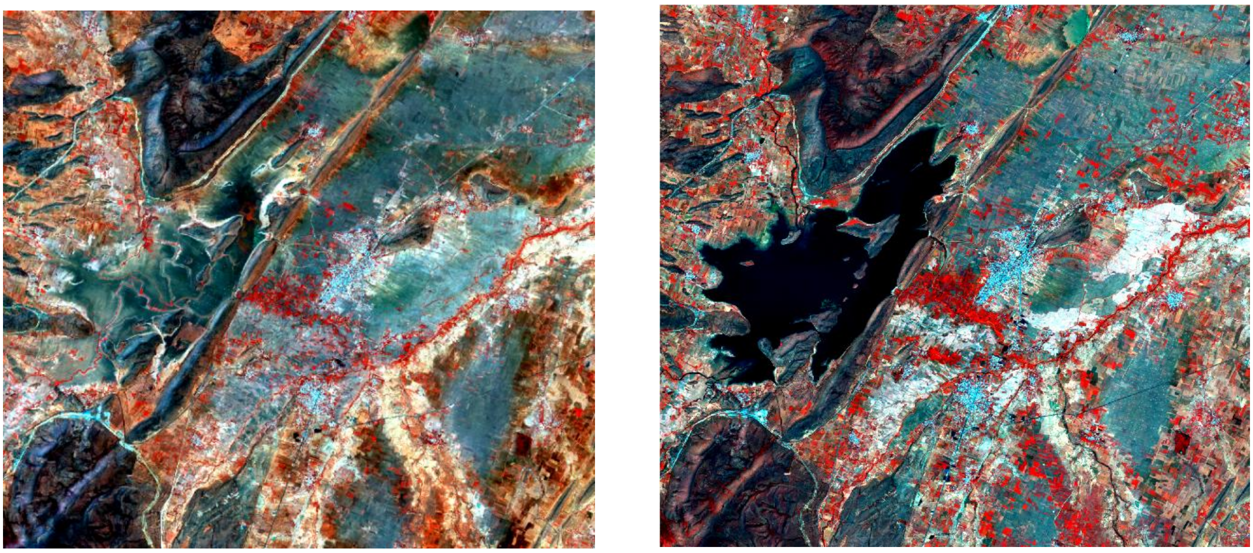

Fig 4.9 Cumbum 2019 and 2022 – Water bodies detection

The Fig 4.9 shows test case images of Cumbum in the timestamps of 2019 and 2022 in order to detect mainly the water body changes happened in between 2019 and 2022. The images are gathered from Google Earth Engine and the name of Satellite is Sentinal-2. The changes between both images in Fig 4.9 are present in image in Fig 4.10.

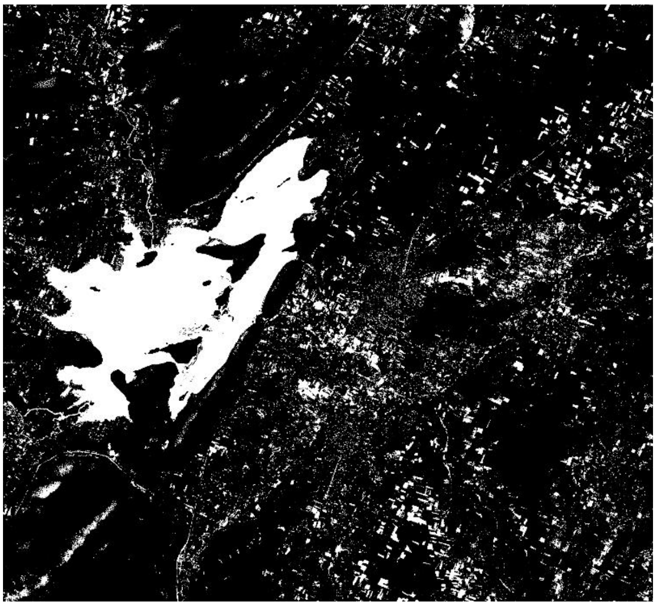

Fig 4.10 Change Map of images present in Fig 4.9 (water bodies)

The Fig 4.10 shows the changes that are detected by the model. It is observed that a large amount of percentage of change was happened in between 2019 and 2022 especially in water bodies. The change in Fig 4.10 was of Cumbum Lake present in Cumbum location. The algorithm used for detecting changes present in Fig 4.10 is Slow Feature Analysis which is an Unsupervised-learning based Algorithm. Generally, this type of algorithms can be better used to detect changes happened on water bodies. There is clear difference between results of FCNN and Slow feature analysis which can be observed from Fig 4.8 and Fig 4.10.

