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Segmentation of Multiple Sclerosis in MR images by Deep Learning

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Segmentation of Multiple Sclerosis in MR images by Deep Learning

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Thinks

Above all, we would like to thank GOD for granting health, the possibility and the will to start and continue our studies.

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In addition, we would like to acknowledge our parents for their love, care, prayers, scarifies and for being always there for us.

Dedicate

From the deepest of my heart, I dedicate this modest work to those who have supported, helped and advised me throughout my life. I express my gratitude and respects to:

My dearest mother for all her love and devotion,

My father ***Mourad*** who gave me a magnificent model of hard work and perseverance,

My dear sisters ***Lynda***, ***Leila***, ***Meriem*** for their moral support and sacrifices throughout my training,

My dear binomial ***Sabrina Benbatata*** and her family,

All my colleagues in the university,

Finally, for all people who participated directly or indirectly in the realization of this work.

Louiza

Dedicate

With all my heart, I dedicate this modest work to those who have supported, helped and advised me throughout my life find in this thesis the expression of my most deep gratitude, all my respects:

For my father ***Bachir***,

For my dear mother,

For my sisters **Khalida Lamia Fatima** and My dear binomial ***Louiza Benhizia*** and her family

For all the family ***Benbatata, Ben hammada***,

For all my friends.

Not to mention, of course all those who participated in far in the realization of our project.

Sabrina

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General Introduction

Multiple sclerosis (MS) is a neurological and an inflammatory disease which affects the human's central nervous system. Until now, the causes of being ill with MS are unknown. The latest statistics showed that 2 millions people around the world suffer from this disease [1]. Unfortunately, the number of MS patients increased from 2.3 million in 2013 to 2.8 in 2020 [2]. MS healthcare costs 10 billion dollars a year in the USA [3]. However, the early diagnosis of MS costs less in the treatment and is very important in planning the treatment of patients. Due to the considerable progress in medical image acquisition devices comprises different modalities and processes, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET) and among others. The medical data is quite voluminous.

Magnetic resonance imaging (MRI) is considered as a core paraclinical tool for diagnosing and predicting long-term disability and treatment response in MS patients. Where, the MRI allows precise visualization of anatomy of the central nervous system tissue (brain, spinal cord). MRI is a device that uses a large magnetic, radio waves and computer to create a detailed, cross sectional image of the internal organs and structures.

The manual multiple sclerosis diagnosis is often painstaking and requires significant and tedious efforts on the part of the medical expert that can be highly subjective, evaluations and prognoses can be slow. MRI does not achieve the diagnosis without an expert neuroradiologist, and there is no standard method that can be developed for the segmentation of MS. Therefore, the automatic detection of MS becomes significant because it could be used to help neuroradiologists to improve the diagnosis and follow-up evaluation of MS patients.

Recently, Deep Learning (DL) has various techniques which have been adopted in MS segmentation studies following their success in general areas of image analysis, such as image classification, object detection and semantic segmentation. A commonly used deep learning method for image segmentation is to train a Convolutional Neural Networks (CNN).

In this work, Our proposal presents a Unet method to segment MS in MR images. The proposed network uses a public multiple sclerosis dataset. Unet is a convolutional neural network that was developed for biomedical image segmentation which consists of several neural network layers connected in a sequential order.

Manuscript organization

This dissertation consists of the following four chapters :

Chapter 1 : Medical and technical concepts

This chapter it's an overview about medical context. We represent multiple sclerosis disease (definition, symptoms,causes…etc), the fundamental principles of the technique of magnetic resonance imaging, where the problem posed in detail on MS disease.

Chapter 2 : Deep learning

In this chapter, we present the concepts of deep learning and their different deep learning architectures. We focus the most on Unet architecture.

Chapter 3 : State of the art on multiple sclerosis segmentation methods

In this chapter, we present state of the art related to segmentation of MS from MR images with a summary of some methods used in the segmentation of MS from MRI.

Chapter 4 : Contribution

In the last chapter, we present our proposal for MS segmentation and the results of this study and we illustrate how the system works on real medical images.

Chapter 1

Medical and technical concepts

1.1 Introduction

The central nervous system (brain and spinal cord) allows human beings to think, learn, control and move. It controls all aspects of our body. Any disease that touches this important system affects our body. One of those diseases is Multiple Sclerosis (MS). MS is a neurological disease that attacks our central nervous system. It is a big challenge for doctors to diagnose MS. And with the advance of medical technologies, MRI is still the best choice for doctors to diagnose it.

In this chapter, we are going to introduce medical concepts of our work. We start with what MS is? MS causes, forms and symptoms. Then we are going to present magnetic resonance imaging (MRI), it's components. After that, we are going to show What are MR images of MS patients are like? Finally, we are going to present the advantages and limitation of MRI in MS.

1.2 Multiple Sclerosis disease

Multiple sclerosis (MS) is an autoimmune disease of the central nervous system that can affect the brain, spinal cord and optic nerves. So, what is the central nervous system?

1.2.1 The central nervous system

The human nervous system consists of two parts the central nervous system (CNS) and the peripheral nervous system. The CNS consists of the brain and the spinal cord, and the peripheral nervous system connects the CNS with the sense organs [4].

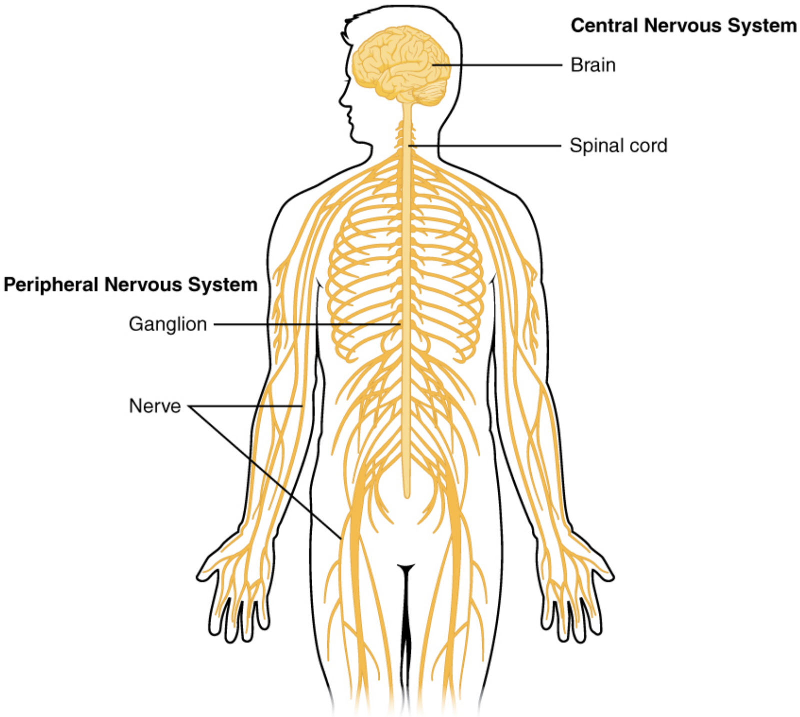

Figure 1.1: Human nervous system [4].

1.2.2 What is multiple sclerosis?

Multiple Sclerosis (MS) is an autoimmune disease in which the body's immune system attacks its own central nervous system. In MS, the immune system attacks and damages or destroys myelin, a substance that surrounds and insulates the nerves. The myelin destruction causes a distortion or interruption in nerve impulses traveling to and from the brain. MS lesions known as plaques which may form in CNS white matter in any location. MS patients develop multiple areas of scar tissue in response to the nerve damage. This can result in a wide variety of symptoms [5]. As we show in Figure 1.2 two nerves fibre where the nerve fibre with myelin sheath is the normal case and the second one the scarred myelin is abnormal case MS.

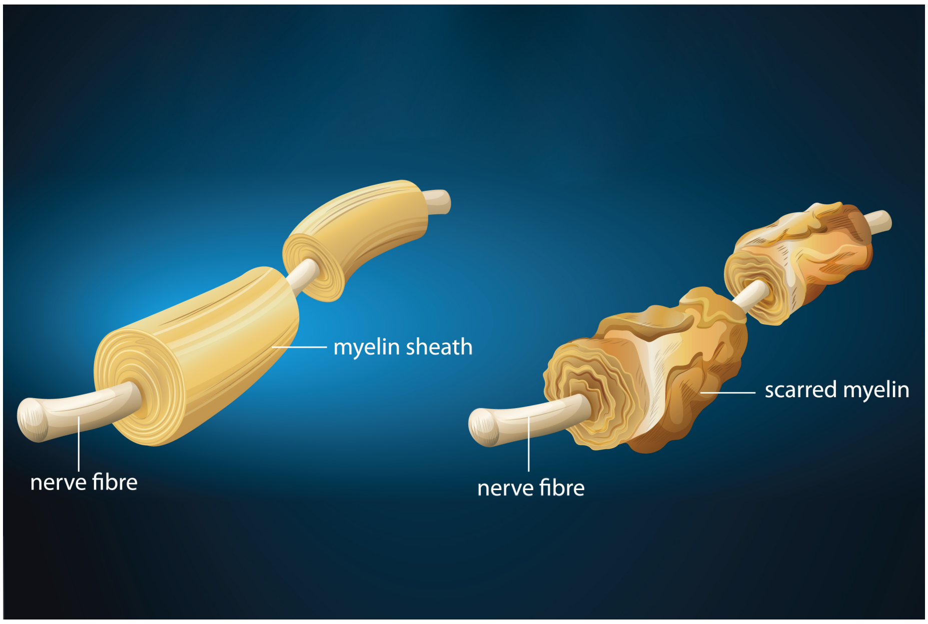

Figure 1.2: Multiple Sclerosis with demyelination [5].

The disease typically presents in young adults (who are 20 to 45 years of age) and affects twice as many women as men. And persons of Northern European descent appear to be at highest risk for the disease (As we show in the picture below Figure 1.3) [6].

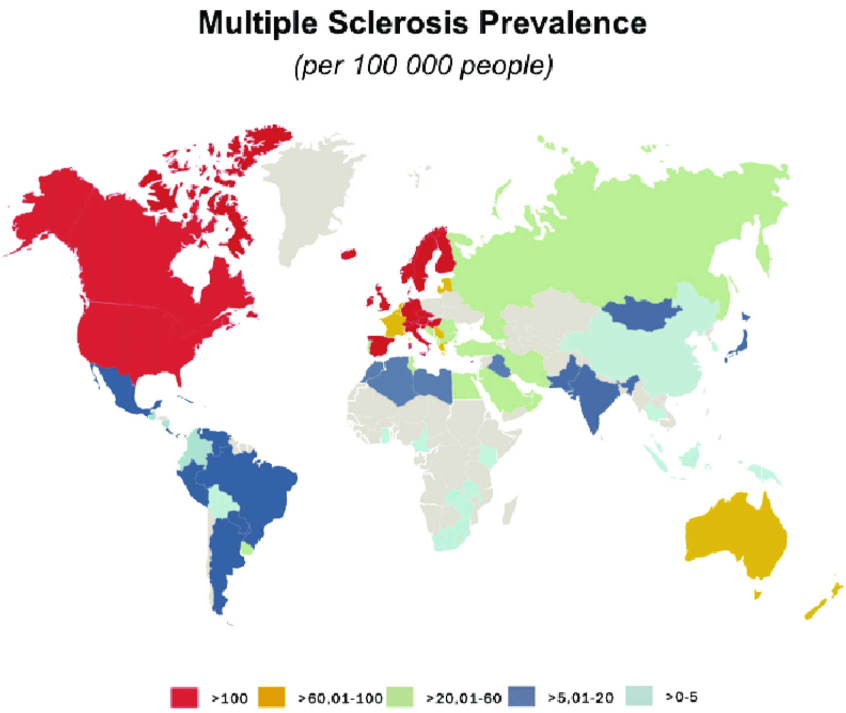

Figure 1.3: MS prevalence [7].

1.2.3 Causes of MS

There are not specific causes which determine the MS but there are alot of possible causes like we show:

- **Immune system cause :** The immune system malfunctions and attacks the CNS. Researchers know that the myelin sheath is directly affected, but they don't know what triggers the immune system to attack the myelin.
- **Genetic cause :** According to the National Multiple Sclerosis Society, if one parent or sibling has MS, the chances of getting the disease are estimated to be around 2.5 to 5 percent in the United States. The chances for an average person are approximately 0.1 percent.
- **Environment cause :** Epidemiologists have seen an increased pattern of MS cases in countries located farthest from the equator. This correlation causes some to believe that vitamin D may play a role. Vitamin D benefits immune system function.
- **Infection cause :** Researchers are considering the possibility that bacteria and viruses may cause MS. Viruses are known to cause inflammation and a breakdown of myelin. Therefore, it's possible that a virus could trigger MS.

1.2.4 Forms of MS

1. **Pure relapsing-remitting forms**

   The residual disability is variable, as is the interval between relapses (from a few months to more than 10 years). They represent more than 80% of all patients.

2. **Progressive forms**

   Either from the outset in a more or less long period of relapsing-remitting form. Illness and disability worsen over a period of more than a year.

3. **Relapsing-progressive forms**

   Chronic progression of disability with worsening episodes followed by progressive improvement.

1.2.5 Symptoms of MS

The symptoms of MS vary widely from person to person and can affect any part of the body. The main symptoms include :

- Visual disturbances (blurred vision, uncontrolled eye movements).
- Dizziness or vertigo.
- Increasing fatigue and fatigability.
- Numbness, tingling.
- Urinary bladder dysfunction.
- Dysesthesia in the face.
- Skin sensitivity disorders: tingling, itching, decreased sensitivity to touch and pain.

1.2.6 Diagnosis of MS

In recent years, the diagnosis of multiple sclerosis has improved significantly. In 70 % of cases, MS starts on average from the age of 30, and more generally between the ages of 20 and 40. As there are no biological markers of the disease, visible in the blood for example, doctors base their diagnosis on a set of clinical, para-clinical and evolutionary arguments.

