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Topic

Change Detection in Satellite Imagery by Combining Algebraic Methods and Convolutional Neural Network

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Acronyms

RS	Remote Sensing
GT	Ground truth
CD	Change Detection
IOU	Intersection over Union
ReLU	Rectified Linear Unit
DNN	Deep Neural Networks
NDBI	normalized difference Build-up index
IR	Image Ratioing
CNN	Convolutional Neural Networks
NDVI	Normalized Difference Vegetation Index
NIR	near-infrared
SWIR	Short Wave Infrared
DI	Difference Images
AI	Average Intensity
PCA	Principal component analysis

Acknowledgements

Writing a Acknowledgements is not always an obvious and easy thing to do, find the right words and express gratitude through the people who have contributed to the accomplishment of this thesis.
Like any Muslim, First I thank God for all the good people I have been able to meet all along in my thesis redaction and particularly my teacher Pr.Mohammed lamine Kherfi who agreed to supervise me and gives me the right indications and advice to complete this work, my co-workers who took in charge my daily work tasks at ALSA2 satellite control centre. My mother who knew encourages me when I was tired and lost, My husband and my three little girls daughters Imen Ritag and Malak to be beside me and support me. I have a very special thought for my father, that God is peace to his soul.

Abstract

Change information detection has played an important role in the exploitation of satellite images, it has improved our ability to monitor land use/land cover and has assisted us in estimating the damage caused by disasters (floods, fires) and used for military target detection. There are many traditional methods used in multispectral remote sensing images for change detection, but these often do not provide the accuracy and precision that we require and robustness. To overcome this constraint, we combined multiple differences images with a deep convolutional neural network-based approach to change identification of urban areas, using the dataset ONERA satellite changes detection 2015-2018. This method incorporates pre-existing deep learning neural networks, specifically the U-net network, in the aim to increase the accuracy of the change obtained from the unet model. The results obtained are quite satisfactory.

Keywords: Remote sensing, change detection, Unet, algebraic methods.

Résumé

La détection des informations qui changent a joué un rôle très important dans l'exploitation des images satellites ; il a amélioré notre capacité à surveiller et à utiliser les terres/l'occupation des sols et nos aidées aussi à estimer les dommages causés par les catastrophes naturelles (inondations, incendies) et la détection des cibles militaires. Il existe de nombreuses méthodes traditionnelles utilisées sur les images de télédétection multispectrales pour la détection des changements, mais celles-ci n'offrent souvent pas la précision et la robustesse dont nous avons besoin. Pour surmonter cette contrainte, nous avons combines différentes d'images générées par des méthodes algébriques avec une approche basée sur un réseau de neurones à convolution profonde pour l'identification de changement dans zones urbaines, en utilisant les données de détection de changements par satellite ONERA 2015-2018. Cette méthode intègre des réseaux de neurones d'apprentissage en profondeur préexistants, en particulier le réseau Unet, dans le but d'augmenter la précision du changement obtenu à partir du modèle. les résultats obtenus sont tout à fait satisfaisants.

Mots clés : Télédétection, détection de changement, Unet, méthodes algébriques.

ملخص

لعب الكشف عن المعلومات المتغيرة دورًا مهمًا للغاية في استغلال صور الأقمار الصناعية؛ لقد حسنت قدرتنا على مراقبة واستخدام ا واستغلال الأراضي وساعدتنا أيضًا في تقدير الأضرار الناجمة عن الكوارث الطبيعية (الفيضانات والحرائق) واكتشاف الأهداف العسكرية. هناك العديد من الطرق التقليدية المستخدمة في صور الاستشعار عن بعد متعددة الأطياف لاكتشاف التغيرات، ولكنها غالبًا لا توفر الدقة والمتانة التي نحتاجها. للتغلب على هذا القيد، قمنا بدمج صور مختلفة تم الحصول عليها بواسطة استخدام الطرق الجبرية المستعملة لاستخراج التغيرات من الصور مع نهج قائم على الشبكة العصبية التلافيفية العميقة لتحديد التغيير في المناطق الحضرية، باستخدام قاعدة بيانات اكتشاف تغير القمر الصناعي او يغا. تدمج هذه الطريقة بالشبكات العصبية للتعلم العميق الموجودة مسبقًا، ولا سيما شبكة اونت، بهدف زيادة دقة التغيير الذي تم الحصول عليه من نموذج. النتائج التي تم الحصول عليها مرضية تماما.

الكلمات المفتاحية: الاستشعار عن بعد ،كشف التغيير ، الطرق الجبرية ، اونت.

Chapter 1

General Introduction

1.1 Introduction

Detecting changes in image processing is a set of encompassing problems areas as remote sensing and microscopy. It has been the subject of many publications and several methodological approaches are introduced in an attempt to solve this problem, often under a particular condition. The resolution of this problem in a generic framework seems almost impossible in the sense that it calls for a high level of interpretation. The most encouraging results in the field are quite naturally linked to very specific applications (medicine precision). This is often linked to the fact that in these cases one can define finer hypotheses regarding the modelling, which facilitates our interpretation.

1.2 Related Work

The availability of multi-temporal Multi-spectral satellite imagery was helpful for developing a variety of approaches for identifying changes to the earth surface and to overcome the difference constraint caused by spectral, spatial, radiometric and sun and temporal effects. Three leader approaches are musty used for change in multispectral satellite images [5].

- **Algebra based Approach:** The algebra methods are widely used for their simplicity, straightforward, ease of implementation and interpretation, but the choice of the thresholds value to outlining significant changed or no changed areas is difficult. Image differencing by the subtraction pixel value of a time-image to the corresponding pixel of another time image for each band is the must-use method, rationing image, change vector analysis, image regression, background subtraction techniques and vegetation index differencing also fall under this approach[6].

- **Transformation Approach:** The space feature transformation Is a multivariate analysis approach used to reduce the number of spectral components until a few components are obtained, the aim is to reflect the variance of the images and accentuate certain image characteristics. PCA, KT Gramm–Schmidt, and Chi-square transformations fall under this approach. As an algebraic approach, in the transformation approach, it is difficult to define the threshold value and interpret the change information results[7].

- **Classification:** Recent methods, such as neural networks, have also been implemented for the changes' detection in remote sensing images. These methods employ training big data set to create classified images with decreasing the external factors. Different Supervised or unsupervised techniques, such as the k-means clustering method and the genetic algorithm, can be used to detect changes, also Convolutional neural networks, post-classification comparison, change detection fall under this approach [8].

Different change detection Methods can be combining to increase change detection accuracy, these methods can belong to the same approach or a different approach as an example, [9] use the fusion of Difference Images for Change Detection Over Urban Areas, they used the fuzzy set theory to fusion Difference image, rationing image, Euclidean distance and Chi-Square Transformation of multi-temporal Rs images.[10] apply principal component analysis (PCA) to the different images and Fuzzy set theory were used to combine change information from different images band in one single image.

Many research for CD in RS image using just CNN was published [11] use convolutional neural network features-based change detection in satellite images.[12] apply detecting urban changes with recurrent neural networks from multi-temporal Sentinel-2 data. But few of them used the combination of CNN with another approach. [13] use change detection in multi-temporal VHR Images Based on Deep siamese multi-scale convolutional Neural networks. They use a different image from Change vector analyse (CVA)and Fuzzy C Mean (FCM) for training, DSMS-CN. This paper[14]published in Oct 2018, explores the two ways to input two images of the same place but at different times. They first explore the "Early Fusion" architecture, which consists of concatenating the two image pairs as the first step of the network. The input is then processed as a single patch. The second architecture is the CNN Siamese, the two images are processed in parallel by two branches and the outputs are concatenated. They then use 2 fully connected layers to obtain output values as before.

What we are trying to present in this thesis is to perform a two-level of combination, first combine the traditional algebraic method uses in extracting the characteristic of change in urban areas like difference images and average intensity than the fusion to get a single one image as results, the second level is to fit the single one image to the CNN (U-Net) as a data set for predict the change.

1.3 Motivation

As administrator of segment ground centre of ASAL [15], every day since 2010 we take an image from different Area on the surface of the earth, with two satellites ALS2A and ALS2B. The images taken have 17*17 km for 250/200/100 km. We get two types of images, Panchromatic with 2.5 m of resolution and 10 m for multi-spectral. These images are requests from different organisms like Agriculture, disaster analyses cadastral, militaries. Urban evolution to produce more detail about the images request to form our clients, several fields of treatment image are created, and change detection is one of the important fields that we study.

Although there are great efforts to find solutions in detecting changes in remote sensing by offering several effective methods. However, these methods have limitations or can achieve better results, which motivates our work. We are trying to merge two or more algebraic methods for change detection so that the accumulated change detected by each method into a single frame and run it on a CNN to predict the change. This approach aims to increase the IOU between the GT and the predicted image

1.4 Problem formulation

Detecting changes in the Urban scene in remote sensing images is a very challenging research problem, it has been the subject of a large number of publications and methodological approaches comparing with the forest or sea scene, the urban scene is composed of a diverse object (building, forest, road, shadow) and the change makes very quickly caused by human activate. Another difficulty related to the satellite sensor which themselves can be different between two shots, further increasing the problems related to the detection of changes. The objective of this work is the detection of changes in pairs of multi-spectral Earth observation images, particularly in urban area. The diversity of problems has led to the development of solutions based on very different approach.

1.5 Outline

There are four chapters in this document. The state of the art at the methodological level in change detection for satellite images is briefly described in the first chapter.

We do not limit ourselves to the topic of remote sensing in the second chapter, thus attempting to describe some approaches that may be applied in our framework, along with basic RS and CD concepts.

The next two chapters are organized in the logical sequence of a processing chain. Starting with the generation of the image differences based on the algebraic methods defined in chapter 3 plus an overall description of the approach (architecture) used.

In chapter 4 we will present the different results of our experiments, plus a comparative analysis of the results.

Chapter 2

Change detection in remote sensing

2.1 What is remote sensing?

2.1.1 Remote sensing

The American Society of Photogrammetry and Remote Sensing defined remote sensing as the measurement or acquisition of information of some property of an object or phenomenon, by a recording device that is not in physical or intimate contact with the object or phenomenon under study [16]. Environmental Systems Research Institute (ESRI) in its geographic information system (GIS) dictionary defines remote sensing as "collecting and interpreting information about the environment and the surface of the earth from a distance, primarily by sensing radiation that is naturally emitted or reflected by the earth's surface or from the atmosphere, or by sending signals transmitted from a device and reflected back to it (ESRI, 2014).