The Slow feature analysis technique can also give changes in clouds. The main interest to get changes in land cover regardless whether there are any clouds present which to be considered as noise. Therefore, coming to conclusion the FCNN when compared to Slow Feature Analysis gives less noise but it gives better results in case of detecting changes in water bodies[16].

4.3 OBSERVATION FROM THE WORK

The table 4.1 shows observations from our model. It shows how much is the performance with 4 different FCNN architectures they are Unet, FresUnet V1, FresUNet V2, Siamese conc and Siamese Diff. The performance measures considered are Accuracy, Precision and Recall.

Some pairs of images from OSCD Dataset were separated to use for testing and remaining for training. The training was done on each Architecture present in Table 4.1 and then the resulting model weights are saved for future use. The testing pairs are used to test the model's performance by using performance measures that are mentioned above. The performances of each FCNN architectures are noted down into table 4.1. The results can be observed from the table 4.1.

Table: 4.1 Performance of Different Architectures

Network Architecture	Accuracy	Precision	Recall
FC-EF	**93%**	86%	88%
Siamese Conc	**89%**	78%	80%
Siamese Diff	**90%**	83%	83%
FC-EF Res	**94%**	86%	85%
FC-EF Res2	95%	87%	86%

From the table 4.1 it is clear that Fully Convolutional Early Fusion and FC-EF Res2 Architectures are giving higher performance as compared to other Architectures. This can be due to the number of layers used and parameters are fitting better with given input data.

In FC-EF res, residual connections are used between the encoder and decoder layers. This allows the network to learn long-range dependencies between features in the input and output images. In FC-EF res2, residual connections are used between all layers of the network. This allows the network to learn more complex relationships between features. Both FC-EF res and FC-EF res2 have been shown to be effective for change detection. However, FC-EF res2 has been shown to achieve better performance on some datasets. This is likely due to the fact that FC-EF res2 is able to learn more complex relationships between features.

In FC-EF res the encoder is responsible for extracting features from the input image, while the decoder is responsible for reconstructing the output image. In FC-EF res2 It consists of an encoder, decoder, and a residual block between all layers. The encoder and decoder are the same as in FC-EF res. The residual block is responsible for learning long-range dependencies between features.

These differences make these two models to vary in performance. That's the reason why FC-EF res2 performs well with features with the help of its Residual Blocks.

CHAPTER 5.

CONCLUSION AND FUTURE WORK

This Chapter discusses about the conclusion of work done and future scope of this work.

5.1 CONCLUSION

In conclusion, our project was successful in detecting changes in satellite photos between two timestamps using a fully convolutional neural network (FCNN). We were successful in accurately detecting changes, notably in urban areas like new buildings and roads, by training the FCNN model using the OSCD dataset. The model's performance was assessed using validation criteria like accuracy, precision, and recall, which showed the model's prowess in accurately identifying changes. This project highlights the potential of using FCNNs for change detection on satellite images and its importance in various fields such as urban planning, disaster management, and environmental monitoring. The use of deep learning techniques for satellite image analysis has the potential to revolutionize the field and provide valuable insights for decision-making processes.

The Same model can be used for detecting changes in Cumbum region located in Prakasam district in state of Andhra Pradesh. With the discussion above by using same process the changes between two timestamps in Cumbum region can be detected efficiently and more robustly.

5.2 FUTURE WORK

The performance of model i.e the detection rate of changes can be improved by employing vision transformers instead of using Traditional FCNN'S. The transformers use Attention mechanism which mainly focusses on changes or spots where there is need to be analyzed. Also, the FCNN with different architectures can be used to improve performance it can be achieved with different arrangements of layers i.e topology of network and also increasing the number of layers.

REFERENCES:

[1]. Elyes Ouerghi, A Deep Learning Model for Change Detection on Satellite Images, Image Processing On Line, 12 (2022), pp. 550–557. https://doi.org/10.5201/ipol.2022.439

[2]. W. Yang, H. Song, L. Du, S. Dai, and Y. Xu, "A Change Detection Method for Remote Sensing Images Based on Coupled Dictionary and Deep Learning," Computational Intelligence and Neuroscience, Jan. 2022, doi: 10.1155/2022/3404858.