The clinical examination (that is the examination during the consultation) can suggest the diagnosis of MS. Certain symptoms (MS symptoms) felt by the patient can alert: motor disorders (such as the onset of muscle weakness, which makes it difficult to walk, or even loss of balance), sensory disorders (numbness, tingling), visual disturbances, memory loss, incontinence, sexual impotence ...etc. This clinical examination of symptoms also allows the neurologist to rule out any other condition causing similar symptoms. If multiple sclerosis is suspected, the doctor will order additional examinations (magnetic resonance imaging).

Magnetic Resonance Imaging (MRI) can visualize the central nervous system and thus have precise images of lesions of the brain and spinal cord caused by multiple sclerosis. We stand out particularly in magnetic resonance imaging because it helps locate these lesions, which is our main focus in this thesis.

1.3 Medical imaging

It becomes more and more obvious that medical imaging is surely one of the fields of medicine which has experienced the most progress in the past twenty years. It is a method to be used to establish a medical diagnosis or treatment.

There are several medical imaging modalities such as X-Computed Tomography (CT), Ultrasound, Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI). Today, MRI has become a major tool in modern medical imaging. So, what is MRI.

1.3.1 Magnetic resonance imaging

Magnetic Resonance Imaging (MRI) has progressed over 30 years from being a technique with great potential to one that has become the primary diagnostic investigation for many clinical problems [8]. MRI is a medical imaging technique used in radiology that provides a 2D and 3D view of a region of the human body, it based on the principles of Nuclear Magnetic Resonance (NMR). The high sensitivity of MRI in the depiction of plaques in the brain and spinal cord has made this technique the most important paraclinical tool for the diagnosis of multiple sclerosis MS [9].

1.3.2 The main components of MRI

MRI consists essentially of three basic elements:

- Main magnet.
- The Gradient coils.
- Radio frequency RF coil.

1.3.3 Principle of MRI

The patient lies on a mobile exam bed which must then be retracted into the magnet bore. MRI subjects the body to a very strong magnetic field that will direct hydrogen atoms in the same direction. To perform an MR image, an antenna emits a short radio frequency wave that alters the orientation of hydrogen protons. When the emission stops, these protons return to their original position. They then restore recordable energy in the form of a signal, captured by a receiving antenna. It is by analysing the resonance signals provided by these movements that one can obtain images of successive slices of the organs [10].

1.3.4 MR imaging sequences

MRI is the most used in medical imaging because it has exquisite detail of brain, spinal cord and vascular anatomy. Also, it is able to visualize anatomy in 3 planes : axial, sagittal and coronal (As we show in the Figure 1.4 below).

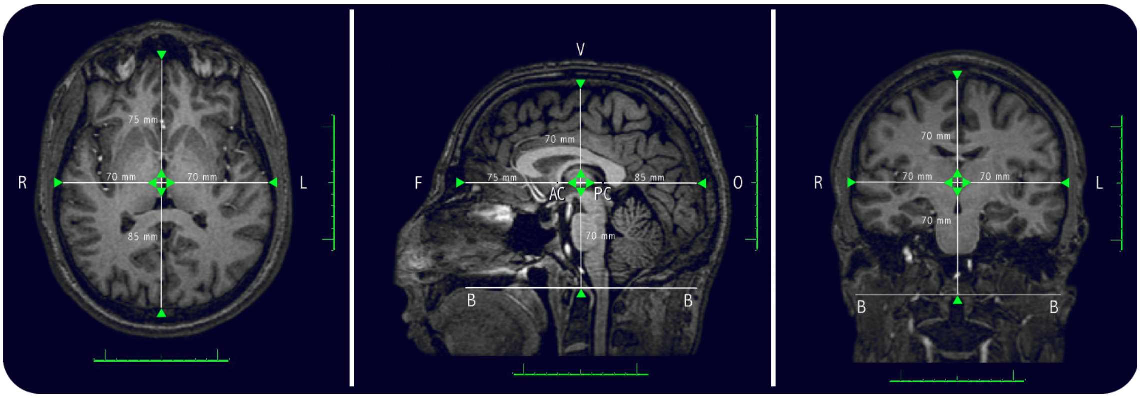

Figure 1.4: Brain anatomy planes : Axial, Sagittal and Coronal [11].

By modifying the acquisition parameter, in particular the time of re-petition between two excitations (TR) or the time between the excitation signal and the echo reception (Echo Time, TE). The choice of all the parameters depends on the clinical study to be performed. T1, T2, proton density...etc. can be obtained [12].

- **Proton density-weighted image**

  For a long TR (of the order of 2s) and a short TE (of the order of 20ms), the difference in proton density between grey matter and white matter is expressed. A sequence is obtained that reflects the location and concentration of the hydrogen nuclei of the different structures. A density-weighted proton sequence is obtained, which reflects the location and concentration of the hydrogenated nuclei of the different structures. Tissues are ordered by increasing grayscale in white matter (MB), gray matter (MG) and cerebrospinal fluid (CSF) [13].

- **T2-Weighted Image**

  For long TRs (about 2s) and long TEs (about 90ms) is less, but very informative on the composition of the tissues (mainly moisture content), signal decay dominates the difference in proton density between tissues. The signal is then sufficient to produce a so-called T2-weighted image, or the tissues are ordered by increasing grayscale in MB, MG, CSF [13].

- **T1-Weighted Image**

  For TR of the order of 600 ms, the contrast between the tissues depends essentially on their magnetization speed, therefore of T1. For TE of about 20 ms, differences in signal decay between tissues do not have time to express themselves, making contrast independent of T2. This results in a T1-weighted image, where tissues are ordered by increasing gray levels in cerebrospinal fluid, gray matter and white matter [13].

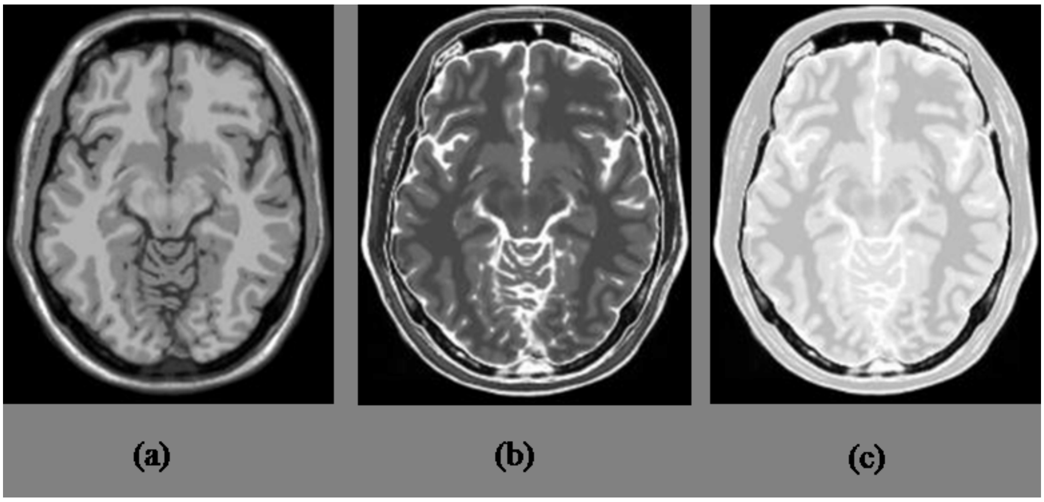

Figure 1.5: Different modalities of MRI brain images: (a) T1-Weighted; (b) T2-Weighted; (c) Proton density-weighted [13].

1.4 What are MR images of MS patients like?

The presence of water molecules in the brain, and more precisely hydrogen nuclei is the cause of why MRI has become a powerful technique in clinical practice for MS. MRI scanners can provide volumetric soft tissue information with a high contrast. By tuning the MRI parameters, different volume sequences can be acquired. The most widely used images in MS trials are PD-w, T1-w, T2-w, and FLAIR [14]. In Figure 1.6, we show MS in MRI brain slices with different volume sequences acquired.

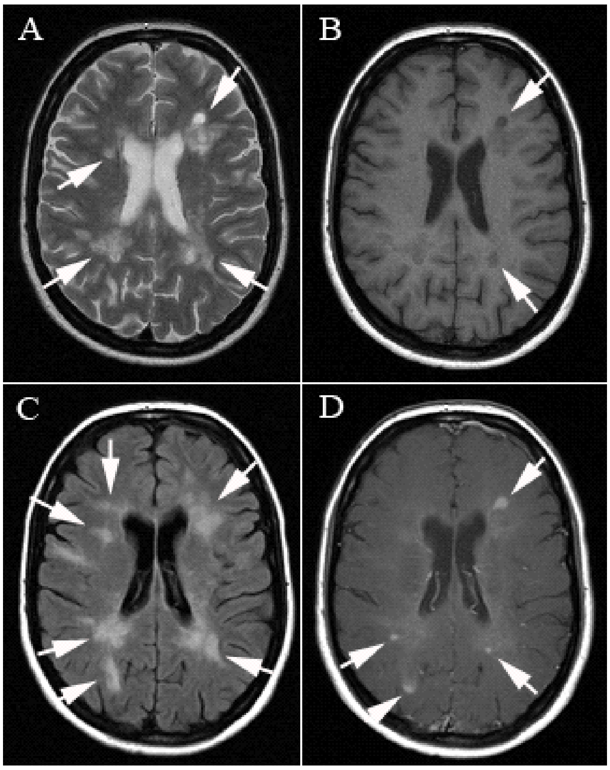

Figure 1.6: Axial brain slices of a patient by different MRI sequences showing MS lesions: (A) T2-weighted image; (B) T1-weighted image; (C) FLAIR image; (D) T1-weighted gadolinium enhanced image showing enhancing lesions [15].

1.5 Advantages of MRI in MS

MR scans have improved the ability to diagnose the disease that provides a quick start in the MS treatments. Since MRI is also a tool for following disease progression, it allows patients to make decisions about treatment options based on observed progression.

1.6 Limitations of MRI in MS

Even with the precision of MRI, this technique does not allow to visualize all the plaques present in the brain. Contrary sometimes, MS plaques appear on magnetic resonance imaging without showing symptoms for the patient. Therefore, magnetic resonance imaging will not be useful to confirm the disease.

1.7 Conclusion

In this chapter, we have presented some medical and technical concepts. We started with multiple sclerosis disease and its cause, symptoms and forms. Next, we talked about MR imaging and how does it work. In the end, we focused on the diagnosis and the techniques used mainly by medical imaging, particularly MRI. Although the MRI is the best way to detect MS but it is still difficult to diagnose it. So, it needs to use an automatic way which is deep learning. We are going to present deep learning in the next chapter.

Chapter 2

Deep Learning

2.1 Introduction

Artificial intelligence (AI) and machine learning (ML) are scientific fields looking for problem-solving methods but sometimes you may face complicated problems like dealing with large volumes of data and deep learning is considered as the best solution because its networks are similar to the human's brain networks.

Deep Learning (DL) has played an important role in the medical field like medical image processing, computer aided diagnosis, image interpretation, image fusion, image registration, image segmentation and the other domain like detecting objects, recognizing speech, translating languages, making decisions ...etc. The relation between the AI, ML and DL shows in the picture below Figure 2.1.

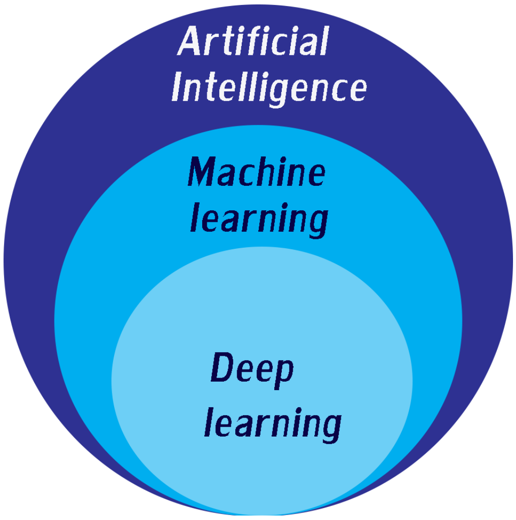

Figure 2.1: The relation between the AI and ML and DL .

In this chapter, we are going to focus on deep learning, we are going to remember the history of deep learning and why does deep learning exist. We are going to mention some applications created by DL. Then, we are going to explain the different deep learning architectures. Finally, we are going to focus on Unet architecture.

2.2 Deep learning

DL is a branch of machine learning which is a sub field of AI. DL works on teaching computers to do what comes naturally to humans: learn from experience. The deep learning system is a system based on artificial neural networks which is composed of a set of hidden layers. The word deep means the number of hidden layers (as shown in Figure 2.2 below).

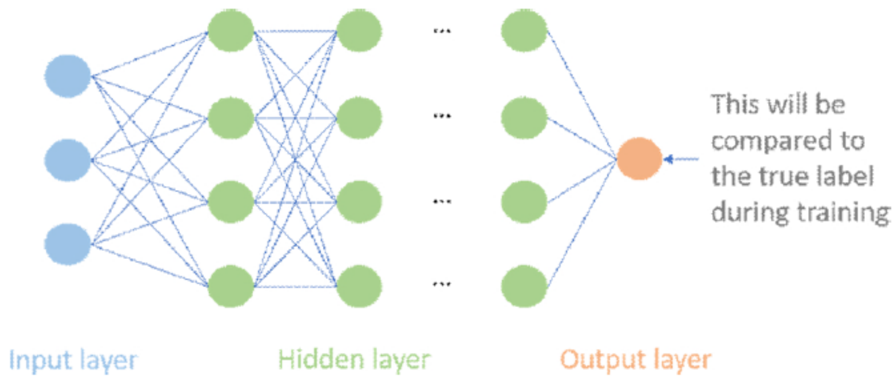

Figure 2.2: How does deep learning work [16].

The learning algorithms use computational methods to "learn" information directly from data without relying on a predetermined equation as a model. Deep learning uses convolutional neural networks (CNNs) to learn useful representations of data directly from images. Neural networks combine multiple nonlinear processing layers, using simple elements operating in parallel and inspired by biological nervous systems. Deep learning models are trained by using a large set of labeled data and neural network architectures that contain many layers, usually including some convolutional layers [16].