The usual source of passive remote sensing data is the measurement of reflected or transmitted electromagnetic radiation (EMR) from the sun across the electromagnetic spectrum (EMS); this can also include acoustic or sound energy, gravity, or the magnetic field from or of the objects under consideration[16]

2.1.2 Different Type of RS

There are two types of remote sensing technology, active and passive remote sensing.

in this work, we will use an image get from an optical remote sensing image satellite (Passive)

Active sensors, provide their own source of energy to illuminate the objects they observe. An active sensor emits radiation in the direction of the target to be investigated. The sensor then detects and measures the radiation that is reflected or backscattered from the target, the radar satellites are the most famous type of active sensors.

Passive sensors, on the other hand, detect natural energy (radiation) that is emitted or reflected by the object or scene being observed. Reflected sunlight is the most common source of radiation measured by passive sensors[17].

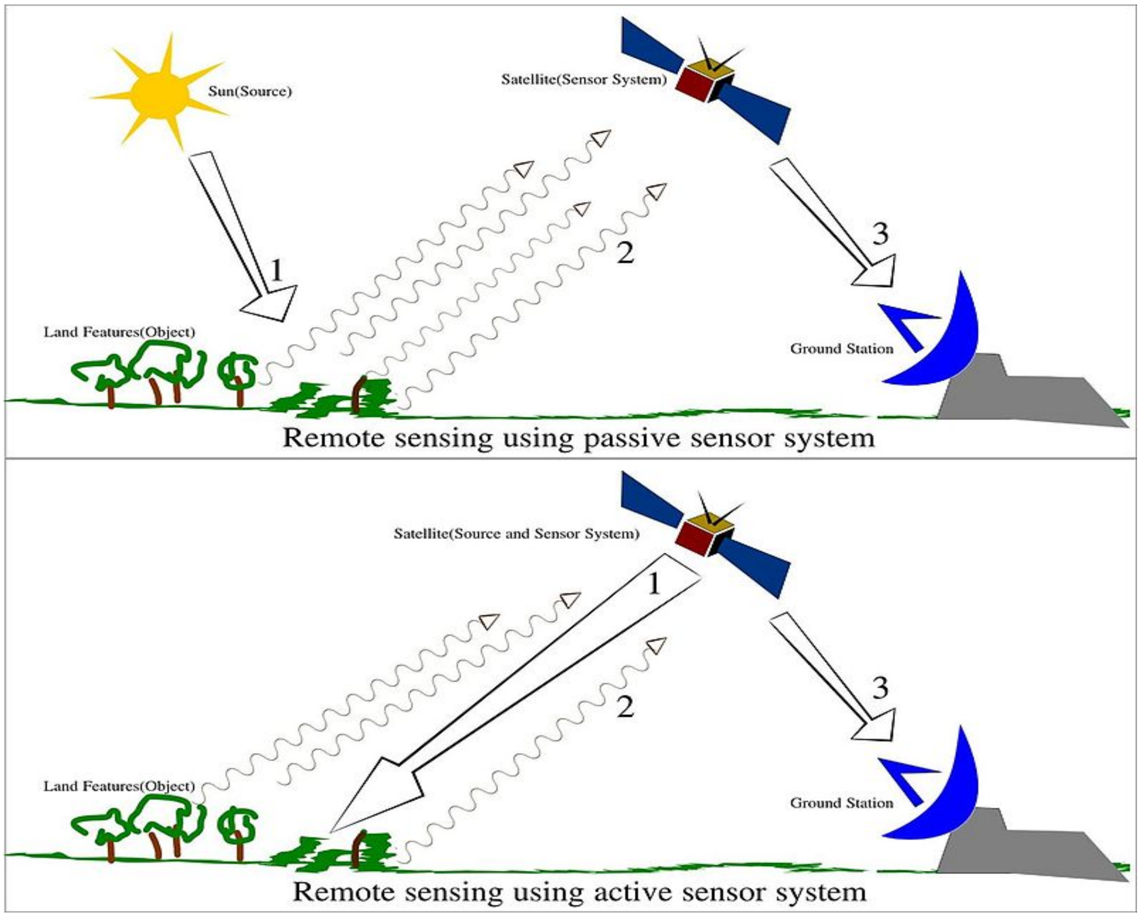

Figure 2.1: Illustration of remote sensing [1]

2.1.3 Resolution of RS satellite images

In Remote sensing, the term resolution is used to represent the resolving power which include not only the capacity to identify the presence of two objects but also their proprieties. The resolution is the number of details that can be observed in an image.

- *In this work, we work with images of 10m of resolution.*

2.2 Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times.[18]

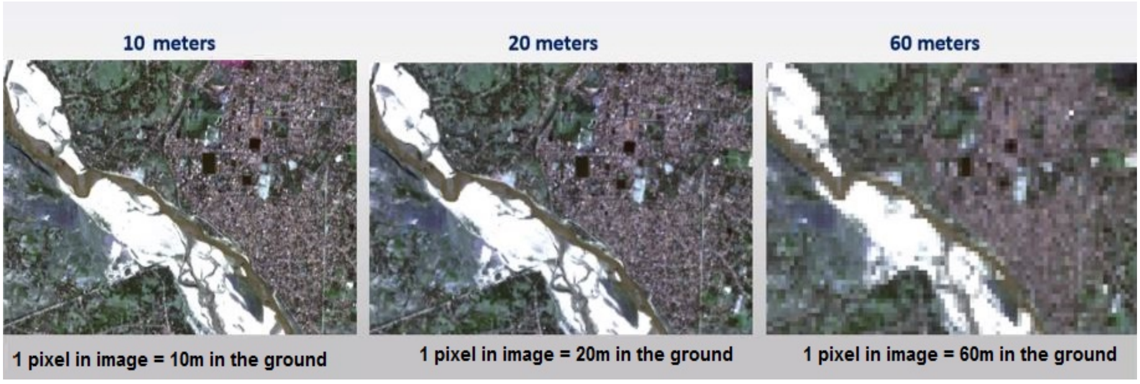

Figure 2.2: Illustration of resolution of Remote sensing satellite image

2.2.1 What is CD for RS?

Every day we can see that the surface of the earth is changing rapidly due to various reasons at local and regional scales with significant repercussions for people and for the environment. To better understand, analysing and predicting these changes, remote sensing satellite imagery is an inexhaustible source of useful information. Remotely sensed satellite observations from space have fundamentally changed the way in which scientists study the atmosphere, oceans, land, vegetation, glaciers, sea ice, and other environmental aspects of the Earth's surface.

2.2.2 Difficulties of change detection in RS satellite imagery

There are several characteristics that make the manipulation of satellite images difficult, the first is the size of the object detected (for example if we take an image of a football stadium, on a single image it contains hundreds of pixels. Whereas a satellite image with a resolution of 10 m represents only 10 pixels.

If you compare a satellite image with a classical image they do not have the same number of channel (3 channels in classical image red, blue, green) but in the satellite image, you may have 200 channels.

The angle of the sun with which the image was taken can give us a shadow reflection especially for high objects like buildings and mountains this can be considered as a change between two images with a Basic algorithm.

Something else more important, a satellite image is taken over an area at a specific time so if the image contains Snow clouds or fog you have to deal with these constraints.

2.2.3 Differents techniques of CD in RS

There are several Basic methods for detecting change between two satellite images, let's quote someone in a few lines.

Figure 2.3: First image taken on an earlier time - Second image with a new house - Mask showing the new house

- **Image Differencing ID** : Image differencing is the subtraction of two spatially registered imageries, pixel by pixel.

$$Y_{ID} = \left| X_i^2 - X_i^1 \right| \quad (2.1)$$

  X_i^2: Image in time T2/ Number of band i =1...N

  X_i^1: Image in time T1 / Number of band i =1...N

  Advantages: Simple and straightforward, easy to interpret the results

  Disadvantages:Cannot provide a detailed change matrix requires selection of thresholds

- **Image Rationing IR** : is also a simple and rapid means to identify changed areas. It implies calculation of the ratio of two registered images from different dates, on a band-by-band basis. In the changed areas, the ratio values will be significantly greater than 1 or less than 1 depending on the nature of the changes between two dates of the images. Rationing has received criticism due to the non-normal histogram distribution of the resultant image.

$$Y_{IR}^i = \left| \frac{X_i^2}{X_i^1} \right| \quad (2.2)$$

  Number of band in image i=1...N, but this method is specially used for radar images.

  Advantages: Reduces impacts of Sun angle, shadow and topography

  Disadvantages:Non-normal distribution of the result is often criticized

- **Normalized Difference Built-up Index (NDBI):** Produces Built-up Index separately, then subtracts the second-date Built-up Index from the first-date Built-up Index. Using Near inf-red (NIR) and short wave inf-red (SWIR)

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \tag{2.3}$$

Advantages: Emphasizes differences in the spectral response of different features and reduces impacts of topographic effects and illumination

Disadvantages: Enhances random noise or coherence noise

- **Average Intensity (AI)** : Coppin and Bauer[19] propose to normalize the different image by the average intensity between the two images.

$$Y^i_{AI} = \frac{X^2_i - X^1_i}{X^2_i + X^1_i} \tag{2.4}$$

i=1...N number of the band in image

Advantages: This technique can discern the changes that have occurred in areas of shade where the average brightness is lower.

Disadvantages: when the condition vary, it is necessary to call on more operators, often derived from statistics.

- **Euclidean Distance (ED)**: The results describe the change information, where a large value represent higher probably of change, and no change for small value.

$$Y^i_{ED} = \sqrt{\sum_{i=1}^{n} \left| X^i_2 - X^i_1 \right|^2} \tag{2.5}$$

i=....N number of band in image for multi spectral image.

It is possible to combine multiple of these methods to get better results

- **Image regression**: Establishes relationships between bi-temporal images, then estimates pixel values of the second-date image by use of a regression function, subtracts the regressed image from the first-date image

$$Y_{IR} = aX + b \tag{2.6}$$

Where Y represent the regressed image, x is the first image, a is slope, and b is intercept.

Advantages: Reduces impacts of the atmospheric, sensor and environmental differences between two-date images.

Disadvantages: Requires developing accurate regression functions for the selected bands before implementing change detection

2.3 What is semantic segmentation of image ?

In this work, we will apply semantic segmentation for remote sensing. Below a brief and deep definition of semantic segmentation.

Semantic image segmentation is the task of classifying each pixel in an image from a predefined set of classes. Suppose you want to know where an object is in the image, the shape of that object, which pixel belongs to which object, etc. that each pixel in the image is given a label. Thus, the task of image segmentation is a neural network to produce a pixel-by-pixel mask of the image. It helps to understand the image at a much lower level i.e. at the pixel level. Image segmentation has many applications in medical imaging, self-driving cars, and satellite imagery to name a few. There are three common type of semantic segmentation within computer vision[2]

1. Classification
2. Object detection
3. Image segmentation

With classification, the goal is to only identify what objects and other properties exist in an image. With object detection, you go one step further and also find the position (bounding boxes) of individual objects. With image segmentation, the goal is to recognise and understand what's in the image at the pixel level. Every pixel in an image belongs to a single class, as opposed to object detection where the bounding boxes of objects can overlap. As shown in the image segmentation example above, the two birds belong to the class bird, so the model is able to identify all the pixels belonging to bird.