[3]. B. Zhao, P. Tang, X. Luo, D. Liu, and H. Wang, "3M-CDNet-V2: An Efficient Medium-Weight Neural Network for Remote Sensing Image Change Detection," IEEE Access, Jan. 2022, doi: 10.1109/access.2022.3201129.

[4]. S. Fang, K. Li, J. Shao and Z. Li, "SNUNet-CD: A Densely Connected Siamese Network for Change Detection of VHR Images," in IEEE Geoscience and Remote Sensing Letters, vol. 19, pp. 1-5, 2022, Art no. 8007805, doi: 10.1109/LGRS.2021.3056416.

[5]. K. Meshkini, K. Meshkini, F. Bovolo, and L. Bruzzone, "A 3D CNN APPROACH FOR CHANGE DETECTION IN HR SATELLITE IMAGE TIME SERIES BASED ON A PRETRAINED 2D CNN," The international archives of the photogrammetry, remote sensing and spatial information sciences, May 2022, doi: 10.5194/isprs-archives-xliii-b3-2022-143-2022.

[6]. Z. Zheng, A. Ma, L. Zhang and Y. Zhong, "Change is Everywhere: Single-Temporal Supervised Object Change Detection in Remote Sensing Imagery," 2021 IEEE/CVF International Conference on Computer Vision (ICCV), Montreal, QC, Canada, 2021, pp. 15173-15182, doi: 10.1109/ICCV48922.2021.01491.

[7]. T. Chen, Z. Lu, Y. Yang, Y. Zhang, B. Du, and A. J. Plaza, "A Siamese Network Based U-Net for Change Detection in High Resolution Remote Sensing Images," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Jan. 2022, doi: 10.1109/jstars.2022.3157648.

[8]. J. Chen et al., "DASNet: Dual Attentive Fully Convolutional Siamese Networks for Change Detection in High-Resolution Satellite Images," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 1194-1206, 2021, doi: 10.1109/JSTARS.2020.3037893.

[9]. H. Cai, T. Chen, R. Niu and A. Plaza, "Landslide Detection Using Densely Connected Convolutional Networks and Environmental Conditions," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 5235-5247, 2021, doi: 10.1109/JSTARS.2021.3079196.

[10]. R. Caye Daudt, B. Le Saux and A. Boulch, "Fully Convolutional Siamese Networks for Change Detection," 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, Greece, 2018, pp. 4063-4067, doi: 10.1109/ICIP.2018.8451652.

[11]. D. Peng, Y. Zhang, and H. Guan, “End-to-End Change Detection for High Resolution Satellite Images Using Improved UNet++,” Remote Sensing, Jun. 2019, doi: 10.3390/rs11111382.

[12]. P. Chao, W. Jiang, D. Jian, S. Can, and X. Gui-Song, “Detecting Building Changes with Off-Nadir
Aerial Images,” Jan. 2023, doi: 10.48550/arxiv.2301.10922.

[13]. H. Li, F. Zhu, X. Zheng, M. Liu and G. Chen, "MSCDUNet: A Deep Learning Framework Built-Up Area Change Detection Integrating Multispectral, SAR, and VHR Data," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 5163- 5176, 2022, doi: 10.1109/JSTARS.2022.3181155.

[14]. M. Liu, Z. Chai, H. Deng, and R. Liu, “A CNN-Transformer Network With Multiscale Context Aggregation for Fine-Grained Cropland Change Detection,” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Jan. 2022, doi: 10.1109/jstars.2022.3177235.

[15]. P. Ebel, S. Saha, X. X. Zhu, and X. X. Zhu, “Fusing Multi-Model Data For Supervised Change. Detection,” The international archives of the photogrammetry, remote sensing and spatial information sciences, Jun. 2021, doi: 10.5194/isprs-archives-xliii-b3- 2021-243-2021.

[16] Y. He, Z. Jia, J. Yang, and J. Yang, “Multispectral Image Change Detection Based on Single-Band Slow Feature Analysis,” Remote Sensing, Jan. 2021, doi: 10.3390/rs13152969.