2.2.1 History of deep learning

years	**Contributor**	**Contribution**
300 AC	Aristotle	Introduction of associations, beginning of the history of humans trying to understand the brain.
1873	Alexander Bain	Introduction of Neural Groupings as first models of neural networks.
1943	McCulloch et Pitts	Introduction of the McCulloch Pitts (MCP) model considered as the ancestor of artificial neural networks.

1949	Donald Hebb	Considered as the father of neural networks, he introduced the Hebb Learning Rule which will serve as the Foundation for Modern Neuron Networks.
1958	Frank Rosenblatt	Introduction of the first perceptron.
1974	Paul Werbos	Introduction of back propagation.
1980	Teuvo Kohonen	Introduction of self-organizing cards.
1980	Kunihiko Fukushima	Introduction of Neocognitron, which inspired convolutional neural networks.
1982	John Hopfield	Introduction of Hopfield networks.
1985	Hilton et Sejnowski	Introduction of Boltzmann machines.
1986	Paul Smolensky	Introduction of Harmonium, which will later be known as restricted Boltzmann machines.
1986	Michael I. Jordan	Definition and introduction of recurrent neural networks.
1990	Yann LeCun	Introduction of LeNet and demonstrated the capacity of deep neural networks.
1997	Schuster et Paliwal	Introduction of bi-directional recurrent neural networks.
1997	Hochreiter and Schmidhuber	Introduction of LSTM, which solved the problem of vanishing gradient in recurrent neural networks.
2006	Geoffrey Hinton	Introduction of the Deep Belief Network.
2009	Salakhutdinov and Hinto	Introduction of Deep Boltzmann Machines.
2012	Geoffrey Hinton	Introduction of AlexNet which won the ImageNet challenge.
2014	Ian Goodfellow	The birth of Generative Adversarial Neural Network also known as GAN.

2016	Google DeepMind's	Deepmind's deep reinforcement learning model beats human champion in the complex game of Go.
2019	Yoshua Bengio, Geoffrey Hinton, and Yann LeCun	They win Turing Award 2018 for their immense contribution in advancements in area of deep learning and artificial intelligence.

Table 2.1: The summary of the deep learning history [17][18].

2.2.2 Why deep learning?

Over the past few years, The machine learning algorithms described in the first part work well for a wide variety of problems but ML has failed to solve a variety of problems of AI such as voice recognition and object recognition. So, it has emerged the different algorithms of deep learning :

- Development of traditional algorithms in such a task of AI.
- Automatically extracts characteristics, The deep learning algorithms have the feature extraction step. In traditional ML algorithms feature extraction is done manually.
- To develop a large amount of data such as big data, the more data provided the greater the performance of a deep learning algorithm.
- Adapt to any type of problem.
- It gets its results faster.

2.2.3 Deep learning application examples

Deep learning is used in many areas such as :

(a) **Face recognition :** DL algorithms will learn to detect on image the eyes, the nose, the mouth. . . etc. By first giving a certain number of images to the algorithm. Then, through training the algorithm will be able to detect a face on an image. Recently, DL algorithms have achieved promising results in face recognition [19].

(b) **Automatic machine translation :** Automatic translation has existed for a long time which phrases given in one language are automatically translated into another language. But deep learning provides the best results in two area:

- Automatic text translation.
- Automatic translation of images.

Text translation could be performed without any prior processing of the sequence, allowing the algorithm to learn the dependencies between words and their correspondence with a new language [19].

(c) **Photo descriptions :** The objective is to describe every existing element in a photograph. Firstly, we have to detect objects in photographs. Then, we have to generate labels for these objects, and the next step is to turn these labels into a coherent sentence description. Generally, for the detection of objects on photographs we involve very large convolutional neural networks after that a network of recurring neurons to transform labels into a coherent sentence.

(d) **Sentiment analysis :** Sentiment analysis is the process of understanding/ analyzing people's sentiments through natural language processing, text analysis, and statistics. For example, they used neural network architectures on tweets. It has given a very good results.

(e) **Self driving cars :** It teaches a computer to understand certain important parts of driving using digital sensor systems instead of the human. To do this, companies usually start by training algorithms using a large amount of data. It is like a children learn through constant experiences and replication.

(f) **Voice search and voice assistants :** The most popular use of DL is voice search and intelligent voice assistants. Voice assistants can be found on almost all smartphones. Apple's Siri has been on the market since October 2011. Today, Google is a voice assistant for Android. The latest smart voice assistants is Microsoft Cortana [19].

2.2.4 The different architectures of deep learning

Nowadays, deep learning is a fast-growing technique which has a lot of new architectures or algorithms. The following Figure 2.3 represents the different architectures of deep learning.

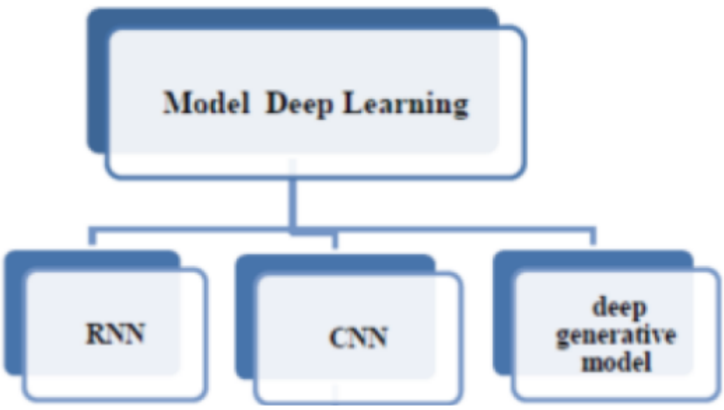

Figure 2.3: Architecture of deep learning [20].

2.2.4.1 Convolutional Neural Networks (CNN)

A convolutional neural network is a type of neural network which has a topology like a grid and its networks are similar networks of the human's brain. Until now, It is most often applied to image processing problems, also used in natural language processing.

CNN has two distinct parts. In the input, an image is provided as 2 dimensions matrix of pixels for a grayscale image and 3 dimensions matrix of pixels for a color image (Red, Green, Blue).

The first part of a CNN is the convolutive part. It works as an extractor of image characteristics. An image is passed through a succession of filters, or convolution kernel for creating new images called convolution maps. Some intermediate filters reduce the resolution of the image. Finally, convolution maps are concatenated into a vector of characteristics, called CNN code.

The output of the convolutive part "CNN code" is the input of a second part. The main role of this part is to combine the characteristics of the CNN code to classify the image. The output is a final layer with one neuron per category.

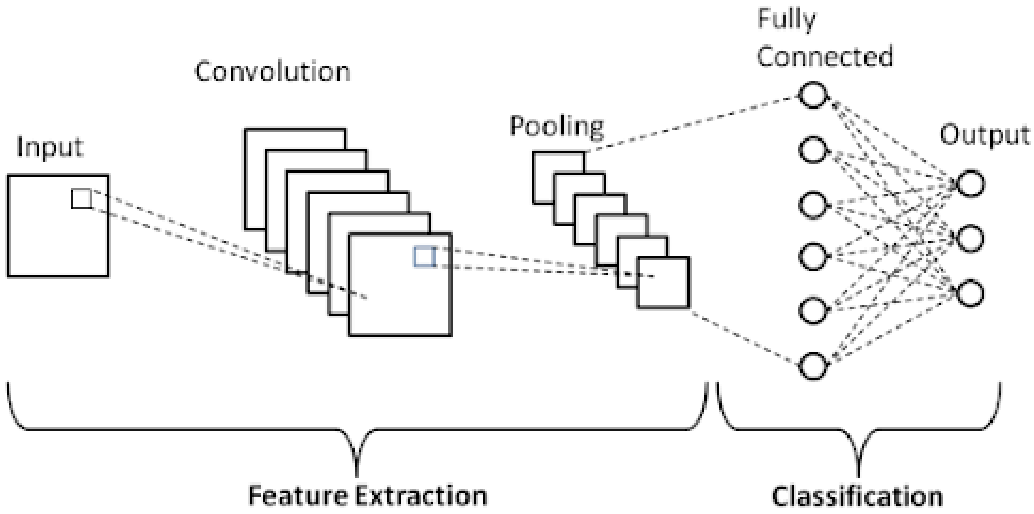

Figure 2.4: Convolutional neural network [21].

The different layers of CNN

There are four main layers in CNN. As we show in the following Figure 2.5 :

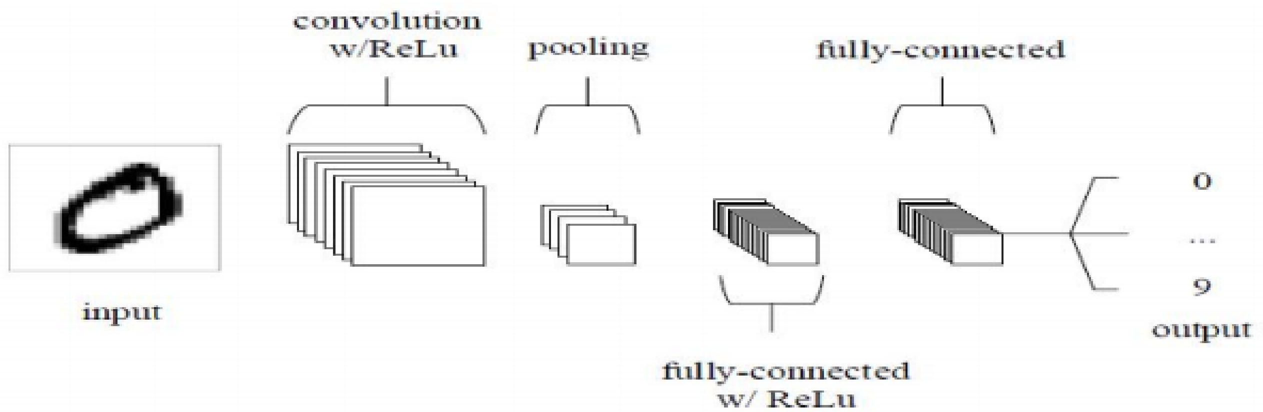

Figure 2.5: CNN layers [22].

1- Convolution Layer : is the most important layer and usually the first layer for CNN. There are three main elements that enter into the convolution operation :

- Input image.
- Feature detector (filter).
- Feature map (output).

A convolution takes an image and a filter as an input and applies calculations. In the end we return a new image called activation map, or feature map.

The activation map values are calculated using the following formula:

$$G[m;n] = (f * h)[m;n] \text{ [22].}$$

$\boldsymbol{f}$ is the input image.

$\boldsymbol{h}$ is its filter.

$\boldsymbol{m}$ and $\boldsymbol{n}$ values are indices used to scroll through the image.

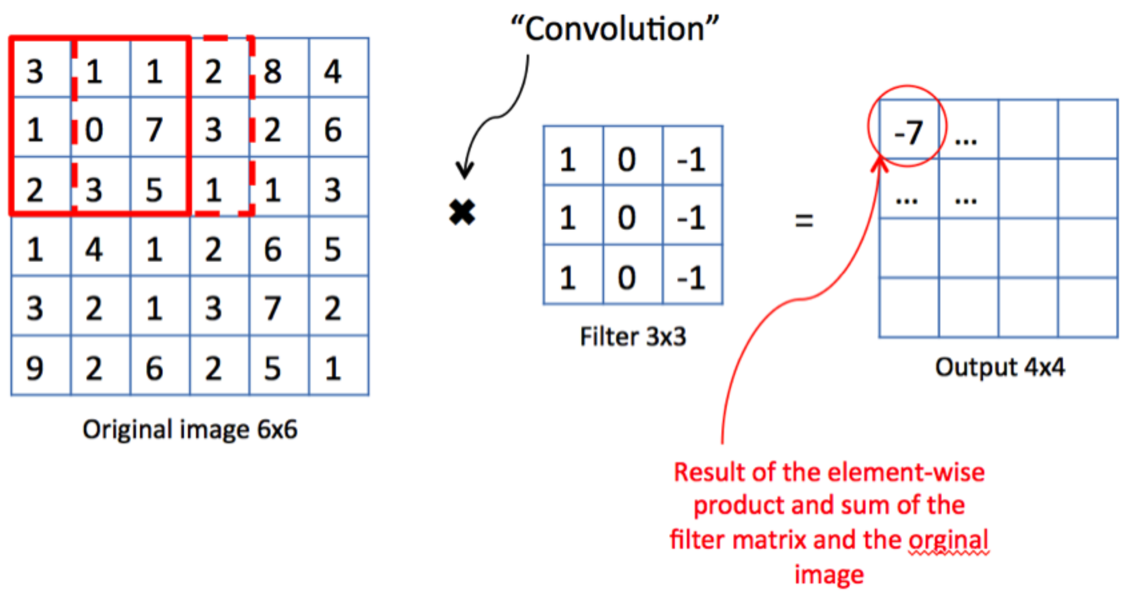

Figure 2.6: Convolution layer [22].

2- Correction Layer (ReLU) : is a mathematical function (activation function) used after each convolution operation for improving the efficiency of processing. It replaces all negative pixel values to zero. The Relu function formula is :

$$f(x) = max(0;x)$$

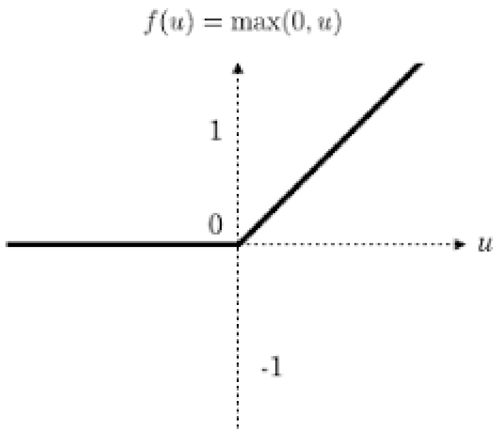

Figure 2.7: Correction layer ReLU [23].