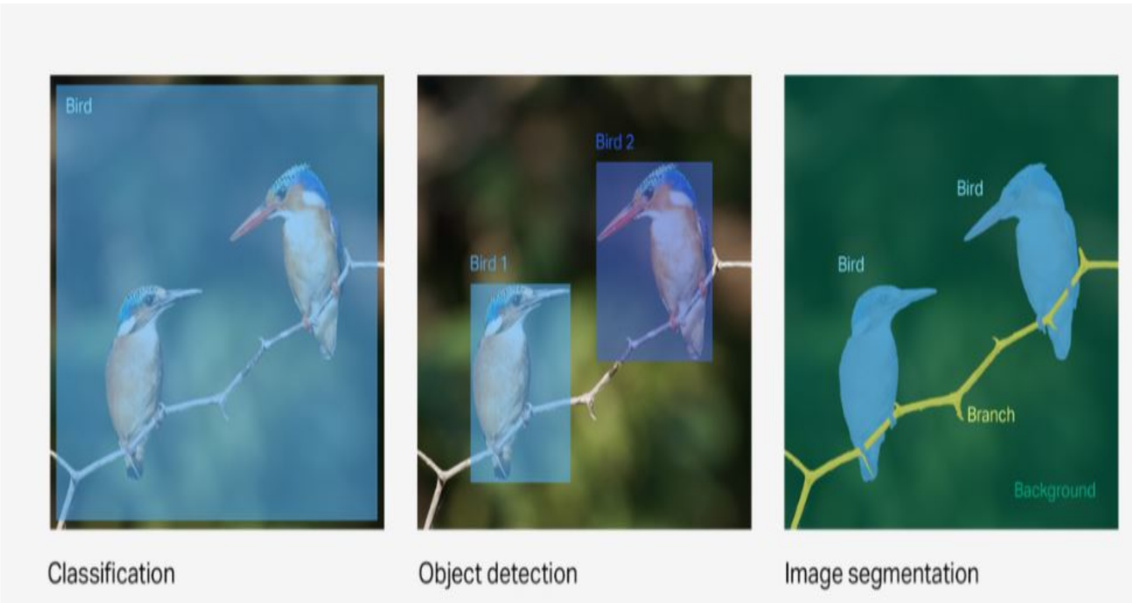

Figure 2.4: Illustration of three common type of semantic segmentation within computer vision [2]

2.4 Deep leaning network

Remote sensing is a great application of deep learning because the huge amount of data available. European Space Agency(ESA) archive of Sentinel imagery contains 10PB but unfortunately, there is a small part from there are labels for remote sensing images because they are often extremely difficult to produce.

2.4.1 What is Deep Convolutional Neural Network?

Convolutional neural networks are neural networks used primarily to classify images (i.e. name what they see), cluster images by similarity (photo search), and perform object recognition within scenes. For example, convolutional neural networks (ConvNets or CNNs) are used to identify faces, individuals, street signs and many other aspects of visual data [20].

The efficacy of convolutional nets in image recognition is one of the main reasons why the world has woken up to the efficacy of deep learning. In a sense, CNNs are the reason why deep learning is famous. The success of a deep convolutional architecture called Alex-Net in the 2012 Image-Net competition was the shot heard around the world. A convolution neural network has multiple hidden layers that help in extracting information from an image. The four important layers in CNN are:

1. **Convolution layer**

   Feature extraction with a convolutional kernel

   A convolutional kernel is a series of filters. A filter is a matrix of weights that is applied to

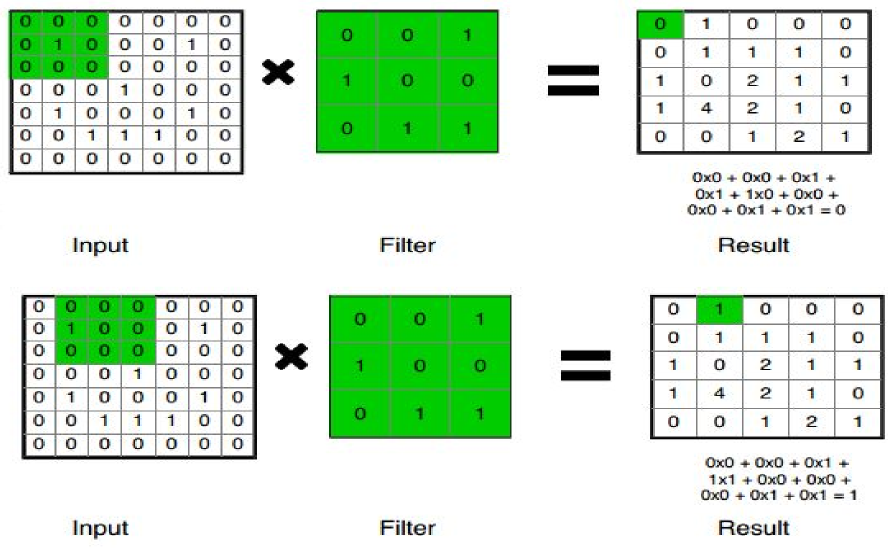

Figure 2.5: Illustration of the First two steps of a convolution

a subset of the input pixel values. It produces the result coming from matrix multiplication of the corresponding terms from the filter and the input pixels. The result is then summed up. The filter is then slid across the entire activation volume resulting in a feature map, in other words, a filtered version of the image.

2. **ReLU layer Feature map creation with an activation function** An activation function

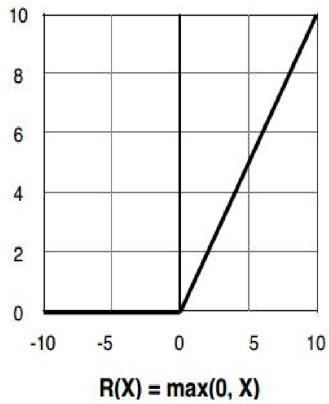

Figure 2.6: ReLU activation function

is a function taking the output of the convolution in the feature map and indicates whether it should send a signal to the next layer. This means that less processing is required and that only the important information is forwarded. The activation function that is used traditionally is the ReLU shown in figure 1.6 for any input under the value of zero, the ReLU outputs a zero. It allows to generalise the learning and diminish the noise within the network.

3. **Pooling layer**
Much like a convolutional layer, a pooling layer reduces the dimensions of the convolved features[21]. There are two reasons for wanting to reduce the dimensions : smaller dimensions means less computations, and it is useful for extracting dominant features. There are two types of pooling: max pooling and average pooling. Max pooling takes the maximum value of the filter and average pooling averages all values.

4. **Fully connected layer**
Once the feature map are all learned and the input is brewed down to its key features, it is time to add a layer that decides what to do with the information. There are different types of granularity in the understanding of an image.

- Image classification
- Object detection
- semantic segmentation (view section 1.4)

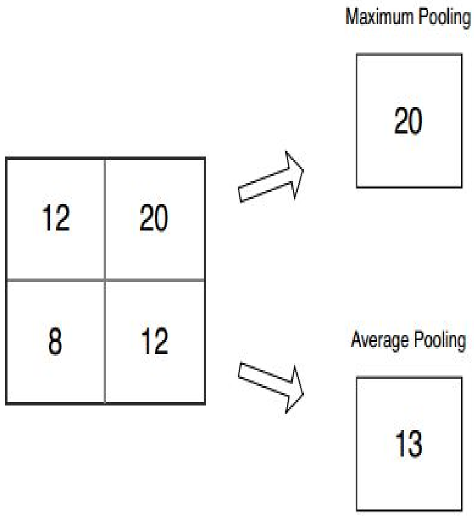

Figure 2.7: Two type of pooling

What we're going to discuss in this thesis is a semantic segmentation.

2.4.2 Typical architecture of a CNN

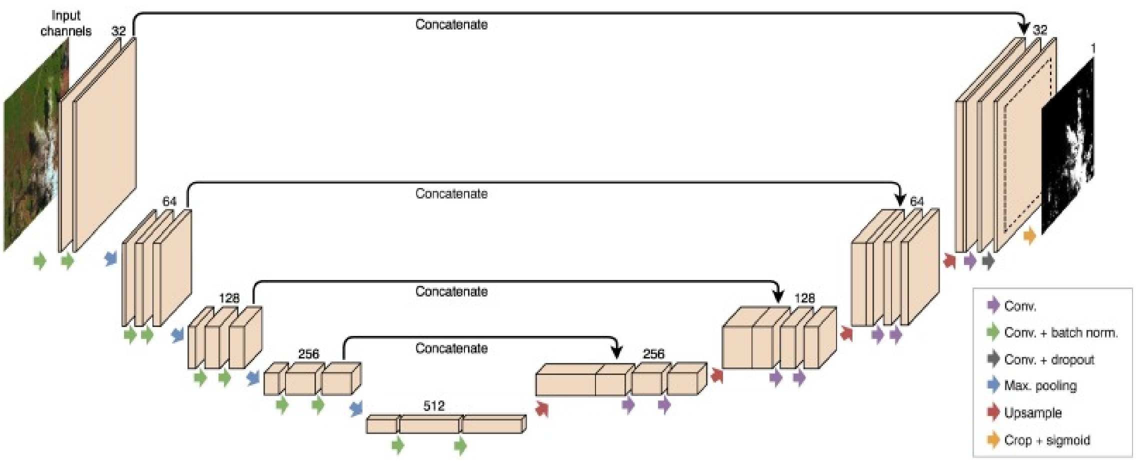

Figure 2.8: Typical architecture of a CNN in semantic segmentation [3]

To have a brief view of the architecture of CNN As shown in figure 2.8, a typical CNN takes an image as input, applies a series of convolution followed by activation function and the pooling layers. This is the feature learning phase. Afterwards, a classification phase is connected. That part is optional and specific to the task of the CNN. The key part of a CNN is the feature learning part[3].

2.4.3 Change detection vs object detection

An important thing is what the neural network should output. There were two main directions to go :

- Build a network that produces a segmentation mask to detect buildings on a single image. Then repeat the process on a second image of the same location, at a different time. The change detection mask is obtained by taking the differences between the two produced masks. That amounts to build a network specialised in object detection.

- Build a network that takes the two images together and processes them at the same time. It directly outputs a mask with the changes found. This means that the network specializes in change detection.

- Make the difference between images using basic Algorithm then fit the network to get mask as output.

