first

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Abstract

Stroke is one of the leading causes of death and disability. Therefore the manual segmentation of it's lesions is time-consuming, automatic segmentation methods of the stroke has recently extracted attentions. One of the successful automatic methods that achieve state of the art is the deep learning (convolutional neural network), this method is used in multiple domains such that image recognition, Medical context, natural language processing etc ...

The need for a short prediction time and an accurate segmentation is a challenge to work on that's why all the present and the future works are focusing on the variety architectures witch get the score and to achieve the state of the art. We intent in this work to build a Convoultional neural network for the task of the segmentation,our contribution is that we based our model on the Auto-encoder network by inspiring from their main idea and by using a CNN layers with multispectral MRI images to improve the robustness of our model.

Resumer

L'AVC est l'une des principales causes de décès et d'invalidité. Par conséquent, la segmentation manuelle de ses lésions prend beaucoup de temps. Les méthodes de segmentation automatique de l'accident vasculaire cérébral ont récemment attiré l'attention. L'une des méthodes automatiques efficaces qui permet d'atteindre l'état de l'art (réseau de neurones convolutionnel), cette méthode est utilisée dans plusieurs domaines tels que la reconnaissance d'image, le contexte médical, le traitement du langage naturel, etc...

Le besoin d'un temps de prévision court et d'une segmentation précise est un défi à travailler. C'est pourquoi tous les travaux actuels et futuristes se concentrent sur les architectures variétales qui atteignent l'état de l'art et qui obtiennent le score. Nous avons l'intention dans ce travail pour construire un réseau de neurones convolutionnel destiné à la segmentation, notre contribution est de fonder notre modèle sur le réseau Auto-encoder en s'inspirant de leur idée principale et en utilisant des couches CNN avec des images IRM multispectrales pour améliorer la robustesse de notre modèle .

Acknowledgement

I would first like to thank my project supervisor Prof Saouli Rachida for guiding me to the right direction throughout the project and for giving me the sort of feedback that helped shaping this work.

Finally, tremendous thanks the friends and family for their continuous support and belief throughout my entire academic career.

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Chapter 1

General introduction

Magnetic resonance imaging (MRI) is usually the modality of choice for structural brain analysis, since it provides images with high contrast for soft tissues and high spatial resolution and presents no known health risks. While modalities such as computed tomography (CT) and positron emission tomography (PET) are also used to study the brain, but the MRI modality is the most useful and popular one. Although the extensively use of quantitative analysis of brain for characterization of brain disorders such as Alzheimer's disease, epilepsy, schizophrenia, multiple sclerosis(MS), cancer, stroke etc... [1],but MRI images present some problems such as intensity, inhomogeneity, or different intensity ranges among the same sequences and acquisition scanners.

A stroke is a*"brain attack"* and it is one of the most leading causes of disability and death globally, eighty percent of strokes are caused due to cerebral ischemia, the most dangerous kind of stroke is Ischemic stroke. Their Lesions are caused by lack of oxygen to the brain so the brain cells begin to die. The abilities controlled by that cells such as memory and muscle control are lost[2]. Since the treatment offered by doctors for the ischemic stroke is the segmentation of their lesions as possible as fast, MRI is very useful in finding lesions in clinical practice, MRI sequences providing different information of brain tissues that can help The good follow up treatment given fast by doctors.

Our study is about **"An Efficient Classification Of Ischemic stroke Lesions"**, stroke's affected tissue can be divided into three concentric regions depending on the recovery The core witch is formed by irreversibly damaged tissue,the penumbra located around the core, it can be recovered if blood flow is restored and the benign oligemia witch is the outer most ring,but is not at risk of damage.

Time treatment of ischemic stroke is very short, It's dark area around the core can be recovered as a function of time after a stroke onset, manual segmentation of stroke remains a laborious and time-consuming task for segmenting these, so automatic segmentation methods are highly recommended. Various methods have been proposed and one of this methods is use the deep learning models based on the Convolution Neural Networks CNNs that have proven best results to handle such kind of tasks[3], for this, we aim in this work to develop an effective deep learning model based on CNN architecture for the automatic segmentation of lesions of stroke in MRI.

For that, chapter2 presents a state of the art on the methods of segmentation of MRI images which is a crucial task in the analysis of medical images. In addition this chapter presents a description of the approaches deep learning based on neural networks as well as a synthesis of some works proposed in the literature relative to the objectives launched in this project.

Chapter3 proposes the architecture developed and its implementation. The CNN architecture based on the Autoencoder model to segment lesion regions from brain images MRI.This model essentially uses the downsampling phase of the MRI multi-modalities inputs and the second the upsampling phase to reconstruct the resulting images. Some data techniques are applied on the input to match them to be adopted for the model implementation desired.