There are several activation functions like correction by sigmoid function, correction by hyperbolic tangent and correction by the hyperbolic saturating tangent. But, Relu would be preferable because the results of Relu in neural networks are faster than the other functions.

3- Pooling Layers : reduce the size of the image to keep only the most important information and the important features. There are a lot of types:

- **Max pooling**

  It takes the maximum value of patch of the feature, the output of this layer is a 2X2 matrix. Max pooling is the most used type.

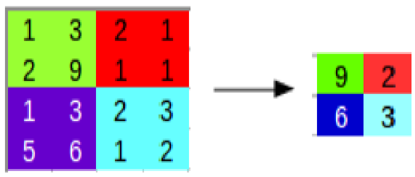

Figure 2.8: Max pooling [24].

- **Min pooling**

  It is the inverse of max pooling, that it takes the minimum value of patch of the feature.

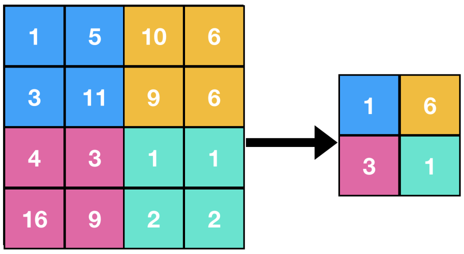

Figure 2.9: Min pooling [24].

- **Average Pooling**

  It calculates the average for each patch the feature (sum of all the values and divide by the number of values).

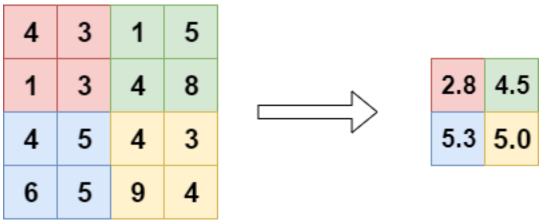

Figure 2.10: Average pooling [24].

- **Sum pooling**

  Sum of all elements in the feature map.

- **Flattening**

  After the pooling functions, we convert all the matrix to vector.

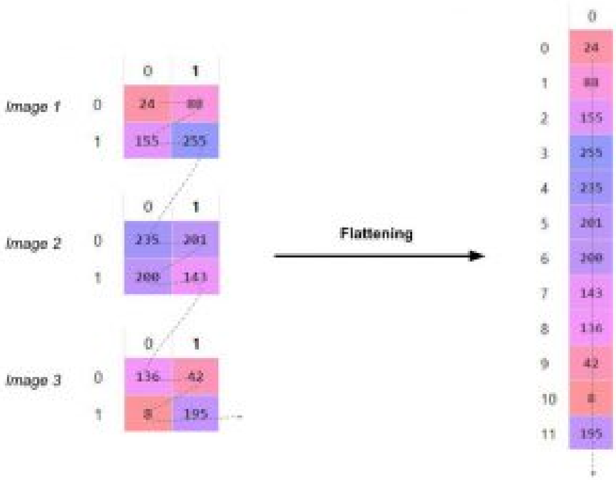

Figure 2.11: Flattening [24].

4- Fully Connected Layer (FC) : after the convolution and pooling layers, the high-level reasoning in the neural network is done in fully connected layers. The output of flattening is the input of FC layers which are the same as artificial neural networks and carry out the same mathematical operations. The last fully-connected layer uses an activation function such as sigmoid or softmax to get probabilities of the outputs.

2.2.4.2 Recurrent Neural Network (RNN)

They are the most powerful and well-known subset used to recognize patterns in sequences of data and suited to processing time-series data and other sequential data. They add the concept of recurrent connections. The recurrent neural networks take as input the current input, and add time and sequence into account, we can say that they got a new dimension "temporal dimension".

RNN is a good solution for many problems like text processing, speech recognition, language modeling...etc. The architecture of recurrent neural network is presented in the Figure 2.11 below:

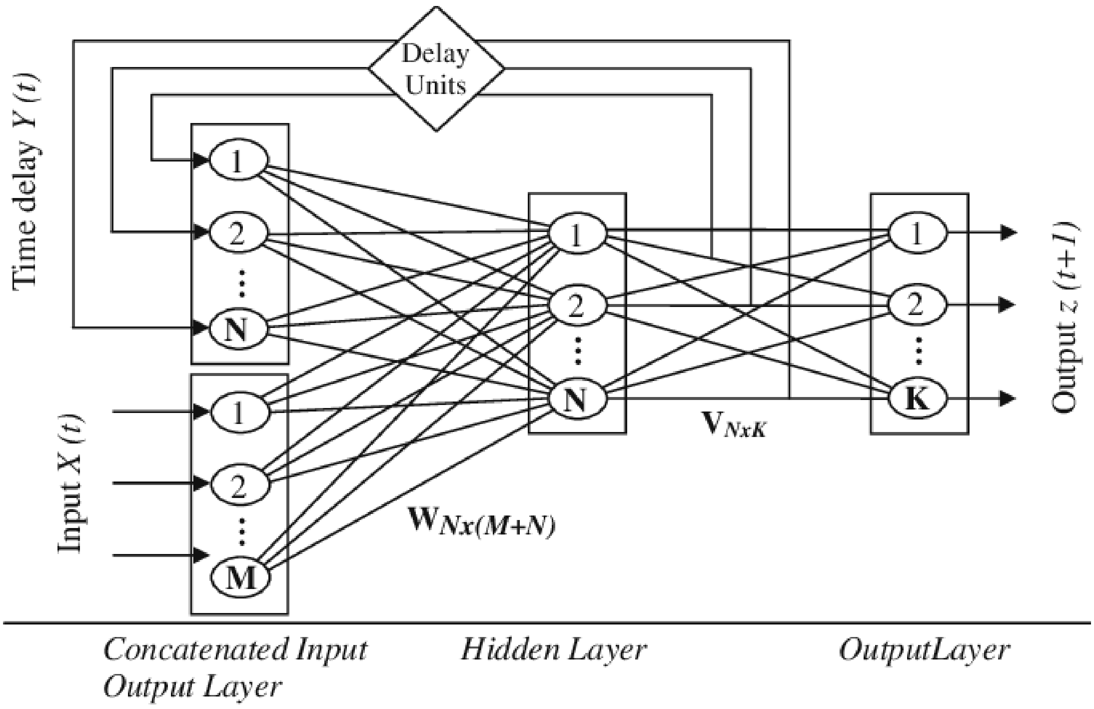

Figure 2.12: A typical architecture of recurrent neural network [25].

2.2.4.3 Deep Generative Model

The generative model describes how to generate the data, it learns and makes predictions using the Bayes law. Some examples of generative models such as: Deep Belief Network, Boltzmann Machines, Generative Adversarial Networks Generative Stochastic Networks.

2.2.5 Hardware used in deep learning

Execution environment: Hardware for network drive: 'CPU', 'GPU', 'Multi-GPU' and 'Multi-CPU'.

. **CPU (Central Processing Unit)**

It is the central processor of the computer. The CPU is responsible for all of the calculations. It is able to do many different tasks.

. **GPU (Graphics Processing Unit)**

It is the processor that equips the graphics card, The GPU only does graphical calculations. It displays pixels, textures and shapes on the screen, as well as video processing.

Training with a GPU is faster than a CPU.

2.3 Unet architecture

The typical use of convolutional networks is on classification tasks, where the output to an image is a single class label. However, in many visual tasks, especially in biomedical image processing, the desired output should include localization, segmentation and classification. A class label is supposed to be assigned to each pixel [26]. So, Unet is the most architecture used for biomedical image segmentation (semantic segmentation). It proposed in 2015. It is called U-net because it is like U. The picture below is the architecture of U-Net from the original paper.

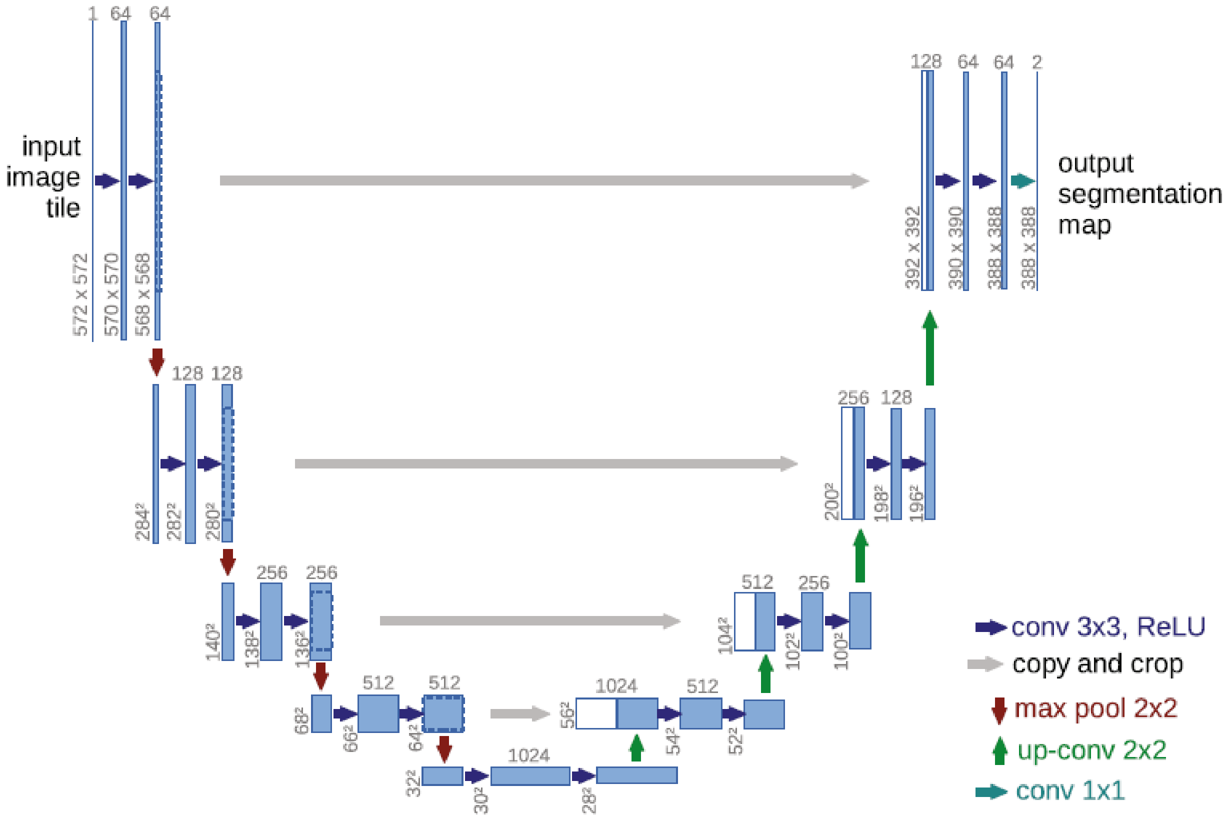

Figure 2.13: The architecture of U-Net [26].

The details of each layer are described up in the part of "The different layers of CNN"

2.3.1 Network architecture

The network architecture is illustrated in Figure 2.13 which comprises of two paths : a contracting path (left side) and an expanding path (right side).

- **Input images**

  It contains image data that has following dimensions : [width x height x depth]. It is a matrix of pixel values.

- **The contracting path**

  It is a typical convolutional network as used in image classification, it based on repeated application of convolution and pooling operations which gives us feature maps spatially smaller to classify better which is the input of expanding path.

- **The expanding path**

  It takes the small feature maps through a series of up-sampling and up-convolution steps to return to the original image size. And to segment or localize better it also uses skip connections by concatenating the upsample representations at each step with the corresponding feature maps at the contraction pathway.

2.3.2 Data augmentation

Data augmentation is essential to teach the network the desired invariance and robustness properties, when only few training samples are available. In case of microscopical images we primarily need shift and rotation invariance as well as robustness to deformations and gray value variations. Especially random elastic deformations of the training samples seem to be the key concept to train [26].

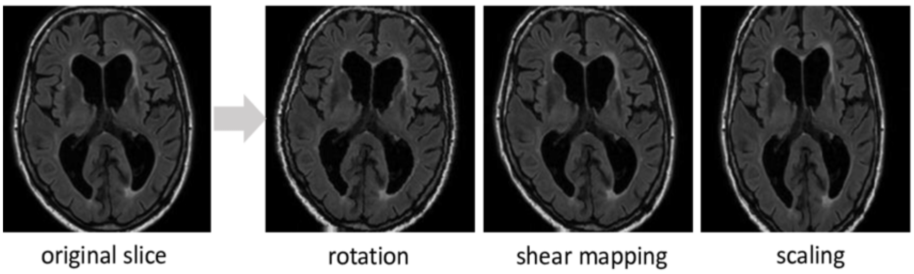

Figure 2.14: Data augmentation example [27].

2.3.3 Why UNet?

- It has a great work efficiently on small datasets through heavy data augmentation.
- It works for binary as well as multiple classes.
- It is scale-invariant because we can make up a lot of models.
- It can be used in a multitude of applications like object detection or segmentation.

2.4 Conclusion

In this chapter, first we have gotten what is deep learning, and why we choose deep learning. Then, we mentioned some deep learning applications in our life. We also talked about the three major models of deep learning, Convolutional neural networks, Recurrent neural network and Deep generative model. Finally, we showed Unet architecture. As we said Unet has many visual tasks like localization, classification and segmentation. In this work, we focus on image segmentation. So, what is image segmentation?. In the next chapter, we are going to talk about image segmentation and state of the art on the methods of segmentation of multiple sclerosis.

Chapter 3

State of the art on multiple sclerosis segmentation methods

3.1 Introduction

Segmentation algorithms have played an important role in the real world, especially in the medical images because there are several techniques to take medical images like MRI, CT and X-rays.

The detection of an object is to identify the location of an object in the image and to make a boundbox on the object. But, In the segmentation you can see the shapes of all the objects. In the image below Figure 3.1 we present the difference between object detection and segmentation.