Change detection with neural networks is a very developed genre already. With the rise of algorithms like YOLO and Resnet, Unet VGG 16 or 19 very fast and very accurate algorithms capable of drawing bounding boxes around all the found objects are accessible to the large public.
Building detection in satellite imagery is an important challenge run every two years or so that gives out large datasets of different cities and the winning Neural Net is the one capable of accurately identifying the most categories of objects (houses, cars, roads illustrated). This made born many Neural Nets.
On the other hand Change detection in satellite imagery is a relatively unexplored branch and when coming to the resolution of remote sensing image the object detection has a big limitation of more than 3m which is not the case for change detection.

2.5 Conclusion

The methods of detecting changes are quite varied and very often depend on the underlying practical application (military application, urban growth monitoring, monitoring of agricultural plots...). We can however distinguish a large family of algebraic methods which focus on calculating a quantity of changes first, then on proposing a decision step using the neural network in order to bring more robustness and accuracy of the change detection results.

Chapter 3

Method and implementation

3.1 Introduction

This chapter contains a detailed description of the data and model were used to train and evaluate the performance of the trained models and a description of each of the methods used to solve the problems brought up in this project.

3.2 Pre-processing

Registration: is the geometric correction of an image or a series of images. Indeed, the shots of the same scene can vary according to the position or the nature of the sensor used in the satellite, which makes this step necessary. This is an important step of the pre-processing to detect changes in remote sensing

Radiometric correction: Most low-level operators are based on comparing radiometric at the pixel level. It is therefore essential that the radiometric of the corresponding pixels are consistent. Among the factors that can cause the radiometric to vary, we can cite changes in global illumination, differences in nature of the sensors or the ageing of the sensor between the different shots. Radiometric image correction is of utmost importance for the quality of change detection.

3.3 Data set Description

The data set used in this project is the ONERA [22]Satellite Change Detection data set that addresses the issue of detecting changes between satellite images from different dates.

It comprises 24 pairs of multi-spectral images taken from the Sentinel-2 satellites between 2015 and 2018. Locations are picked all over the world, the images are obtained by the Sentinel-2 satellites are provided. Images vary in spatial resolution between 10m, 20m and 60m.

Pixel-level change ground truth is provided for all 14 training and 10 test image pairs. The annotated changes focus on urban changes, such as new buildings or new roads. These data can be used for training and setting parameters of change detection algorithms.

3.3.1 Architecture of the appreach

This section can be divided into different steps. The first step aims to build the data set and enrich it using split data in to small images with size 256*256.
The second step aims to generate the difference image between the image before and after using the algorithm define, and also generate the average intensity of difference images in the regression method of change detection, pixels from time T2, are assumed to be a linear function of the time T1, pixels.
N is a number of bands, Y_1^i and Y_2^i. represent the pixels in the band at the time T1 and T2.

$$Y_{DI} = \left| Y_2^i - Y_1^i \right| \tag{3.1}$$

$$Y_{AI}^i = \frac{Y_i^2 - Y_i^1}{Y_i^2 + Y_i^1} \tag{3.2}$$

$$NDBI = NDBI2 - NDBI1 \tag{3.3}$$

i = 1....N (where N is Number of band red, blue, green)

This Two method are chosen according to the Table of RMSE define :

Method Algebraic CD	RMSE with GT
Absolut distance	0.02374042
Image regression	0.14773364
Image ratioing	0.2851192
Euclidian distance = Absolut distance	0.02374042
Average Intencty	0.085121274
NDBI	0.038184557

Figure 3.1: Root mean squared error of generate images and GT

The third step is a fusion of the results with the good RMSE. The aim of fusion of the result of the different methods cited before is to collect all the change information from multiple images and combine them in one single image, the single output image is more information and accurate than any of the source images, and it consists of all the necessary information.

The fusion method used for the change detection is based on the comparison of the weight of the same pixel in the two images, if the pixel has changed in the two generated images, this implies that its value is different from zero (0) in less in one image.

Also, we have tried to combine the images by closing the MAX value of the two pixels. The following algorithm is used to generate the change fusion image.

```
------Filtre ------
1- read image T1
2- read image T2
3-if imageT1 [i, j] = imageT2 [i, j] and = 0
      image-result [i] = 0
4-if imageT1 [i, j] = / = imageT2 [i, j] and = / = 0
      image-result = Min (imageT1, imageT2)
5-if( imageT1 [i, j] = / = imageT2 [i, j] )and (imageT1 [i, j]=0 or imageT2 [i, j]=0)
      image-result = Max (imageT1, imageT2)
```

The following figure show the results after calculate the RMSE for the different combine of the chosen algebraic methods (view figure 3.1)

Combine the two images	RMSE with GT
AI_DI_ Min	0.024263486
NDBI_DI_ Min	0.024111144
NDBI_AI_Min	0.02879437
NDBI_DI_MAX	0.03781384
NDBI_AI_MAX	0.09451146
DI_AI_MAX	0.08517623

Figure 3.2: Root mean squared error of Fusion set theory and GT

The fourth step aim is to do the data augmentation techniques to have a big data set, using lib of Keras **ImageDataGenerator** the fifth step aims to build an initial model based on an existing architecture. This model will then take the differences images as input and produce a mask with the changes made to the buildings. The last step aim will be to customise an architecture tailored to this problem by using the knowledge acquired during the first two steps. As shown on *Figure 3.3*, the workflow has two interlinked steps. Any change in the data set will require a recalculation of the model. But on the other hand, from the model results, we will draw conclusion on whether images need to be added to the data set and what should be on them to correct mistakes from the model's hyperparameters.

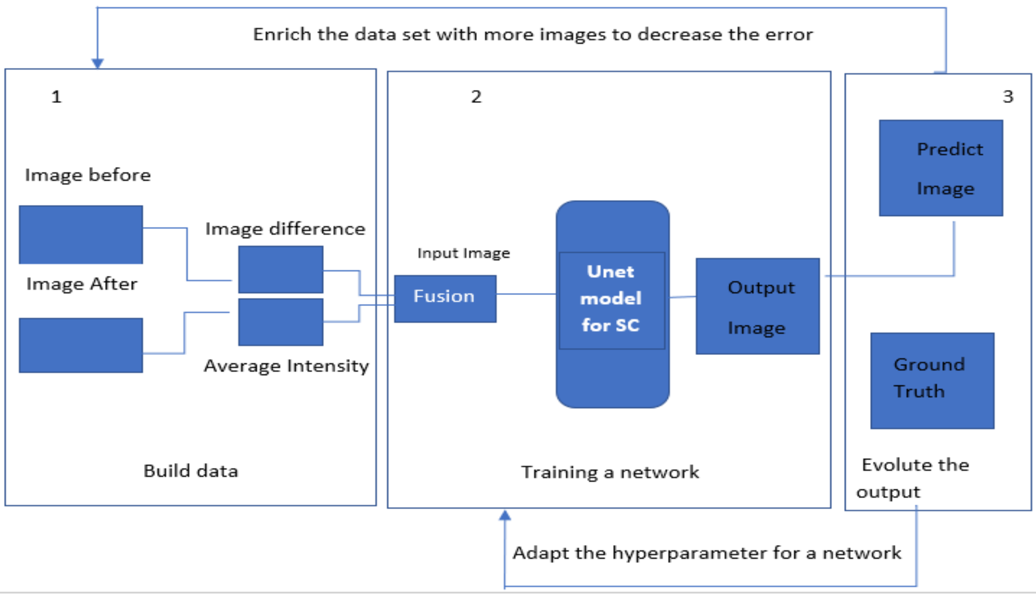

Figure 3.3: Schematisation of our workflow

3.3.2 Selection of Bands in Data set

ONERA data set continent 24 pairs of images before and after respectively and the 24 GT images, every image has 13 spectral bands. In our project, we have select (Red, Green, Blue, SIW, NIR) bands as input of the algebraic methods.

Band number	Band name	Central wavelength (nm)	Bandwidth (nm)	Spatial resolution (m)	Purpose
2 *	Blue	490	65	10	Blue
3 *	Green	560	35	10	Green
4 *	Red	665	30	10	Red
8 *	NIRwide	842	115	10	Sensitive to chlorophyll, biomass and protein
5 *	Rededge 1	705	15	20	Vegetation Classification
6 *	Rededge 2	740	15	20	Vegetation Classification
7 *	Rededge 3	786	20	20	Vegetation Classification
8a *	NIRnarrow	865	20	20	Vegetation Classification
11 *	SWIR 1	1,610	90	20	Sensitive to lignin, starch and forest above ground biomass
12 *	SWIR 2	2,190	180	20	Distinction of live biomass, dead biomass and soil
1	-	443	20	60	Aerosol scattering
9	-	945	20	60	Water vapor absorption
10	-	1,375	20	60	Detection of thin cirrus

Figure 3.4: Spectral band information of Sentinel-2A[4]

3.3.3 Split Data

For our work, we need all images in the data set to have the same size but, unfortunately, the data-set used has a different size, this makes the operation of splitting data in sub-image with the same size necessary. These transformations were made using the software module patchify, and the size given is 256 * 256 * 3 for images and 256 * 256 * 1 for the mask with 64 overlappings. at the end of the operation we get 777 image1 and 2 respectively and 777 masks in the train part

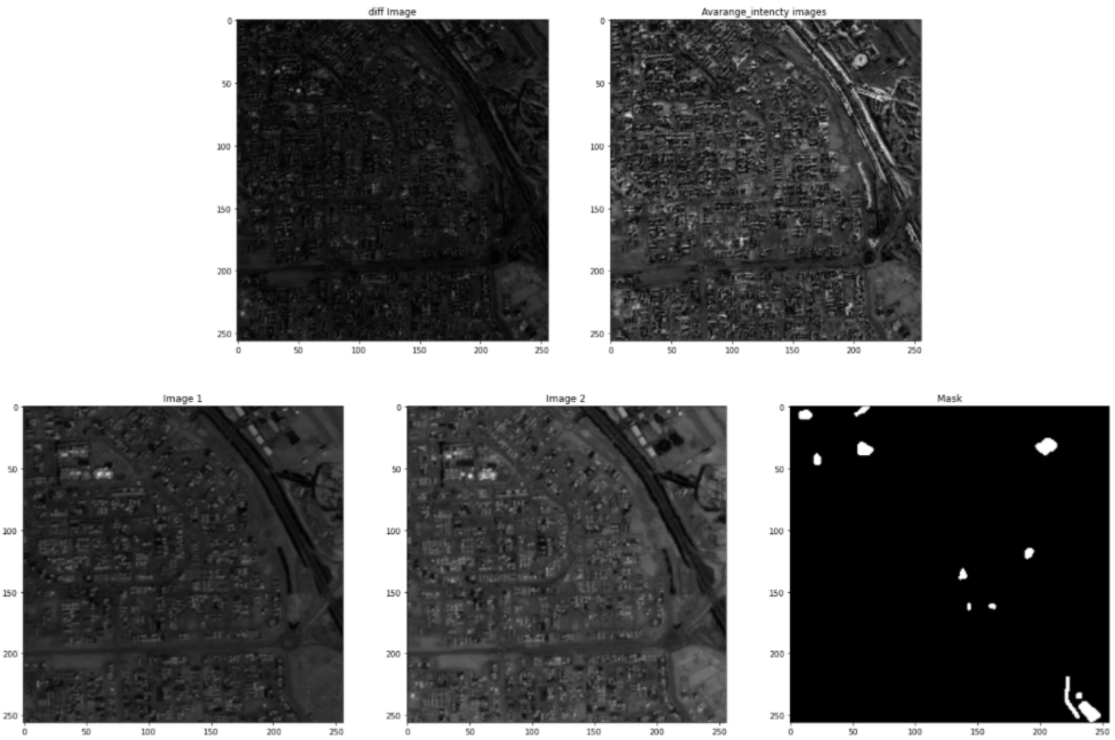

Figure 3.5: (1) diff image (2) Avarange intencty images (3) image after (4) image before (5)Mask

and 279 image 1 and 2, 279 masks for the test part. In our work, we have used just 777 images and divide them into ‰75 for train and ‰25 for a test.