Chapter 2

State of the art: Segmentation methods of MRI images

2.1 Introduction

Image contains lots of useful information and it is a way of transferring them[1]. Understanding and extracting information from the image to accomplish some works is an important area of application in digital image technology. The first step in understanding the image is the image segmentation[4]. Image segmentation is one of the most important tasks in medical image analysis and is often the first and the most critical step in many clinical applications. In brain MRI analysis, image segmentation is commonly used for measuring and visualizing the brain's anatomical structures,for analyzing brain changes, for delineating pathological regions, and for surgical planning and image-guided interventions.In the last few decades, various segmentation techniques of different accuracy and degree of complexity have been developed and reported in the literature[5].

2.2 Definition

Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. Every pixel is allocated to one of a number of these categories. A good segmentation is typically one in which [6]:

- pixels in the same category have similar greyscale of multivariate values and form a connected region.
- neighbouring pixels which are in different categories have dissimilar values.

Image segmentation is the process of dividing an image into multiple parts.This is typically used to identify objects or other relevant information in digital images[7]. The meaningful parts having similar features and properties. It is referred to as one of the most important processes of image processing. The main aim of segmentation is simplification. The basic applications of image segmentation are [8]:

- Content-based image retrieval.
- Medical imaging.
- Object detection and Recognition Tasks.
- Automatic traffic control systems and Video surveillance,etc...

2.2.1 Medical Image Segmentation

- Medical image segmentation is used in various applications, in medical image processing:it is used to analyze and locate tumour, analyze the anatomical structure etc...[4].
- Medical image segmentation provides comparable resolution and better contrast resolution. One of the most important problems in image processing and analysis is segmentation[4].

2.3 Elementary notions

2.3.1 The Segmentation notion

- Image segmentation is the first step in image analysis[9].
- Image segmentation is the division of a digital image into multiple segments i.e.in set of pixels on the basis of some criteria such as color, shape, texture, intensity values[9].
- Image segmentation locate objects and boundaries in image,with the main aim of having clear distinction between object and its background[9].
- Segmentation techniques mainly convert the complex image into a simple image[9].

Figure 2.1: Segmentation Techniques

The choice of a segmentation technique and the level of segmentation over another are decided by the particular type of image and characteristics of the problem being considered[9].

Theoretical definition

If R represents an image, then the image segmentation is simply division of R into subregions $(R_1, R_2..R_n)$, such that[10]

$$R = \bigcup_{n=1}^{n} R_i$$

and is governed by following set of rules:

- R_i is a connected set, i=1,2,. . . ..n
- $R_i \cap R_j = \emptyset$ for all i and j, i≠j .
- $Q(R_i)$ = True for i= 1,2,. . . n..
- $Q(R_i \cup R_j)$ = False for adjoint regions,R_i and R_j

Where $Q(R_k)$ is a logical predicate.The rules described above mentions about continuity, one-to-one relationship, homogeneity and non-repeatability of the pixels after segmentation respectively[10].

2.3.2 IMAGE SEGMENTATION TECHNIQUES

Different approaches of image segmentation are broadly classified based on two properties of image[9].

a) Discontinuity detection

   It includes division of image on the basis of discontinuous intensity values of pixels of regions like in edge detection and boundary detection algorithm of image segmentation.

b) Similarity detection

   It includes partition an image on the basis of some already stated similarity criteria into set of homogeneous regions having similar set of pixels using image segmentation algorithms such as thresholding and region splitting and merging and growing.

There are many approaches to segment an image where some of them are described in the following section and showing in fig 2.2 [9].

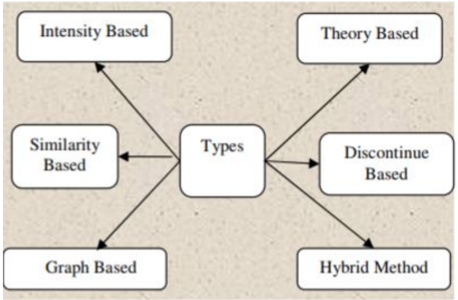


Figure 2.2: Types of Image segmentation

Table 2.1: Comparison between Various Segmentation Techniques[9]

Segmentation technique	Description	Advantages	Disadvantages
Thresholding Method	based on the histogram peaks of the image to find particular threshold values	no need of previous information, simplest method	highly dependent on peaks, spatial details are not considered
Edge Based Method	based on discontinuity detection	good for images having better contrast between objects	not suitable for wrong detected or too many edges
Region Based Method	based on partitioning image into homogeneous regions	more immune to noise, useful when it is easy to define similarity criteria	expensive method in terms of time and memory
Clustering Method	based on division into homogeneous clusters	fuzzy uses partial membership therefore more useful for real problems	determining membership function is not easy
Watershed Method	based on topological interpretation	results are more stable, detected boundaries are continuous	complex calculation of gradients
PDE Based Method	based on the working of differential equations	fastest method, best for time critical applications	more computational complexity
ANN Based Method	based on the simulation of learning process for decision making	no need to write complex programs	more wastage of time in training

Image Segmentation Algorithms

A) **Thresholding**

Thresholding or(**Intensity**)is the simplest method of image segmentation from a gray scale image, it can be used to create binary images.In this method image is segmenting by comparing pixel values with the predefined threshold limit L. Mathematically represented as I (i,j) an image[11]

$$I(i,j)=\begin{cases}0, v(i,j) < L\\ 1, v(i,j) \geq L\end{cases} \qquad 1$$

- where v(i,j)is the pixel value at the position(i,j).