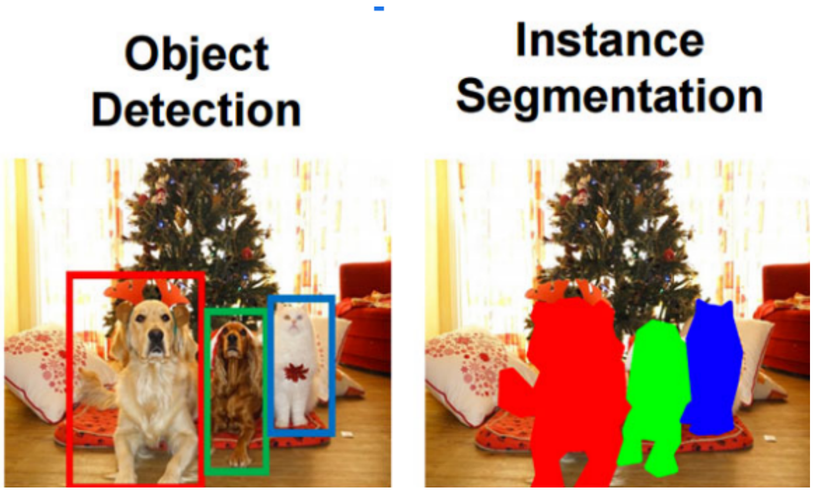

Figure 3.1: The difference between segmentation and detection [28].

Specialists try to use different techniques for segmenting multiple sclerosis (manually) but it is very difficult to segment or detect MS in MR images, it needs a radiologist who has experience but it may make mistakes and errors in their diagnosis. Currently, there are a lot of projects which are working in segmentation and detection of MS using deep learning with RM images. Based on that, researchers are heading to deep learning because it has a great performance in image segmentation and detection, due to their self-learning and ability to use a large amount of data.

Automatic segmentation of MS lesions in brain MRI has been widely investigated in recent years with the goal of helping MS diagnosis and patient follow-up. These plaques of demyelination are typically observed in MRI with different contrasts depending on the image sequence [29].

In this chapter, Firstly we are going to see what image segmentation is?. After that, we are going to provide a review on some of the recent state of the art works related to the segmentation of MS and the methods used. Finally, we are going to show the most deep learning models used in MS segmentation.

3.2 Image segmentation

It can be defined as a specific image processing technique which is used to divide an image into two or more meaningful regions. There are two major types of image segmentation : semantic segmentation and instance segmentation.

. **Semantic segmentation** cannot make deference between two instances of the same object.

. **Instance segmentation** attributes a single label to each instance of the same object

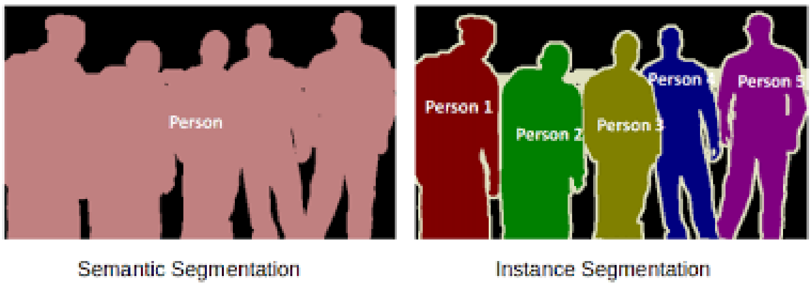

Figure 3.2: The difference between semantic segmentation and instance segmentation [28].

3.3 Multiple Sclerosis dataset

Over the last ten years, many researchers have focused on the segmentation and classification of MS on MRI. But, the main problem we had faced in this project is the collection of data because the production of such a gold standard dataset is a difficult and laborious enterprise, often beyond the capability of each individual research team. We found certain dataset like:

- MR simulator called BrainWeb (Cocosco et al. 1997) enables the creation of synthetic images of T1w, T2w and PDw MR sequences [30].
- Dataset of clinical MR images was created for the purpose of a challenge on MS lesion segmentation (Styner et al. 2008). The dataset consists of 52 cases of MS patients imaged with conventional brain MR sequences T1w, T2w and FLAIR on two 3T Siemens scanners [31].
- The most recent challenge on MS lesion segmentation (Barillot et al. 2016) provides 53 datasets from 4 different sites and 4 different 3T/1.5T MRI scanners. Each set contains FLAIR, pre-contrast and post-contrast T1w and DP/T2w sequences [32].
- MR Image Dataset of multiple sclerosis patients with lesion segmentation based on multi-rater consensus provides 30 MS patients. Each patient's MR scans consisted of a 2D T1-weighted, 2D T2- weighted and 3D FLAIR image [33].

- MS dataset of eHealth laboratory was provided by the University of Cyprus eHealth Laboratory for scientific studies [34]. The MR images in the dataset were acquired using a T2-w sequence.

3.4 Related work

Due to the manual segmentation of MS lesions by experts takes a lot of time and is tiring. Many researchers have contributed to the segmentation of MS from MR images. The most promising work uses deep learning models. The methods and results of the most recent work are summarized in the following table:

Reference	Database	MRI sequences	Methodology	Evaluations
Maleki et al [35].	Their own dataset	Flair MR images	classification of MS lesion via CNN	The network performance was evaluated by sensitivity, specificity and accuracy it achieved : Sensitivity= 96.120, Specificity= 97.578, Accuracy= 92.933. Evaluations were limited to lesion detection only.
Brosch and al [36].	MS lesion segmentation challenge 2008	T1-w, T2-w, FLAIR	Segmentation of MS lesions using deep convolutional encoder networks	They evaluated their method on the challenge data set using Dice similarity coefficient (DSC) between the predicted segmentation and the resampled ground truth: DSC=35.52. Detection performance can be increased.

Brosch and al [37].	MICCAI 2008 and ISBI 2015	T1-w, T2-w, FLAIR	MS lesion segmentation via deep 3D convolutional encoder networks with shortcuts for multiscale feature integration	They evaluated their method on the challenge data set using Dice similarity coefficient (DSC) between the predicted segmentation and the resampled ground truth: DSC=68.3. Detection performance can be increased.
Birenbaum and Greenspan [38].	ISBI 2015	T1-w, T2-w, FLAIR	MS lesion segmentation using multiview longitudinal CNN	They evaluated their method on the challenge data set using Dice between the predicted segmentation and the resampled ground truth Dice=0.627. But, the dataset is limited to only 5 patients.
Gabr and al [39].	Their own dataset	3D T1-w, T2-w, PDw, 2D FLAIR	lesion segmentation in MS using fully convolutional neural network	They evaluated by DSC values which was 0.82. The results can be compared with different methods.
Valverde and al [40].	MICCAI 2008	T1-w, T2-w, FLAIR	a novel automated MS lesion segmentation with a cascaded 3D CNN	They evaluated their method on the challenge data set using DSC which was 56.0
Zhang and al [41].	eHealth, their own dataset (private)	T2-w	MS lesion identification using an improved CNN based on parametric ReLU and dropout	Their method achieved a sensitivity of 98.22%, a specificity of 98.24%, and an accuracy of 98.23%. Evaluations were limited to lesion detection only.

Mehmet Süleyman Yıldırım1, Emre Dandıl2 [42].	UMCL MS dataset for MS lesion detection and eHealth	T1-w, T2-w, FLAIR, PD-w	Automatic detection of multiple sclerosis lesions using Mask R-CNN on magnetic resonance scans	Their method achieved a Dice= 84.90%
Mostafa Salem [29].	Their own dataset	T1-w, T2-w, PD-w, and FLAIR	A fully convolutional neural network for new T2-w lesion detection in multiple sclerosis	Their method achieved a Dice similarity coefficient of 0.83.

Table 3.1: Related work on MS.

3.5 Used methods in the segmentation of multiple sclerosis

Since, there are alot of methods to segment MS from MR images using deep learning. In this part, we chose three methods which showed good results. As following, we show :

3.5.1 Mask Region-Based Convolutional Neural Network (Mask RCNN)

It created in 2017 is basically an extension of Faster RCNN. Faster RCNN used for object detection tasks and segmentation tasks. It is used in image processing which returns the class label and bounding box. So let's first understand how does Faster RCNN work. This will help us to understand Mask RCNN as well.

Faster RCNN :

- Extract feature maps from the images used a ConvNet.
- Then, those feature maps pass in a Region Proposal Network (RPN), it returns the candidate bounding boxes.
- Next, we apply an RoI pooling layer on these candidate bounding boxes, for get the same size of those candidates.
- And in the end, the proposals are passed to a fully connected layer this step are return the bounding boxes for objects.

Now let's understand **Mask RCNN** step by step :

- **Backbone Model :** In this step, it used RestNet 101 architecture for extract features. It is like ConvNet in the Faster R-CNN.
- **Region Proposal Network (RPN) :** Now, we take the feature maps and apply a region proposal network (RPn). This step predicts if the present object or not. In this step, we get those regions or feature maps which the model predicts contain some object.
- **Region of Interest (RoI) :** In this step we convert all the regions obtained from the (RPN) to the same shape, we apply a pooling layer. Then, the regions are passed through a fully connected network and it returns the predict class label and bounding boxes. For all the predicted regions, we compute the Intersection over Union (IoU) with the ground truth boxes. We can computer IoU like this:

$$IoU = \frac{Area \quad of \quad the \quad intersection}{Area \quad of \quad theunion}$$

Now, only if the IoU is upper or equal to 0.5, we consider it as a region of interest.

The Figure 3.3 shows how does Mask R-CNN work.

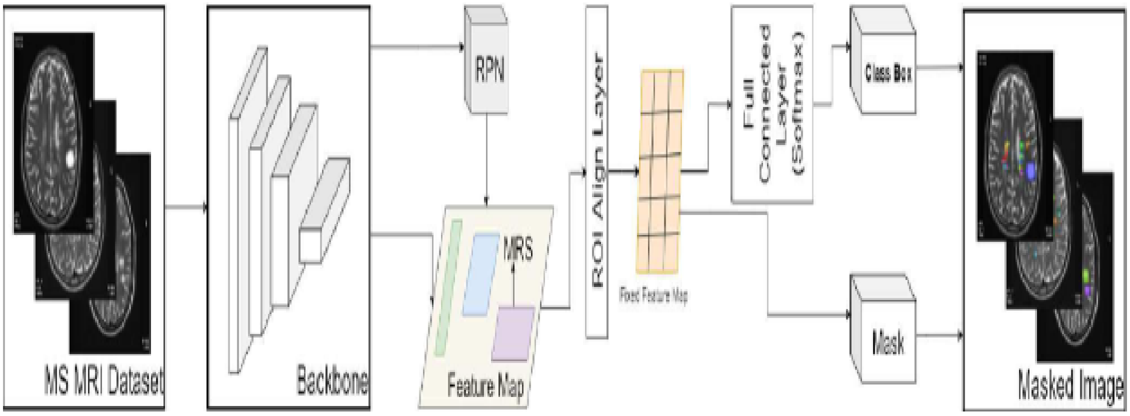

Figure 3.3: Mask RCNN [42].

3.5.2 3D Convolutional Neural Networks (3D CNNs)

3D Convolutional Neural Networks (3D CNNs) applies a 3 dimensional filter to the dataset and the filter moves 3-direction (x, y, z) to calculate the low level feature representations. Their output shape is a 3 dimensional volume space such as cube or cuboid. They are helpful in event detection in videos, 3D medical images etc. They are not limited to 3d space but can also be applied to 2d space inputs such as images. With three-dimensional convolutional layers. Instead of three dimensions in the input image (the two image dimensions and the channels dimension, you will have four: the two image dimensions, the time/height dimension, and the channels dimension). As such, the feature map is also three-dimensional. This means that the filters move in three dimensions instead of two: not only from left to right and from the top to the bottom, but also forward and backward. Three-dimensional convolutional layers will therefore be more expensive in terms of the required computational resources.

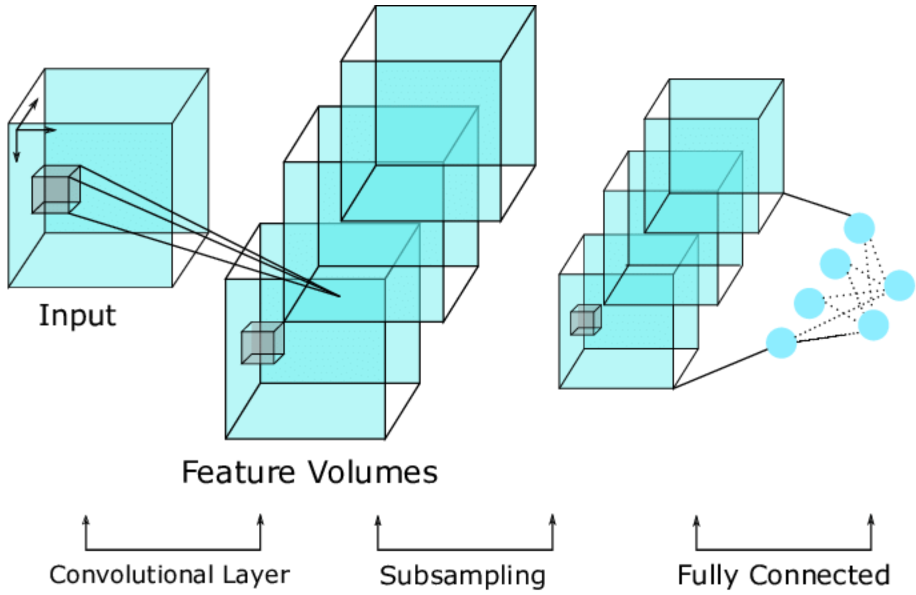

Figure 3.4: 3D CNN [43].

3.5.3 Fully Convolutional Network (FCN)

A Fully Convolutional neural network (FCN) Created in 2015 which is a normal CNN. It is supervised learning. So, It needs a dataset in the input. It has used for semantic segmentation. It uses both forward decomposition and backwards decomposition.