3.3.4 Creation of difference images

The data-set is composed of 2 images, Image 1 taken at the time T1 and image 2 taken at time T2, the aim is to get the change between two images. In order to facilitate the work, we opted to generate the difference between images with the following code using module ImageOps from PIL before generating the augmentation data.

```
Diff1= abs(imgs2-imgs1) --> DI
Diff2 = abs((imgs2-imgs1)/(imgs2+imgs1)) --- > AI
Diff3= NDBI2-NDBI1 > NBDI differency
```

3.3.5 Data augmentation

Data augmentation is a technique that has proven to be effective when training deep neural networks with data scarcity constraints. This is a common problem in satellite imagery a field where collecting labelled data is often complicated and cost a lot of time and money and need craft hand experience. These transformations were made using the software module ImageDataGenerator, described in section 3.3. This module allows for the following transformations: random rotation, horizontal shift, vertical flip and random shear or crop. A very important note when doing the augmentation data set for remote sensing imagery of satellite, there are same augmentation not authorised for this kind of imagery, In order not to lose information in the satellite images like (Zoom) and It should be noted that we exploit flips, translations and rotations as the data augmentation operations because they do not change the scene topologies in remote sensing imageries, which are essentially important for consistent scene classification[23]

3.4 Method and Implementation

- **The software:** This work is developed using the python programming language (version 3.8) Python was the chosen language for this project due to its simplicity, taking also into consideration the fact that it supports most of the recent deep learning frameworks (TensorFlow, Keras, PyTorch, ...). The software modules that were used in this project were responsible for image pre-processing, data augmentation and training neural networks.

- **The hardware:** The hardware requirements for training a deep learning model. As it is common knowledge, deep learning requires a lot of computational power to avoid long training periods. for this reason, we chose to use the resource of **Google Colab** platform. it is a free cloud service offered by Google to encourage machine learning and artificial intelligence research. They provide Jupyter notebooks attached to back-ends that include an Nvidia Tesla K80, 12 GB of dedicated VRAM, 12 GB of RAM and 30 GB of disk storage [24]. This is the best solution to train our models quickly at no cost.,

3.4.1 Image pre-processing

The original data set consists of 24 (10 for test and 14 for the train) RGB images of different size (width x height x number of channels) and their binary ground truth pairs (being both tif files). because the images are big and with different size, I had to split it's in sub-image with 256x256x3 and their masks to 256x256x1 in order to match the input size of the U-Net architecture. This operation was performed using the function patchify() from the library patchify [25].

3.4.2 Data Augmentation

Several techniques were tested in order to increase the limited size of the available data set (24 images with their respective binary masks). The data augmentation software module used for this task was Keras.preprocessing.image.ImageDataGenerator [26]. This module allows for image transformations on the fly as it feeds the model with training 16 batches that do not need to be stored in memory. This solution, although more efficient in terms of memory (avoids writing all data augmented images to disk), did not allow for direct manipulation nor visual examination of the transformed images. keras.preprocessing.image.ImageDataGenerator also allows for these images to be saved to disk. We constructed the ImageDataGenerator using the following call: **For the difference image**

```
img_data_gen_args =dict(rotation_range=90,
                     width_shift_range=0.3,
                     height_shift_range=0.3,
                     horizontal_flip=True,
                     vertical_flip=True,
                     fill_mode='reflect')
```

For the mask image

```
mask_data_gen_args = dict(rotation_range=90,
                     width_shift_range=0.3,
                     height_shift_range=0.3,
                     horizontal_flip=True,
                     vertical_flip=True,
                     fill_mode='reflect',
                     preprocessing_function = lambda x:
                     np.where(x>0, 1, 0).astype(x.dtype))
                     #Binarize the output again.
```

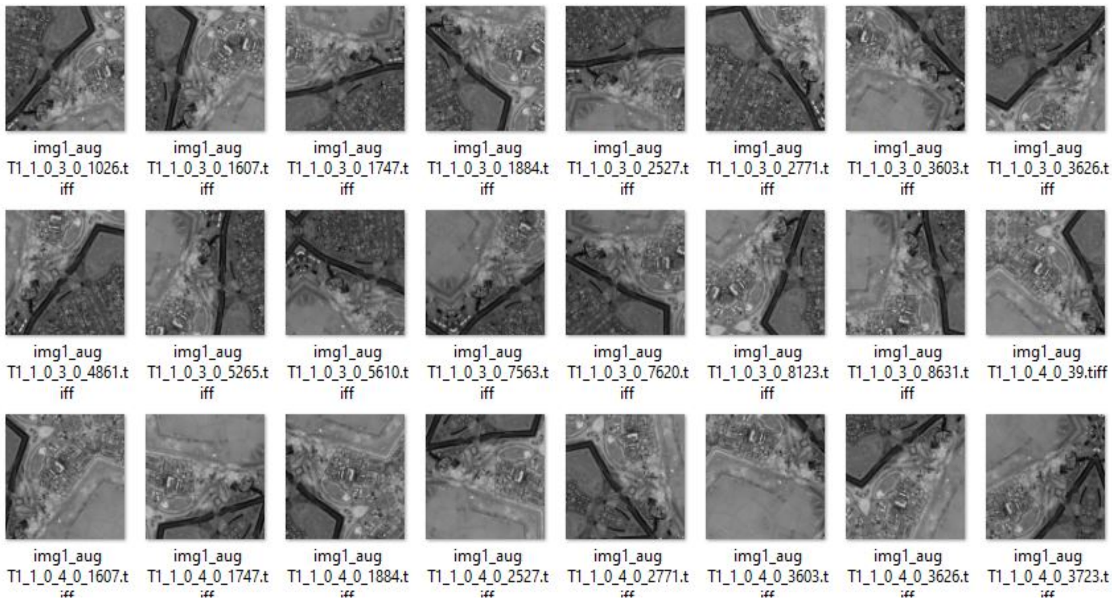

Figure 3.6: Example of an augmented image with rotation range of 90.

3.4.3 U-Net

U-net is a convolutional neural network that was specifically designed for image segmentation for biomedical images. Its architecture consists of an almost symmetrical encoder- decoder architecture of fully convolutional layers (see figure 3.6). The encoder (or feature extractor) compresses The input image into dense feature vectors through a series of convolution and Max-pooling operations, the decoder decompresses the feature vectors and uses high-resolution feature maps from previous down-sampling steps to get spatial information of the features.

3.4.4 Why the UNet ?

There are multiple reasons this architecture has been chosen as the basic architecture for our network.

- First, it is a very simple architecture, which means it is easy to implement and debug.
- It is very good for image segmentation. Although it is a couple of years old, it is still used in competitions.
- Its output is in the same resolution as the input. Because we are trying to obtain masks that are as precise as can be, that is important.
- The authors of the U-Net claimed in their paper presenting the network that it is designed to build good prediction models even with a smaller data set but using excessive data augmentation.

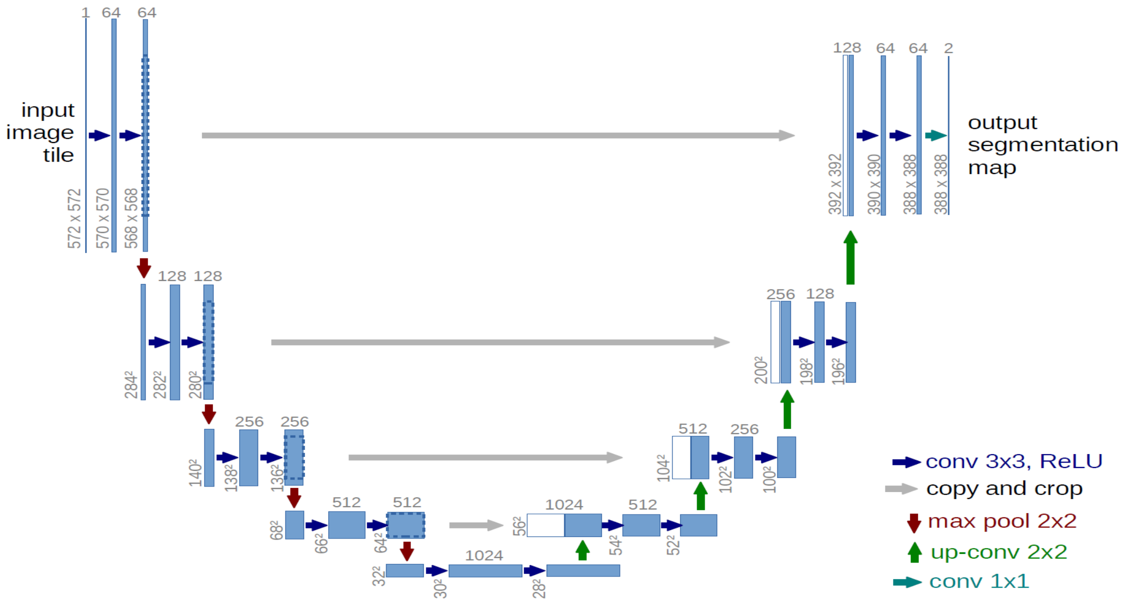

Figure 3.7: U-Net architecture composition. Image taken from U-Net: Convolutional Networks for Biomedical Image Segmentation

- On the contrary to the ResNet or other nets, it doesn't have a very heavy architecture and its training time is shorter.