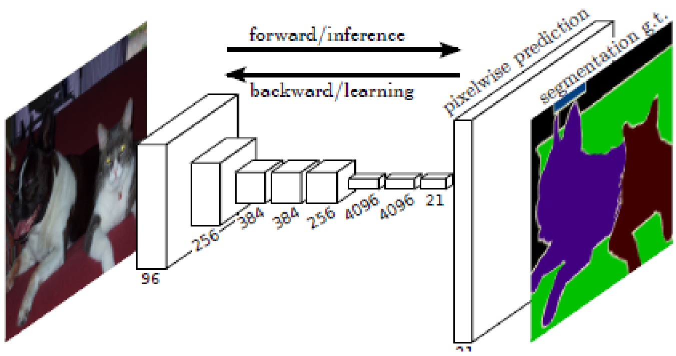

Figure 3.5: Fully convolutional networks [39].

Network that does not contain any "Dense" layers (as in traditional CNNs) instead it contains 1x1 convolutions that perform the task of fully connected layers (Dense layers) step by step how FCN working :

- CNN shrinks features to shape of 1* 1* Channel.

- Upsampling outputs the semantic segmentation mask E.g: Transposed Convolution.
- Applying softmax at the end for pixel classification.

3.6 Conclusion

In this chapter, we have understood what image segmentation is?. We talked also about multiple sclerosis dataset and we mentioned some related work. Finally we talked about the most used deep learning MS segmentation models.

In the next chapter, we are going to talk about our proposed approach. We are going to explain used tools and method and showing dataset used and configuration. Finally we are going to see the result and evaluation.

Chapter 4

Contribution

4.1 Introduction

MS diagnosis from MR images is a vital task and often performed manually. For this, automatic segmentation methods have been developed in order to avoid laborious and long manual work while it gives a fast and reproducible result.

Nowadays, deep learning is the best choice for an automatic segmentation which is developing with more sophisticated and complex architectures. And with the difficulty to form a great model with datasets available in the medical field due to their limited size and the lack of ground truth segmentation. There is a strong need to fix the problem of MS segmentation with simple and powerful architectures. To achieve this goal, we are going to present in this chapter a deep learning model based on Unet architecture that takes an MR images as input and produces its corresponding segmentation mask as the output.

4.2 Proposed approach

In our work to create a deep learning model, we have passed a lot of steps and tasks. First, we were collecting data (dataset) and preprocessing it with data augmentation. After that we created the model then we did the training and evaluation of the model and finally the prediction as we show in Figure 4.1.

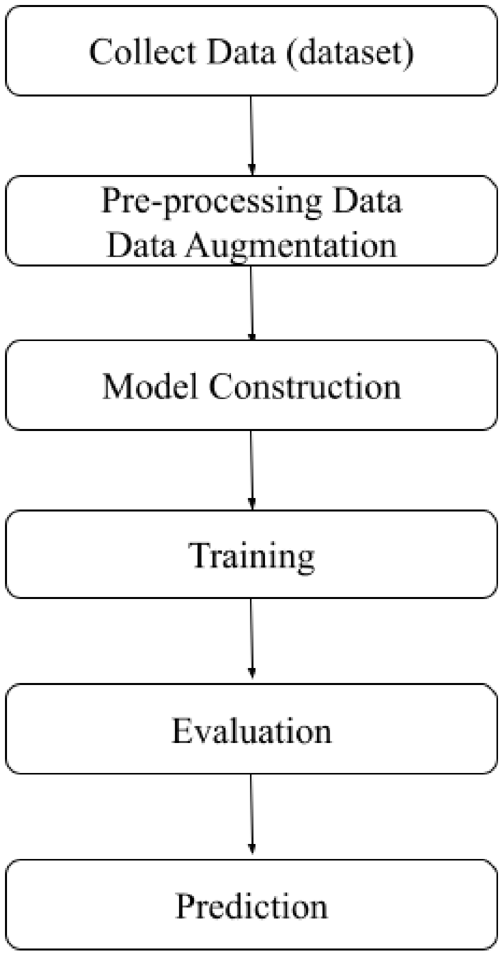

Figure 4.1: General architecture of our proposed approach.

4.2.1 Collect data

In this work, it has been a big challenge to collect data due to the limited data of MS from MRI. But, finally we used a public dataset which is MR images dataset of multiple sclerosis patients with lesion segmentation based on multi-rater consensus which provides 30 MS patients were imaged at the University Medical Center Ljubljana (UMCL) [33]. Each patient's MR scans consisted of a 2D T1-weighted, 2D T2- weighted and 3D FLAIR image. We choose to work with T2-weighted MR sequences because this type of sequence improves the MS visualization. The Figure 4.2 below shows some slices of the images used with their corresponding segmentation masks.

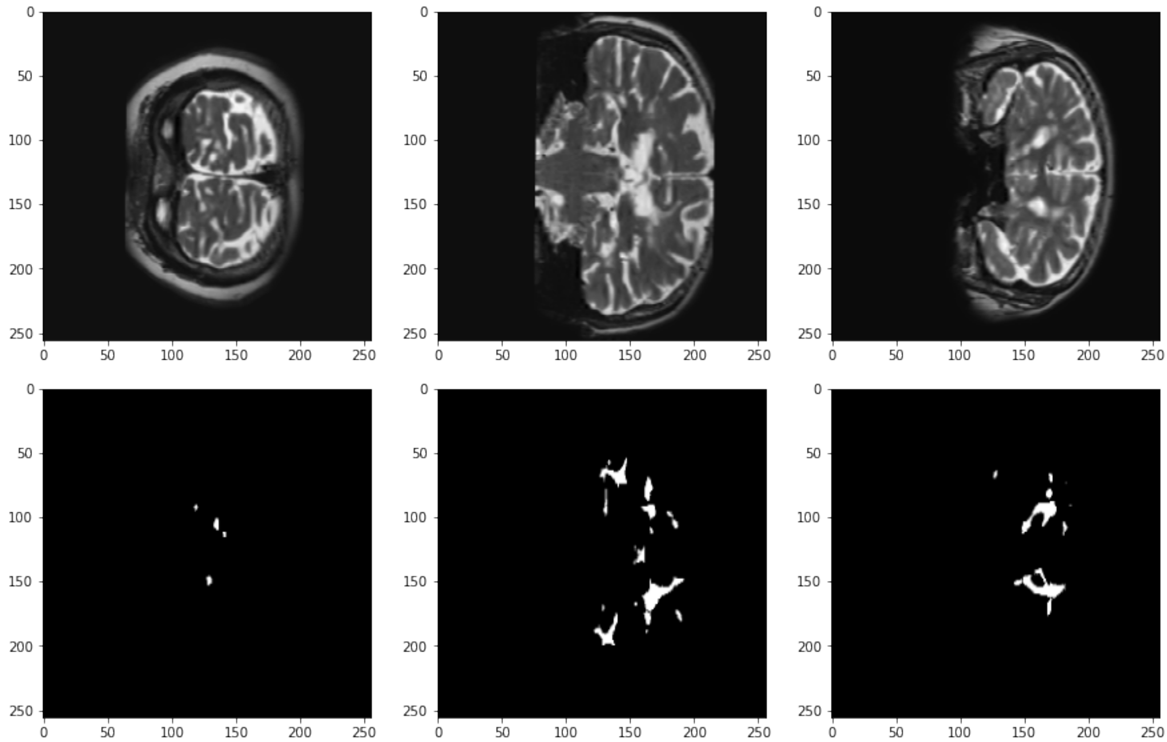

Figure 4.2: T2-weighted MR axial slices with their corresponding segmentation masks.

4.2.2 Image pre-processing and data augmentation

The images set in our dataset contains 30 three-dimensional MR volumes T2-weighted. Initially, all T2 have the size of (256 * 256) with a slice number equal to 512. So, the pre-treatment is required for our model.

Firstly, We have normalized and readjusted the size of all images to use them with the deep learning model to (128 * 128). After that, In order to augment the dataset, we transformed each image by rotation, shift and horizontal flip.

In addition, all the segmentation masks have been a similar preprossissing that we have normalized and readjusted the size of all them to (128 * 128). Moreover, we have transformed each image mask by rotation, shift and horizontal flip to augment the dataset.

4.2.3 Proposed Unet architecture for segmentation

In this work, we propose a semantic segmentation model which segments image pixel by pixel. Semantic segmentation allows to give the segmentation mask for each input image. Therefore, we use a Unet architecture which shows in the Figure 4.3 below.

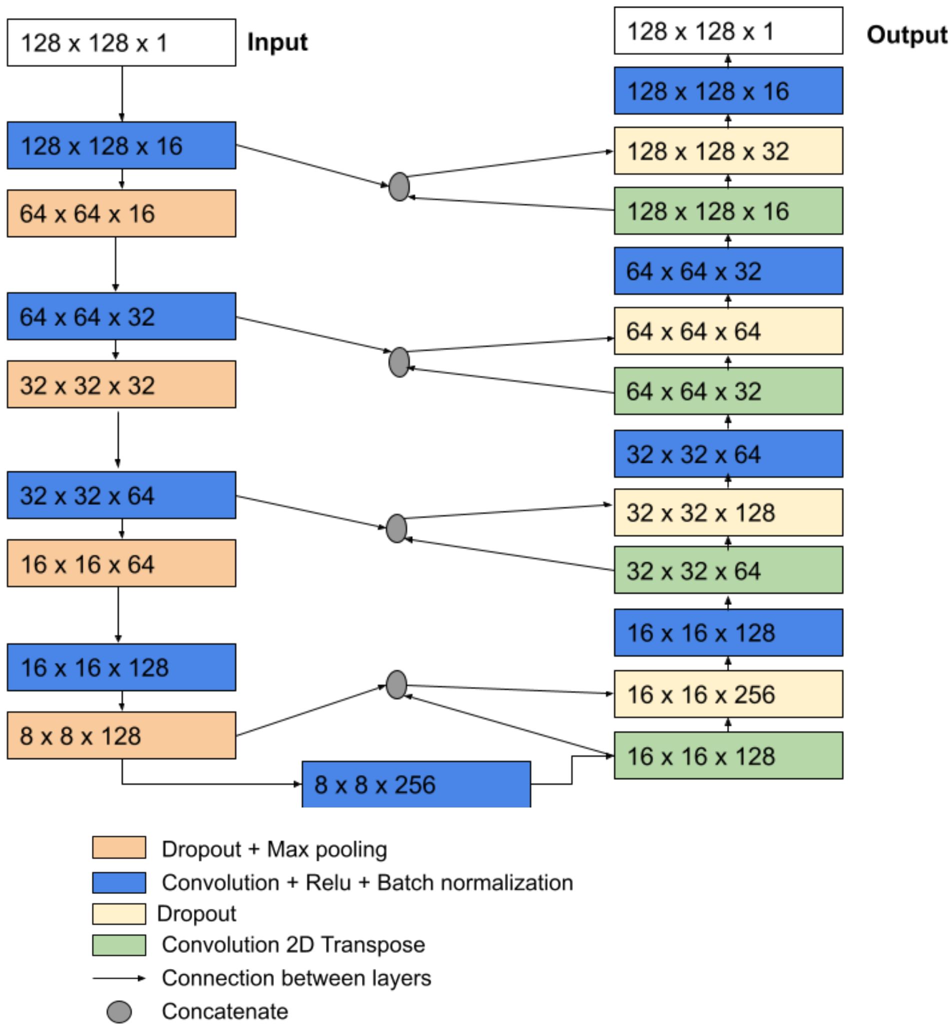

Figure 4.3: Unet model proposed for the segmentation of Multiple Sclerosis.

As we talked in chapter 2 about Unet. We have two parts : the contracting path in the left in the other side (right) the expanding path.

4.2.3.1 The contracting path

It consists of several convolutions layers which are extracting more specific characteristics to the image that upgrade from low-level representations in first convolutions to high-level representations in deep convolutions. We are augmenting the number of convolution filters to extract the necessary characteristics in the image "Feature Map".

The contracting path consists of 5 convolution layers with the ReLU activation function and normalization layer which are following by dropout layers and the max pooling layer is an operation that reduces the image size.

Dropout a simple way to prevent neural networks from overfitting.

Batch Normalization is a layer that allows every layer of the network to do learning more independently. It is used to normalize the output of the previous layers.

Relu used after each convolution operation for improving the efficiency of processing. It replaces all negative pixel values to zero.

4.2.3.2 The expanding path

The expanding path takes the feature map of the contracting path and processes them with successive convolutions and convolutions transpose to reproduce the same resolution of the input images and at the same time create segmentation maps.

In this part, we have 4 convolutions transpose that allow to resize up the image size and 4 convolution with the ReLU activation function and normalization layers that reduce depth. between these layers there are dropout layers.

4.2.3.3 Connection between layers

We may lose detail of features in the extraction because we have a deep convolutional network. In the expanding path the network can connect to the contracting path with concatenation operations that connect the output feature maps of the contracting part to the input of the convolutional layers in the expanding part. If the input of the convolutional layer of a expanding part is (32, 32, 64) and the output of the contracting is (32, 32, 64). So, the result of the concatenation is (32, 32, 128).

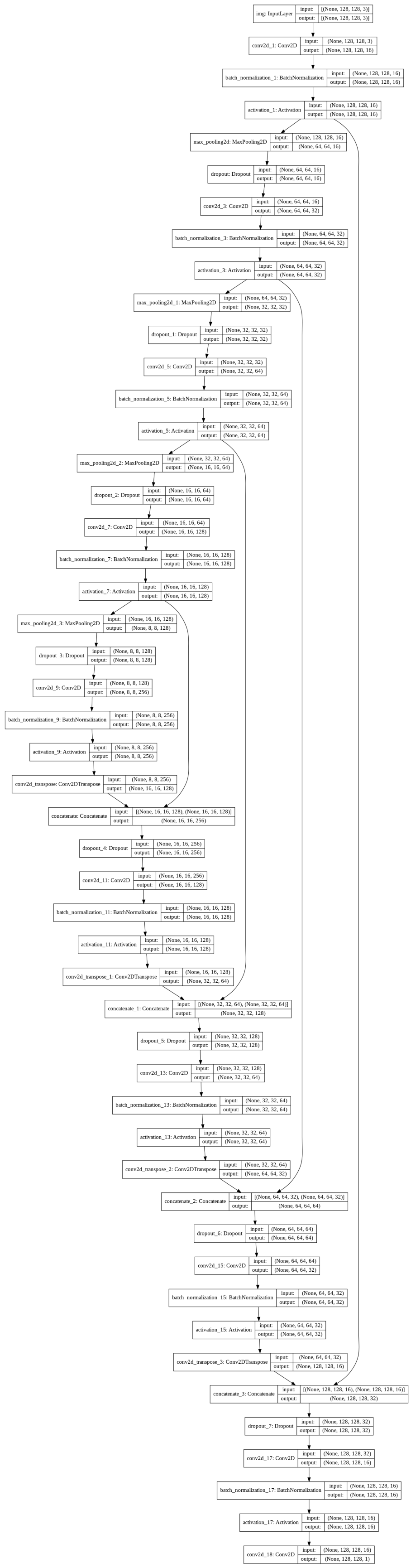

Figure 4.4: Unet model proposed.

4.2.4 Used tools

In our work, we have used some tools (hardware and software), So, we show what have we used in this section:

4.2.4.1 Software

- **Python3** is a high-level programming language, the most widely used programming language in the field of Machine Learning, Big Data and Data Science. Characterized by simplicity, ease of use and learning syntax. In this work, we used Python 3.8.5. It is the newest major version of the Python, and offers many new features and optimizations.

- **LaTex** is a high-quality typesetting system; it includes features designed for the production of technical and scientific documentation. LaTeX is the factor standard for the communication and publication of scientific documents. It is available as free software.

- **Jupyter notebook** is an open source web application that enables you to form and share documents with codes, equations...etc. This browser based tool gives the possibility to edit and execute code from the browser, with results of computations.

- **Colaboratory "Colab"** is a product of Google Research. Colab allows anyone to write and execute the Python code of their choice through the browser. It is an environment particularly suited to machine learning, data analysis and education. In more technical terms, Colab is a hosted Jupyter notebook service that requires no configuration and provides free access to computer resources, including GPUs.

We have used a lot of python libraries in this project like cv2, matplotlib.pyplot...etc. We show the most important libraries in our work such us :

- **Tensorflow-gpu 2.0.0** is an open source Python library for machine learning. It is one of machine learning frameworks released by Google Brain team used to design, build and train deep learning models.

- **Keras 2.3.1** is a high-level open-source library of neural network modules written in Python. It is the most used deep learning framework because it is easy to extend, and to work with python.

- **Numpy** (Numerical Python) is an open-source library intended to manipulate multidimensional matrices or arrays and functions, arithmetic, logical and statistical operations operating on these arrays. The Numpy library allows data to be saved in a file with the extension (.Npy).
- **Pandas** created in 2008 by Wes McKinney. It is a library written in python, used for data analysis.

4.2.4.2 Hardware

Hardware Component	**Configuration**
computer	VivoBook-ASUSLaptop X509JB-X509JB
Central Processor Unit (CPU)	intel(R) core(TM) i7-1065G7 cpu @ 1.30Ghz 1.50Ghz
Memory (RAM)	8,00 Go
Operating System	Windows 64 bits
Graphics Processing Unit (GPU)	NVIDIA GeForce MX110

Table 4.1: Configuration details of the computer used for experimental studies in this study.

4.2.5 Training and evaluation

In our proposed model we have taken 80% of the data for training and 20% for evaluation. It was formed on 30 iterations (epochs). In addition, we did our training in google colab with execution type GPU for fast results.

4.2.6 Results and discussion

Figure 4.5: Accuracy during training and evaluation step on 30 epochs.

Figure 4.5 shows Training Accuracy with Evaluation Accuracy on 30 iterations and the best model. We noted that the average of validation accuracy is 0.99 or 99% which is considered significant.

From 1 to 25 iterations : We notice that training accuracy and evaluation accuracy increase quickly into 0.9996.

From 25 to 30 iterations : We notice a slow increase in the accuracy of training and the accuracy of evaluation. Until, they reach the maximum value in the 28 epoch which is 0.9998. So, we say that there is a direct relation between training accuracy and evaluation accuracy. It is due to the increase of data that improve the network performance by producing more training data.

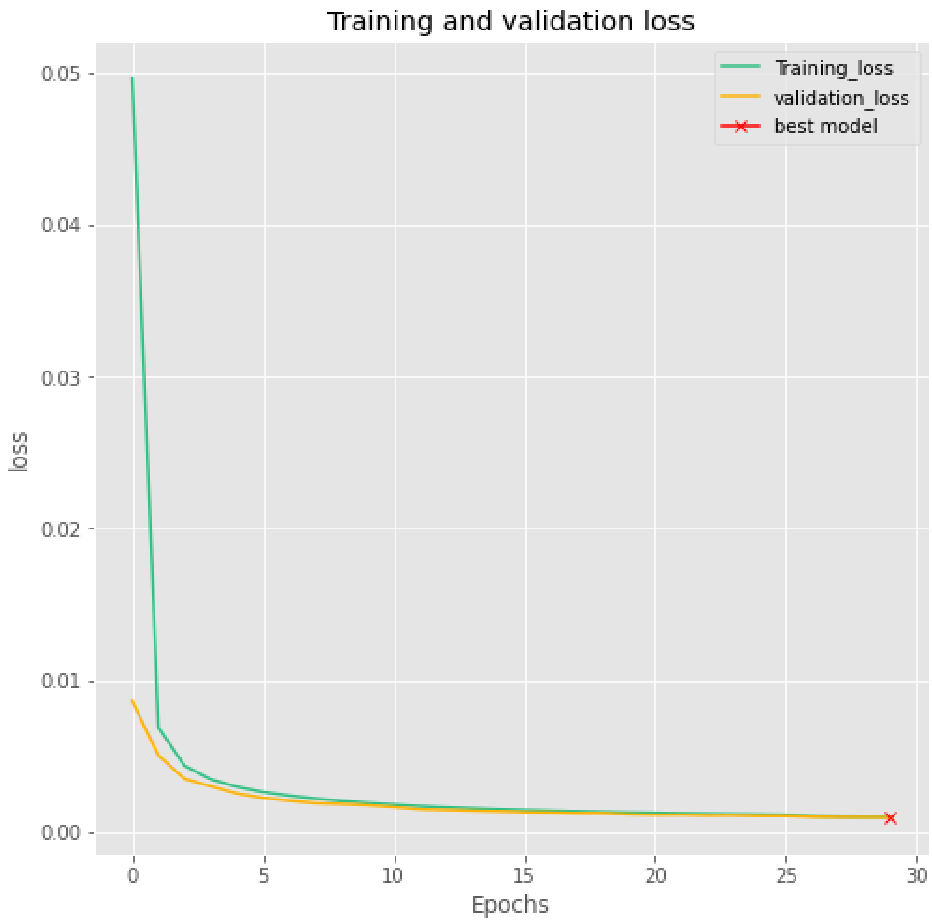

Figure 4.6: Loss of training with loss of evaluation on 30 epochs.

Figure 4.6 represents Loss of Training with Loss of Evaluation on 30 epochs and the best model..

From 1 to 10 epoch : There is a quick and strict decrease in the loss of training and the loss of evaluation from 0.05 to 0.01.

From 10 to 30 epoch : There is a slow decrease in training loss and evaluation loss. So we say that there is a direct relation between loss of training and loss of evaluation. This is due to the increase of the data to improve the network performance by generating more training data.

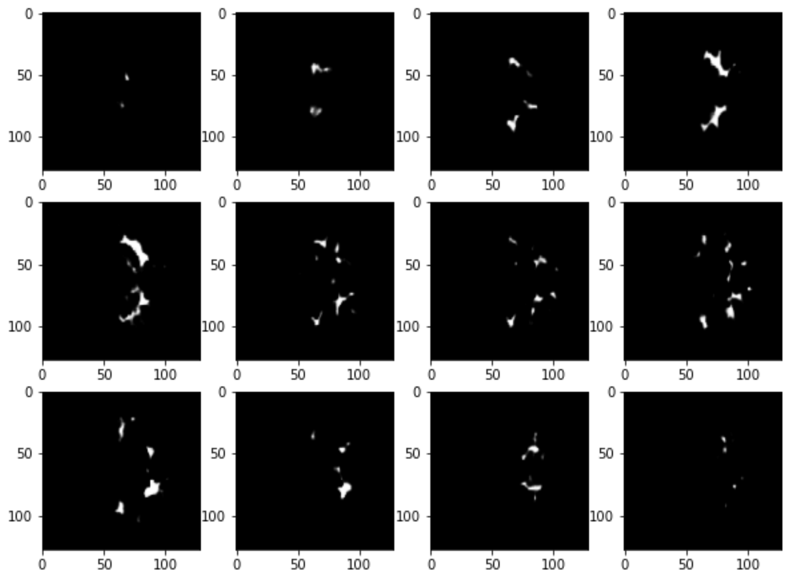

Figure 4.7: Axial slices of the result 'segmentation maps' which used our proposed method.

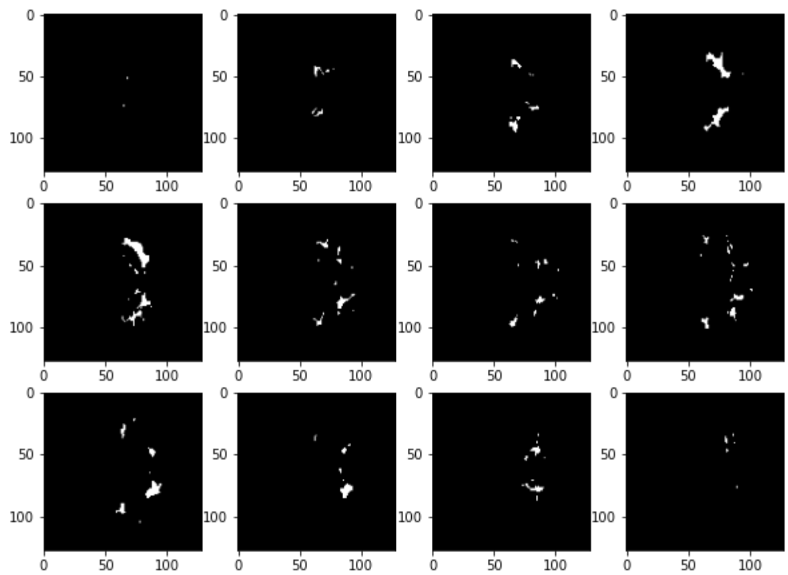

Figure 4.8: Axial slices of ground truth segmentation.

For statistical evaluation, we choose to calculate the Dice Similarity Coefficient ***DSC*** between ground truth and predicted images. the formula of the metric is:

$$DSC = \frac{2*(A \quad \cap \quad B)}{A \quad + \quad B}$$

Where:

A is the ground truth mask.

B is the segmented mask predicate.

DSC takes values in range [0 ; 1].

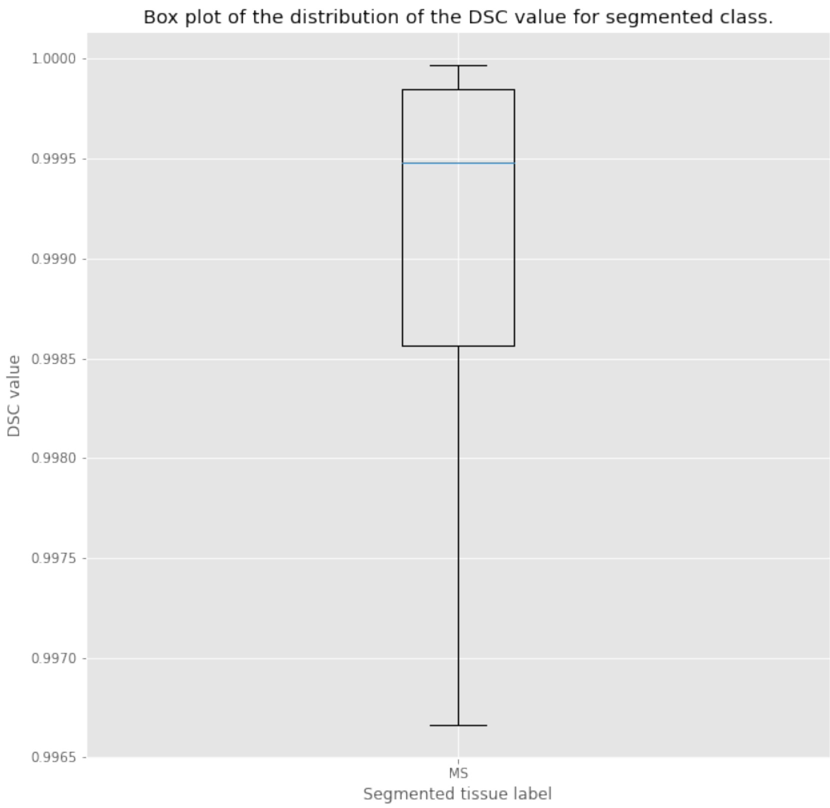

Figure 4.9: Distribution of DSC value for MS segmented class taking into account the evaluation set.

The Figure 4.9 represents the Box plot of the distribution of DSC values for MS segmented class. We notice that MS segmented class has the DSC score with a value of 0.99.

4.3 Comparison of the results

It is very difficult to compare the previous studies on the computer aided segmentation of MS lesions on MR images due to the lack of the same data, different detection and segmentation algorithms, and using different similarity metrics. However, the comparison of the results of this study with some of the previously proposed studies according to the DSC dice similarity coefficient are given in Table 4.2.

Study	**Dataset**	**Method**	**DSC, %**
Ravnik et al. [44]	UMCL	CNN	81.49
Mehmet Süley- man Yıldırım, EmreDandıl. [42]	UMCL and eHealth	Mask R-CNN with proposed ROI detection	84.90
Our proposed method	UMCL	Unet	99

Table 4.2: Comparison of the results of this study with the results of previous studies.