3.4.5 Architecture

We used a based version of this U-net (based on the code publicly available on GitHub [27]) with the following characteristics:

- Encoder: A sequence of four fully convolutional layers with 16, 32, 64 and 128 filters (respectively from input to decoder) followed by 2x2 max pooling filters and RELU as an activation function.
- Decoder: A sequence of four upsampling layers followed by fully convolutional layers with 128, 64, 32 and 16 filters respectively and RELU as an activation function. The upsampling layers are combined with feature maps from encoder convolutional layers in order to recover spatial information instead of just scaling up the information.
- Output layer: A 1x1 convolutional filter with a sigmoid activation function to obtain values between 0 and 1 that will serve as probabilities for pixel classification.

3.4.6 Hyperparameters

The hyperparameters of a neural network are defined prior to any training and will set the behaviour of the network and the way its weights are updated.

- Optimiser:The neural network's optimiser was **Adam**, one of the most commonly used optimisers in classification and segmentation problems with CNN.
- Loss: Since binary classification is the nature of this problem (pixels either has been changed or not change) the loss function of the neural network was set to be **binary cross-entropy** [28], a function that minimizes the difference between probability distributions. In this case, the pixel probabilities of the segmentation map compared to the ground truth.
- Activation function: This function defines the way a single neuron triggers its output considering its input. The activation function of the U-net for this work was **the sigmoid function**. This function is commonly used for binary classification problems [29]

3.4.7 Intersection over Union

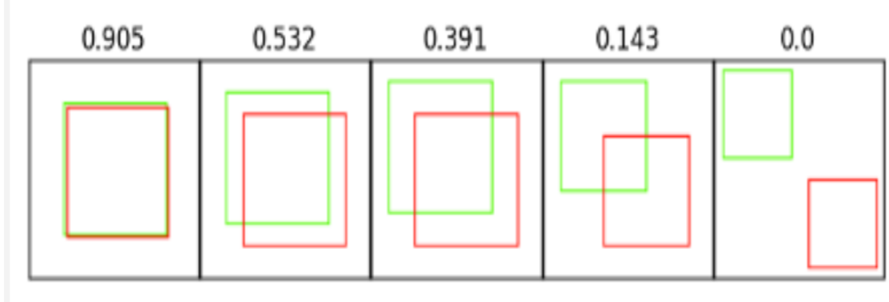

Figure 3.8: Interpreting IOU scores

In order to evaluate our training and the results of the segmentation, we use IOU metrics. The Intersection over Union (IOU) metric, is essentially a method to quantify the percent overlap between the target mask and our prediction output. This metric is closely related to the Dice coefficient, which is often used as a loss function during training. Quite simply, the IOU metric measures the number of pixels common between the target and prediction masks divided by the total number of pixels present across both masks [30].

$$IoU = target \cap prediction / target \cup prediction \tag{3.4}$$

IOU is quite intuitive to interpret. A score of 1 means that the predicted bounding box precisely matches the ground truth bounding box. A score of 0 means that the predicted and true bounding box do not overlap at all.

3.4.8 Training Procedure

Initially, we tried to establish an efficient training procedure applicable for the model, we decide to train the model for Y1 epochs with learning rate Z1, and then Y2 epochs with learning rate Z2, etc... but due to the randomness of the model initialisation for Weights and of our data augmentation method, it was too hard to find a good method that would work ‰100

After training it for a certain number of epochs, we manually checked the metrics (loss functions, Accuracy, IOU). but also the output masks to evaluate whether we could continue the training with a lowered learning rate, or whether we should keep the same learning rate for 10 or 20 additional epochs. We stopped the training process when the model converged and reached its top accuracy.

3.4.9 Thresholds the predicted image

Our change detection problem is a classification problem where the classes are "change" or "no change", but our Neural Network outputs a "continuous" value between 0 and 1 for each pixel. To solve this problem, we simply use a threshold OTSU: Automatic global thresholding algorithms usually have the following steps:[31]

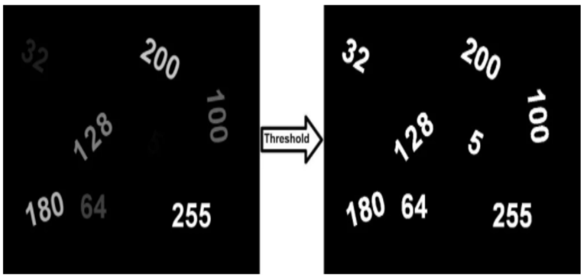

Figure 3.9: threshold principal

- Process the input image
- Obtain image histogram (distribution of pixels)
- Compute the threshold value T
- Replace image pixels into white in those regions, where saturation is greater than T and into the black in the opposite cases.

3.5 Predictions for new data

At the end of the training, the model was saved as HDF5 using **keras. models library** for a future prediction.

Chapter 4

Analyse and discussion of the results

4.1 Introduction

In this chapter, we present the results of the experiments described in Chapter 3. The results are presented in the form of graphs, plots and segmentation samples. also, we interpret and analyses these results and evaluate them.

4.2 Impact of Data Augmentation

The dataset of Urban changes we composed is relatively medium (24 pairs of images in total) from a different country of the world (Paris, Dubai, RIO...). We have several examples where the position of the sun is not the same between the "before" and "after" images, meaning that buildings will cast shadows with different directions and lengths. The position of the satellite also plays a part, since it is rarely perfectly vertical. Colours and tints also vary and colours might change depending on the illumination.

All these changes are not related to the change of Urban Area and should not be detected, but the model needs to learn that they should not be considered. Since our dataset is small and lacks diversity, our model might have a hard time performing on slightly different images (satellite angle, sun angle). Data Augmentation is there to introduce some artificial diversity. But also we have to note that the augmentation of the data may cause deformation of the pixel in the images (transformations, colour space augmentations).

4.3 Method used for analyse

In this last chapter, we will demonstrate how the fusion of the two algebraic and Basic methods used for change detection can even slightly increase the level of change detection using CNN. We will start by training our model With Just the difference image as input,

Then we present the results obtained by performing the training with the second algebraic method Average intensity. Finally, the results of the training with the fusion of these two methods as a data set for the CNN.
We must note in some NDBI images we detect a big change in the water Area see the following figure, this change does not correspond to the Urban change Area and confuses the training. The results for NDBI images were very bad.

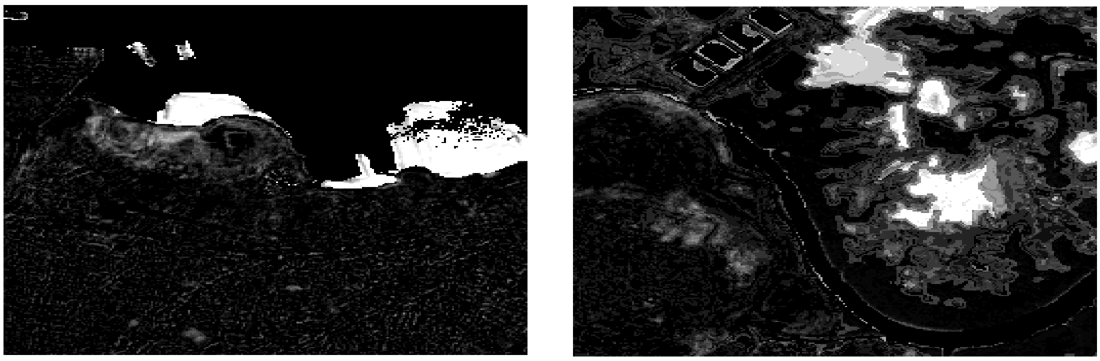

Figure 4.1: NDBI Difference

4.4 Training Unet Model

The training was used by the following hyperparameter :

- NO pre-training are used for this work
- Dropout 0.1, 0.2, 0.3 are used after FC layer
- RELU has been used as activation function and sigmoid for the last layer
- Adam optimiser with initial learning rate 1-3e
- 65 epochs for the training
- Basic UNet: 1.9 million parameters

4.4.1 Difference images and Unet

After generation of the difference images using, X2 is image after and X1 is image before, the result is 777 difference images as we can see in the following figure the change between the tow image it is quite visible. but this change does not represent the reality, because it does not take the atmospheric conditions and the gross or else, the shade and the level of the luminosity.

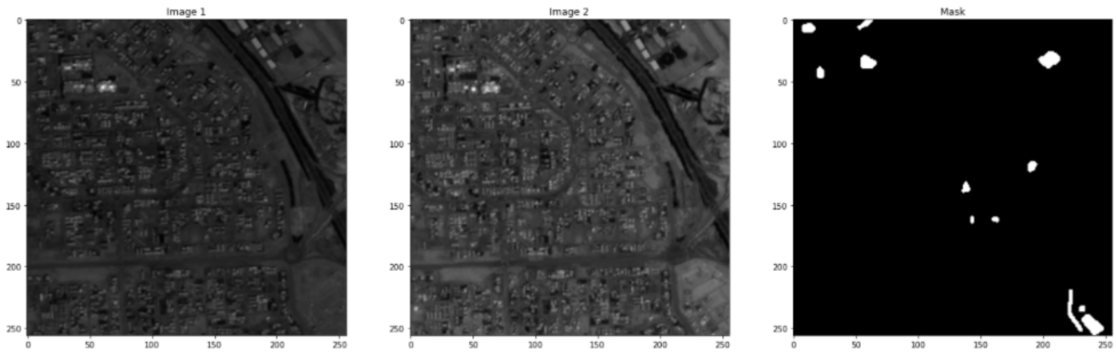

Figure 4.2: 1. images before 2. image after 3. mask

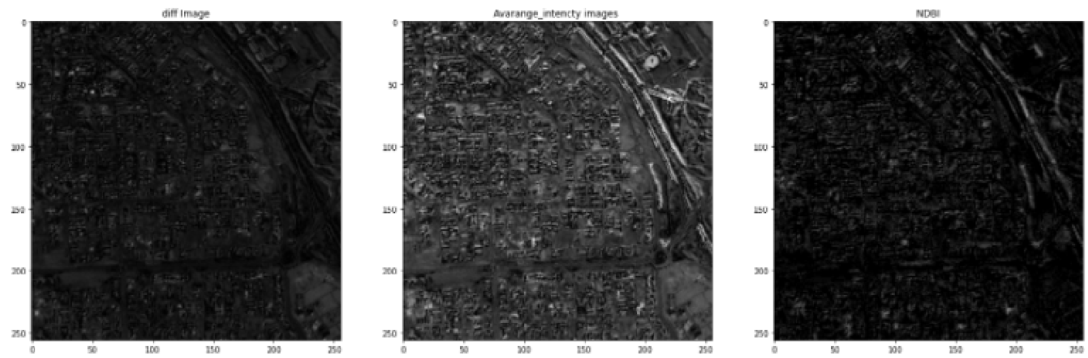

Figure 4.3: 4. difference image 5.Average intensity 6.NDBI

4.4.2 Comparing the results

To demonstrate the good results that are generated by using our approach, we will compare the three training results DI, AI and Fusion-DI-AI, in the following performance on some metrics and quality of the output masks.

4.4.3 Training with DI

The first scenario involves training the model with DI as an input, and then plotting the LOSS and ACC of the training.

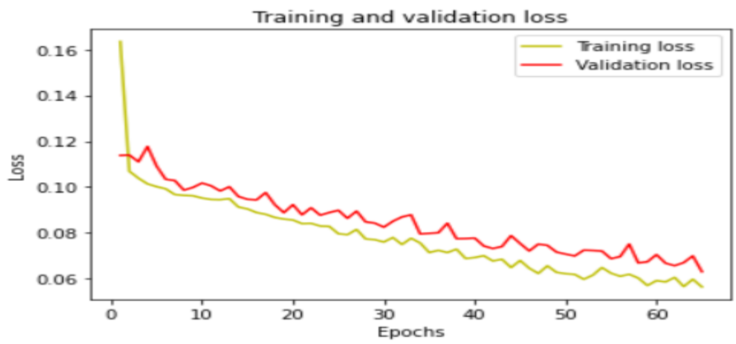

Figure 4.4: LOSS of training difference images as data set

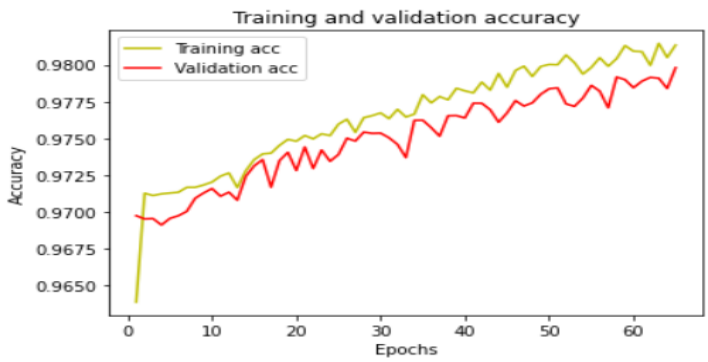

Figure 4.5: ACC of training difference images as data set

4.4.4 Training with AI

The second scenario involves training the model with AI as an input, then plotting the LOSS and ACC of the training.

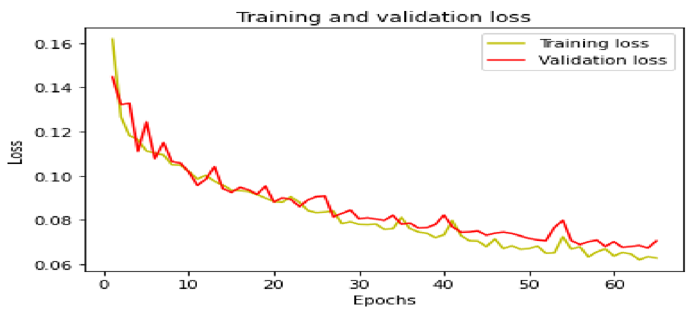

Figure 4.6: LOSS of training Average Intensity as data set

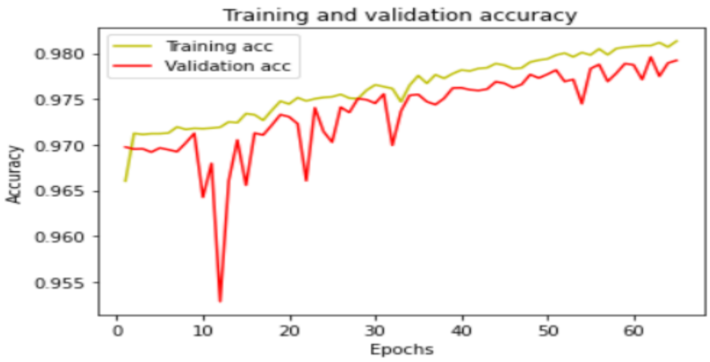

Figure 4.7: ACC of training Average Intensity images as data set

4.4.5 Training with Fusion AI DI

The third scenario is training the model using Fusion f DI and AI as an input, then plotting the training's LOSS and ACC. Metrics comparison on fully trained models in the table :

Figure 4.8: LOSS of training Fusion DI AI as data set

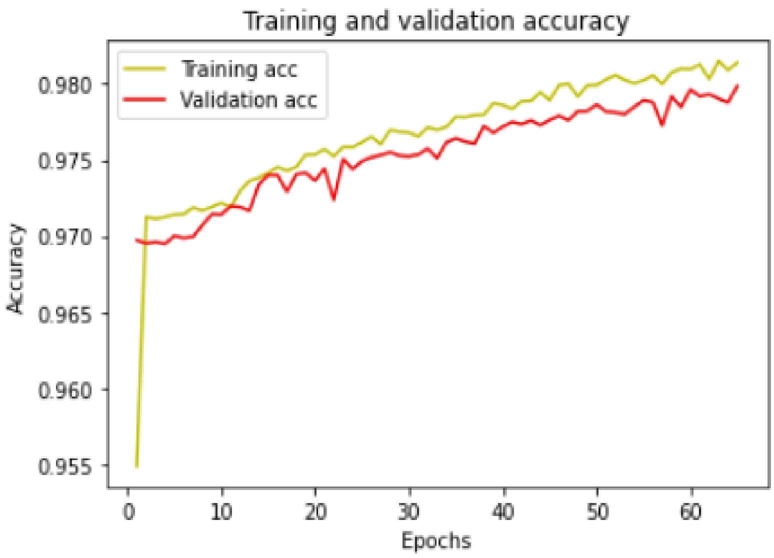

Figure 4.9: ACC of training Fusion DI AI images as data set

Data set	Accuracy	Loss	IOU	F1_score	Precision	Recall
DI	0.9784	0.065	0.2852	0.477	0.7620	0.335
AI	0.9703	0.075	0.1925	0.465	0.7603	0.351
NDBI	0.960	0.1179	0.0866	0.1235	0.5628	0.056
Fusion_AI_DI	**0.9804**	**0.586**	**0.34798**	**0.547**	**0.78**	**0.4626**

Figure 4.10: Comparisons of different approach

4.5 Predict images

In this section, we will look at the masks generated by the Unet model using our approach and the two other cases (DI, AI), UNet has been trained using all the data augmentation methods described in section 3.4.2 All the masks presented contains values between 0 and 1.