Table 4.2 present the comparison of the results of our study with the results of previous studies. So, we choose to calculate the Dice Similarity Coefficient between ground truth and predicted images. First, the experiment of "Ravneet and al " on the UMCL database using CNN method, they achieved DSC=81,49%. Secondly, The experiment of "Mehmet suley man Yidirim and EmreDandil " on UMCL and eHealth databases using a method call Mask RCNN. The value of DSC is 84,90 %. Finally, our proposed method on the UMCL dataset using Unet method, we found DSC=99 %. So, according to the results presented in Table 4.2, our proposed method is considered as the best method to segment MS from MR images. Based on this result, the method we propose allows us to obtain DSC = 99 %.

4.4 Conclusion

In this chapter, we have presented the architecture of our proposed Unet model which consists of the main components: The contracting path, The expanding path and connection between layers. And we showed the process of work and its steps. Then we presented the tools that helped us to implement our application, the programming language and the framework. Finally, we showed the evaluation of our proposed model which proved that our approach has shown good results that can compete with recent approaches.

General Conclusion

Medical image segmentation remains a very vast area of research because there are many diseases which are developing every time or very difficult to detect them in medical images. And multiple sclerosis is one of those diseases. The manual segmentation of MS lesions by physicians consists of subjective and time consuming procedural sequences. For this reason, automatic detection of MS using MR images is important in both terms time consuming and cost. Recently, computer-aided tools assist physicians in detecting, diagnosing and following-up MS on magnetic resonance imaging MRI.

The goal of this work has been segmenting multiple sclerosis from MR images using deep learning. Where, we first presented MS disease and medical imaging and we focused on MRI. After that, we made a literature review on image segmentation using deep learning methods. In our study we chose the Unet method in the public MS dataset for the segmentation of MS from MRI. The process of detecting MS has four fundamental phases, first we collected data (dataset). Then, we did a pretreatment and augment data with rotation, shift and horizontal flip. After that, we trained our dataset on 30 iterations. Finally, we showed the results and we evaluated our model. The results obtained after segmentation on the dataset are satisfying.

Our work is only in its initial version. We can say that it is still open for comparison and/or hybridisation work with other segmentation methods and with other dataset.

Bibliography

[1] A. Almasi-Hashiani, M. Sahraian, S. Eskandarieh, *Evidence of an increased prevalence of multiple sclerosis: a population-based study of Tehran registry during 1999–2018*. BMC Neurol, 2020.

[2] R. King, *The Multiple Sclerosis International Federation*. Atlas of MS, September 2020.

[3] C.L. Gooch, E. Pracht, A.R. Borenstein, *Burden of neurological disease in the United States: a summary report and call to action*. Annals Neurology, 2017.

[4] P. Brodal, *The Central Nervous System*. Oxford University Press, 2010.

[5] C.P. Davis, *What Is Multiple Sclerosis? MS Symptoms, Causes, Diagnosis – A Review*. 11/09/2020.

[6] P.A. Calabresi, *Diagnosis and management of multiple sclerosis*. Am Fam Physician, 2004.

[7] Multiple Sclerosis International Federation, *Atlas of MS 3rd edition*. 2020.

[8] G. Katti, S. Ara, A. Shireen, *Magnetic Resonance Imaging (MRI) – A Review* . International journal of dental clinics, 2011.

[9] A. Rovira, M. Wattjes, M. Tintoré, C. Tur, T. Yousry, M. Sormani, N. de Stefano, M. Filippi, C. Auger, M. Rocca, F. Barkhof, F. Fazekas, L. Kappos, C. Polman, D. Miller, X.Montalban, *Evidence-based guidelines: MAGNIMS consensus guidelines on the use of MRI in multiple sclerosis—clinical implementation in the diagnostic process*. Nature Reviews Neurology, 2015.

[10] S. Lazreg, A. Cheklat, *MRI brain image segmentation using the multifractal approach*. Master's thesis in Genie Biomedical. "Abu Bakr Belkayad" University. Tlemcen. 2016/2017.

[11] P. Roberts and al. *Atlas of the Human Brain in Section*. Book, 1987.

[12] A. Melle Mous, *Segmentation of brain MRI images by classification techniques*. Master's thesis in Genie Biomedical. "Abu Bakr Belkayad" University. Tlemcen. 2016/2017.

[13] K. Zeggai , A. Zebouchi, *Brain 3D MR Image Segmentation and Reconstruction*. Master's thesis in Genie Biomedical."Abu Bakr Belkayad" University. Tlemcen. 2015/2016.

[14] M. Sahraian and A. Eshaghi, *Role of MRI in diagnosis and treatment of multiple sclerosis*. Clinical Neurology and Neurosurgery, 2010.

[15] X. Wu, *Multiple Sclerosis MRI Diagnosis, Potential Treatment and Future Potential for Nanoparticle Applications*. Universitetsservice US-AB, Sweden, 2005 .

[16] C. Yang, h. Lan, f. Gao, f. Gao *Review of deep learning for photoacoustic imaging*. Elsevier, 2020.

[17] H.Wang, B. Raj, E. P. Xing, *On the origin of deep learning*. ArXiv preprint arXiv. 2017.

[18] D. Moualek, *Deep Learning for Image Classification*. Doctoral thesis."Abu Bakr Belkayad" University. Tlemcen. 2017.

[19] A. Medjdoubi, *Sentiment analysis using deep learning*. Master's thesis. "Tahar Moulay" University. Saida. 2019.

[20] N.A.D. Diallo, *Recognition of facial expressions*. Master's thesis. "8 Mai 1945" University. Guelma, 2019.

[21] Phung, Rhee, *A high-accuracy model average ensemble of convolutional neural networks for classification of cloud image patches on small datasets*. Appl.Sci, 2019.

[22] M. Oulmi, S. Kaloune, *classification of objects with Deep Learning*. Master's thesis. "Akli Mohand Oulhadj" University. Bouira. 2018.

[23] B .Ghennam, S. Smara, *Convolutional neuron networks (CNN) for the classication of images associated with parking spaces*. Master's thesis. "Djilali Bounaama" University. Khemis Miliana. 2019.

[24] M. Belabend, *Iris recognition by convolutional neural networks*. Master's thesis."Badji mokhtar," University. 2019.

[25] V. Güldal, H. Tongal, *Comparison of recurrent neural network, adaptive neuro-fuzzy inference system and stochastic models in girdir lake level forecasting*. Springer Science, 2010.

[26] O. Ronneberger, P. Fischer, T. Brox, *U-Net: Convolutional Networks for Biomedical Image Segmentation*. Springer International, 2015.

[27] H. Li, G. Jiang, R. Wang, J. Zhang, *Fully Convolutional Network Ensembles for White Matter Hyperintensities Segmentation in MR Images*. NeuroImage, 2018.

[28] M. Rieder, R. Verbeet, *Robot-Human-Learning for Robotic Picking Processes*.Conference: Hamburg International Conference of Logistics, 2019.

[29] M. Salem, *Deep Learning Methods For Automated Detection of New Multiple Sclerosis Lesions IN Longitudinal Magnetic Resonance Images*. PhD Thesis, the University of "Girona", 2020.

[30] A. Akhondi-Asl, L. Hoyte, M.E Lockhart, S.K Warfield, *A logarithmic opinion pool based staple algorithm for the fusion of segmentations with associated reliability weights*. IEEE Transactions on Medical Imaging, 2009.

[31] M. Styner, J. Lee, B. Chin, M. Chin, O. Commowick, H. Tran, S. Markovic-Plese, V. Jewells, S. Warfield, *3D segmentation in the clinic: A grand challenge II: MS lesion segmentation*. MIDAS Journal, 2008.

[32] T. Uher, M. Vaneckova, L. Sobisek, M. Tyblova, Z. Seidl, J. Krasensky, D. Ramasamy, R. Zivadinov, E. Havrdova, T. Kalincik, D. Horakova, *Combining clinical and magnetic resonance imaging markers enhances prediction of 12-year disability in multiple sclerosis*. Multiple Sclerosis Journal, 2016.

[33] Z. Lesjak· A. Galimzianova, A. Koren, M. Lukin, F. Pernus, B. Likar, Z. Sˇpiclin, *A Novel Public MR Image Dataset of Multiple Sclerosis Patients With Lesion Segmentations Based on Multi-rater Consensus*. Springer Science, 2017.

[34] C.P. Loizou, *MRI Lesion Segmentation in Multiple Sclerosis Database*. eHealth Lab.

[35] M. Maleki, M. Teshnehlab, M. Nabavi, *Diagnosis of Multiple Sclerosis (MS) Using Convolutional Neural Network (CNN) from MRIs*. Global Journal of Medicinal Plant Research, 2012.

[36] T. Brosch, Y. Yoo, L.Y.W. Tang, D. Li, A. Traboulsee, R. Tam, *Deep Convolutional Encoder Networks for Multiple Sclerosis Lesion Segmentation*. Springer International Publishing, 2015.

[37] T. Brosch, L.Y.W. Tang, Y. Yoo, D. Li, A. Traboulsee, R. Tam, *Deep 3D Convolutional Encoder Networks with Shortcuts for Multiscale Feature Integration Applied to Multiple Sclerosis Lesion Segmentation*. IEEE Transactions on Medical Imaging, 2015.

[38] A. Birenbaum, H. Greenspan, *Multi-view longitudinal CNN for multiple sclerosis lesion segmentation*. Science Direct, 2017.

[39] R.E Gabr, I. Coronado, M. Robinson, S.J Sujit, S. Datta, X. Sun, W.J. Allen, F.D. Lublin, J.S Wolinsky, P.A Narayana, *Brain and lesion segmentation in multiple sclerosis using fully convolutional neural networks: A large-scale study*. Multiple Sclerosis Journal, 2019.

[40] S. Valverdea, M. Cabezasa, E. Rouraa, S Gonz alez-Villaa, D. Paretob, J.C. Vilanovac, L. Ramio-Torrent'ad, A. Rovirab, A. Olivera, X. Lladoa, *Improving automated multiple sclerosis lesion segmentation with a cascaded 3D convolutional neural network approach*. Multiple Sclerosis Journal, 2017.

[41] Y. Zhang, C. Pan, J. Sun, C. Tang, *Multiple sclerosis identification by convolutional neural network with dropout and parametric ReLU*. Journal of computational science, 2018.

[42] M.S. Yıldırım1, E. Dandıl, *Automatic detection of multiple sclerosis lesions using Mask R-CNN on magnetic resonance scans*. IET Image Process, 2021.

[43] A. Roy, D. Mishra, *ECNN: Activity Recognition Using Ensembled Convolutional Neural Networks*. Tencon 2019. IEEE, 2019.

[44] D. Ravnik, T. Jerman, F. Pernuš, al, *Dataset variability leverages white matter lesion segmentation performance with convolutional neural network*. Medical Imaging 2018: Image Processing, Houston, TX, United States, 2018.

Abstract

Multiple sclerosis (MS) is one of the most difficult diseases to diagnose or follow-up, especially in the first stage. Magnetic resonance imaging shows the structure of the central nervous system which makes it possible to detect. However, The manual MS diagnosis is often painstaking and requires significant and tedious efforts. Also, MRI does not achieve the diagnosis without an expert neuroradiologist. In this work, we propose an automatic segmentation of MS from MRI using deep learning. Our proposed solution is using a segmentation method called Unet on the public MS dataset, the MR images used in this work are T2. Our proposal was validated in the dataset of MS against other work in terms of the dice similarity coefficient (DSC) metric. The proposed Unet model had an accuracy of 99%, which may compete with recent work.

key-Words : Magnetic Resonance imaging, Segmentation, Multiple sclerosis, Unet.

Résumé

La sclérose en plaques (SEP) est l'une des maladies les plus difficiles à diagnostiquer, surtout au début. Alors que les images IRM du système nerveux central montrent la structure du tissu qui permet de le détecter. Le diagnostic manuel de la SEP est souvent laborieux et nécessite des efforts importants. De plus, l'IRM n'atteint pas le diagnostic sans un neuroradiologue expert. Dans ce travail, nous proposons une méthode de segmentation des images IRM de la SEP par l'apprentissage profond. La solution proposée utilise la méthode de segmentation appelée Unet sur l'ensemble des données SEP, les images IRM utilisées dans ce travail sont une T2. Notre proposition a été validée dans la base de données de SEP contre d'autres travaux en termes de métrique du coefficient de similarité des dés (DSC). Le modèle Unet proposé avait une précision de 99%. Ce qui peut concurrencer les travaux récents.

Mots clés : Imagerie par résonnance magnétique, Segmentation, Sclérose en Plaques, Unet.

ملخص

التصلب المتعدد هو أحد الأمراض الأكثر صعوبة في التشخيص أو المتابعة، وخاصة في المرحلة الأولى. في حين أن التصوير بالرنين المغناطيسي للجهاز العصبي المركزي تظهر بنية الأنسجة التي تجعل من الممكن اكتشافه. ومع ذلك، فإن التشخيص اليدوي لمرض التصلب المتعدد غالباًا ما يتطلب جهداً كبيراً ويستغرق وقتاًا طويلاً. و التشخيص بالرنين المغناطيسي يحتاج إلى أخصائي أشعة أعصاب خبير. في هذا العمل، اقترحنا الكشف التلقائي عن التصلب المتعدد عن طريق التصوير بالرنين المغناطيسي باستخدام التعلم العميق. الحل المقترح لدينا هو استخدام طريقة تقسيم تسمى Unet على مجموعة بيانات التصلب المتعدد، صور الرنين المغناطيسي المستخدمة في هذا العمل هي T2. لقد تم التصديق على اقتراحنا في مجموعة بيانات التصلب المتعدد ضد أعمال آخرى من حيث معامل التشابه (DSC) المتري. نموذج Unet المقترح لديه دقة ٩٩ بالمائة، والتي قد تتنافس مع الأعمال الأخرى.

الكلمات المفتاحية: التصوير بالرنين المغناطيسي، التصلب المتعدد، التجزئة، Unet.