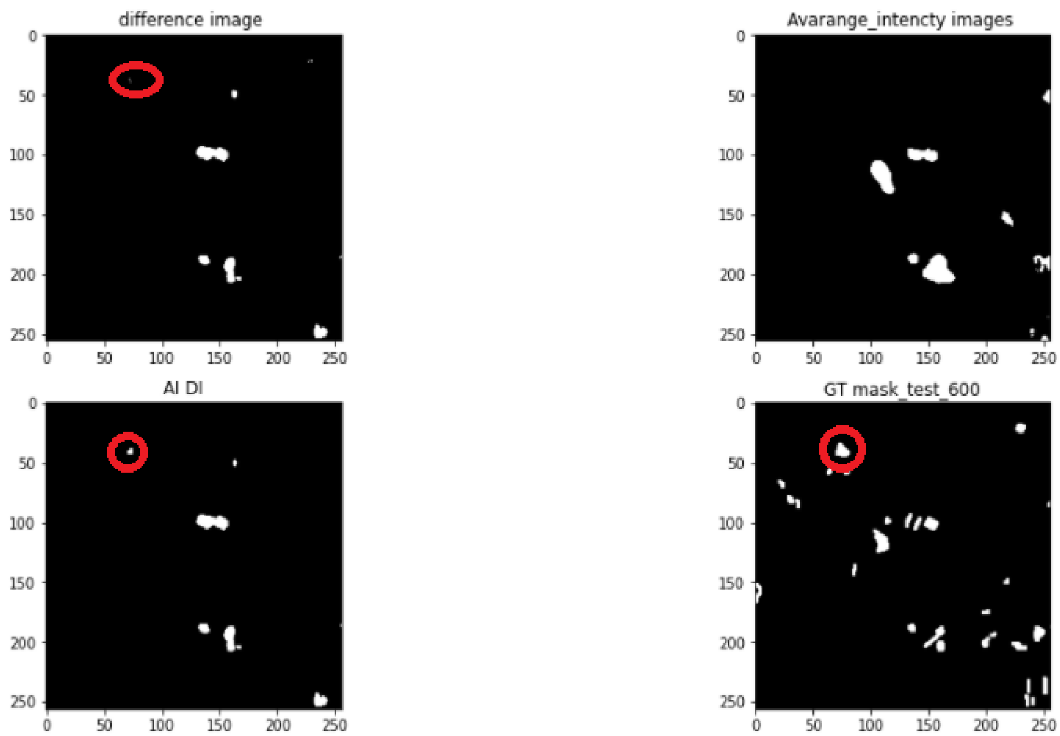

Figure 4.11: Prediction of image N° 600

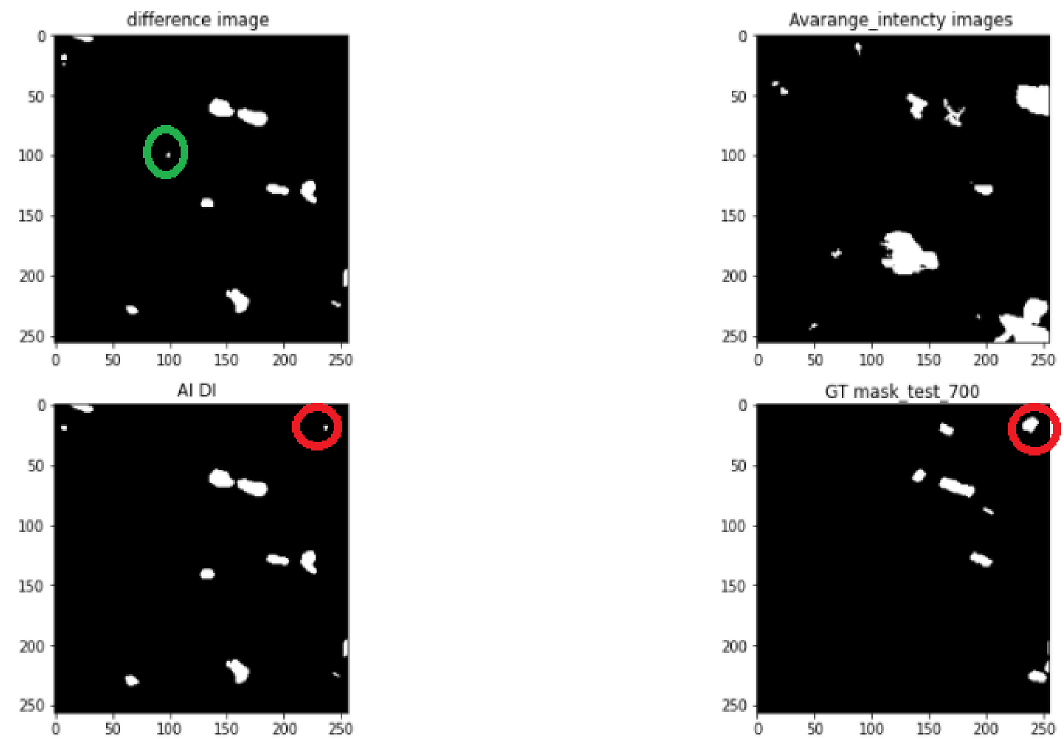

Figure 4.13: Prediction of image N°700

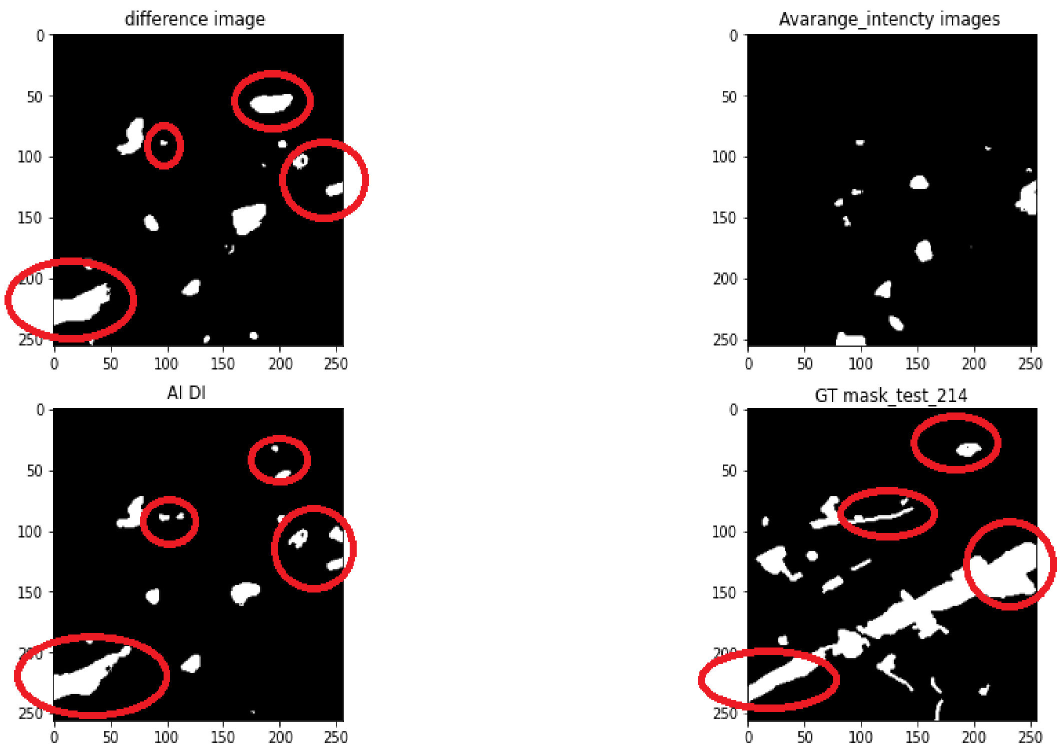

Figure 4.12: Prediction of image N°214

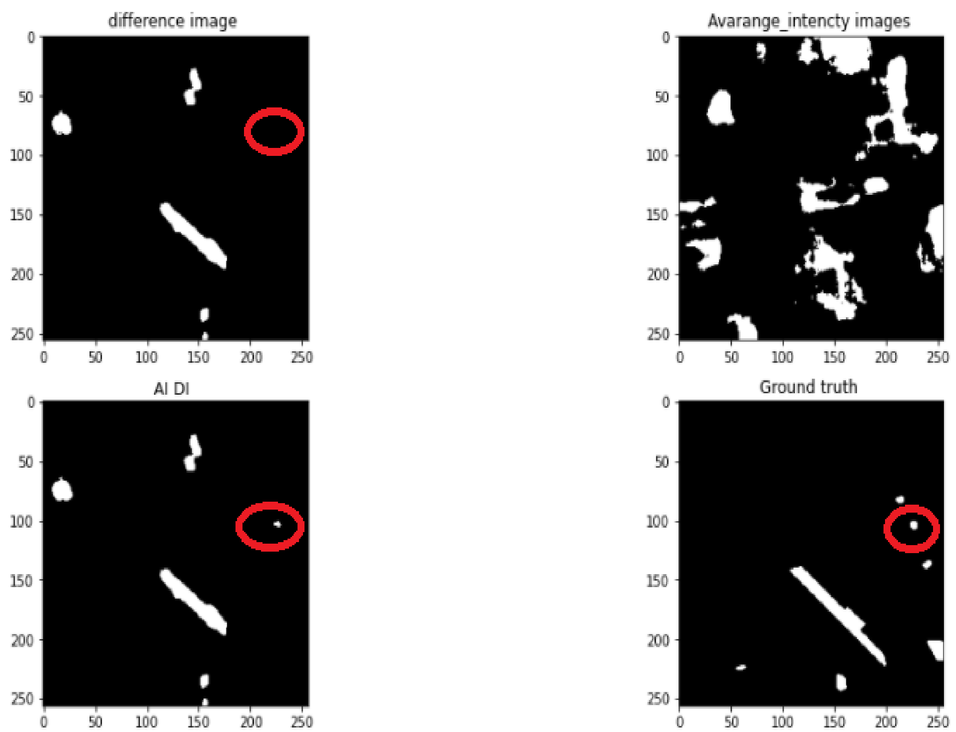

Figure 4.14: Prediction of image

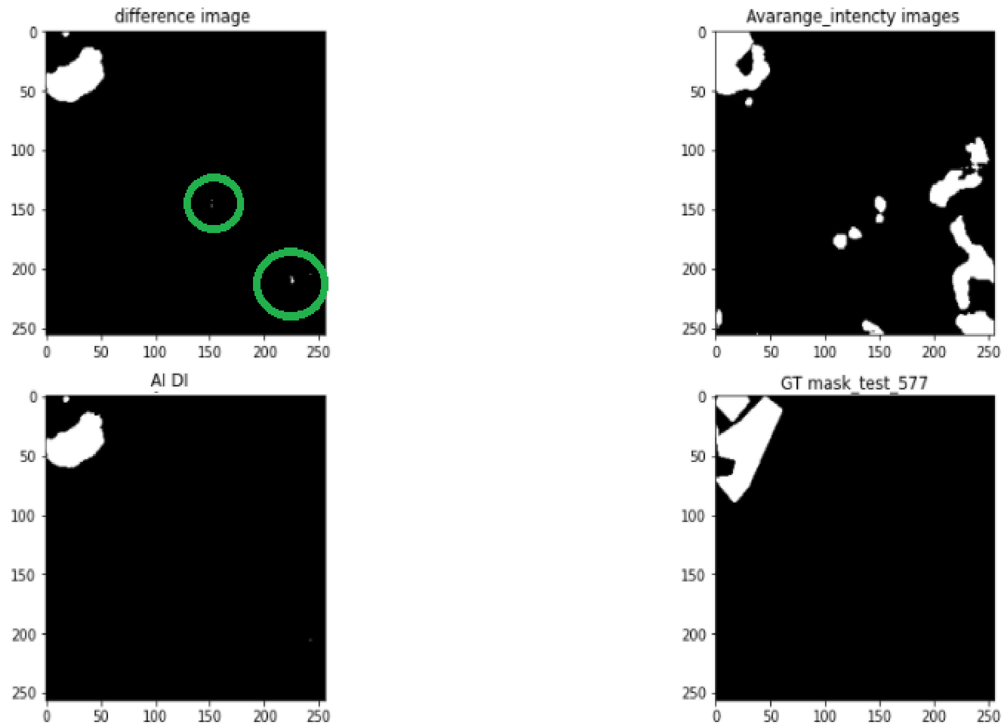

Figure 4.15: Prediction of image test N° 577

4.6 Results and Discussion

As reflected by the results, the prediction generate using AI images as data set for the U-net model have made a worse result by 0.19 of IOU.

Contrary fit U-net model with DI image as data set is better than AI with 0.28 IOU, but using a fusion of two differences images technique as input of the U-net model, we get a good result for urban change detection, and we increase the IOU with 6%.

4.7 Perspective of our work

This section identifies many possibilities for improving the project. Some of them were not realised due to a lack of time.

4.7.1 Data set

The data-set could first be largely extended. Even for a model trained in one environment, the dataset is insufficient. Despite the positive results, a bigger dataset would result in a more robust model.

We could also use all the 13 spectral, band to generate the DI AI images. a recent paper has published [32] that using all 13 band as input for the U-net model increase the ACC 99.49% and

F1 Score 0.66.

4.7.2 Model

There are several architectures that may be studied. We only concentrated on one type because that seems to be the most promising and most appropriate to our requirements. Other UNet variations to consider include the Res-Unet, which is a combination of a UNet and the ResNet architecture, and the attention Res-Unet, which is a version of Res-Unet that uses attention modules. Instead, then trying a lot of different structures, we chose to focus on one and fine-tune it.

4.7.3 Methods of Change Detection

There are many other methods of change detection as PCA and clustering, and different methods of fusion can be done as Fuzzy logic to combine the several results of the different methods to collect all the change information from multiple images in one single image.

4.8 Conclusion

We were able to confirm that our implementation choices, based on combine two algebraic methods DI and AI and used this combination as data set to fit the U-net model. to detect the change in an urban area using remote sensing satellite images with 10 m of resolution. has brought to satisfy result with 6% of difference comparing when we use just DI and 15% when we use AI. the fusion of these two algebraic methods of change detection increases the accuracy of predicting images in the Unet model.

GENERAL CONCLUSION

This thesis focused on developing an approach capable of change detection in satellite imagery using Algebraic method and neural network, by generating a segmentation mask highlighting the evolution in Urban area . It takes two satellite images of the same place taken at different times as input. The output is a segmentation mask classifying each pixel as either change or no change. The segmentation mask has the same resolution as the input images.

We started by building our own dataset focusing first, splitting the data to 256*256 pixel for the two images and mask corresponding, The next step was to select which Algebraic methods will give the best RMES using our data, then we select 3 methods AI, DI, NDBI, the training of each data set in U-net model after applied a data augmentation give respectively the following results : 0.08, 0.19, 0.28 IOU.

To increase the accuracy of the data set we introduce a new approach by combine both DI, AI images, the result obtaining after the training was better than the last two training with 0.34.

There are leads to improve the model : using a larger and more diverse dataset, trying different combination of traditional methods for change detection and different image segmentation architectures such as VGG, or allowing for more trainable parameters by using a GPU with more memory or using smaller input images.

In conclusion, our approach is achieving Pretty good, satisfying image segmentation performances on multi-temporal satellite imagery.

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