- Individual pixels in an image are compared with threshold value and assign "0" or "1" depend upon the condition described in equation(1).
- Threshold is the key parameter in the threshold segmentation. There are several methods to select them :manual selection, Simple automatic threshold selection, the Unimodal threshold selection algorithm due to it's simplicity, and the non require for much specific knowledge of the image ,it is much better to use in medical images [11].

Threshold segmentation of the abnormal brain MRI is shown in fig.2.3.

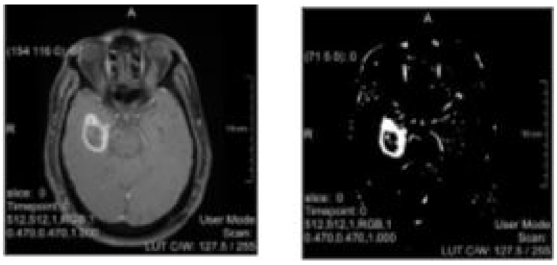


Figure 2.3: Threshold segmentation of the abnormal brain MRI (left) Original image(right) Segmented image

B) **Region Growing Method**

Or **Similarity Based Approach** tries to extract an image connected region based on some predefined criteria such as intensity information and/or edges in the image[11].

Example for this method is seeded region growing described in procedure as follows[11].

(a) It takes a set of seeds as input along with the image. (The seeds spot each of the objects to be segmented).
(b) The regions are iteratively grown by comparing all unallocated neighbouring pixels to the regions.
(c) The difference between a pixel's intensity value and the region's mean, σ, is used as a measure of similarity.
(d) The pixel with the smallest difference measured this way is allocated to the respective region.
(e) This process continues until all pixels are allocated to a region.

C) **Clustering Method**

Is an iterative technique that is used to partition an image into clusters, where the number of clusters K is an input parameter. can be selected manually, randomly, or based on some conditions. Distance between the pixel and cluster center is calculated by the squared or absolute difference [11].

The Procedure for the clustering is :

(a) Pick K cluster centers, either randomly or based on some heuristic.

(b) Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center.

(c) Re-compute the cluster centers by averaging all of the pixels in the cluster.

(d) Repeat steps b and c until convergence is attained (e.g.no pixels change clusters).

There are three commonly used clustering algorithms; k-means algorithm, the fuzzy c-means algorithm, and the expectation-maximization algorithm[12].

Clustering segmentation of the abnormal brain MRI is shown in fig.2.4.

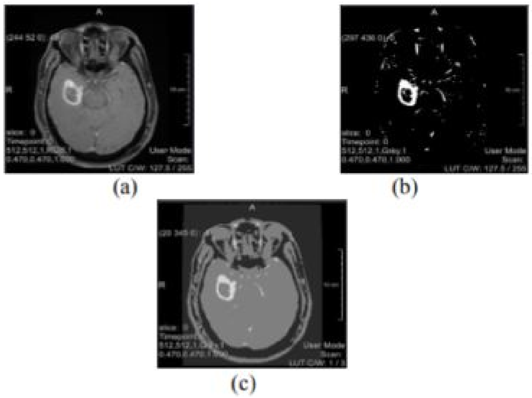


Figure 2.4: Clustering segmentation of abnormal brain MRI (a) original image (b) segmented output (c) merged image of (a) and (b)

D) **Artificial Neural Networks** :

They are parallel networks of processing elements or nodes that simulate biological learning.Each node capable to perform computations. Learning is achieved through the adaptation of weights assigned to the connections between nodes. It is most widely used in medical imaging as a classifier in which the weights are determined by using training data and then it is used to segment new data. They can also be used in an unsupervised method[12].

E) **Discontinuity Based Approach**:

This approach is based on the variations in the intensity value of pixels near edges and boundaries of image that the Spatial masks are used to detect all the three types of discontinuities in an image, thus follow edge detection approach witch is done using two methods[9].

- Gray Histogram Technique
- Gradient Based Method

F) **Theory Based Approach**:

This type includes various algorithms with derivatives from **Clustering Techniques** and **Artificial Neural Network-based segmentation**[9].

G) **Graph Based Approach**

Is an effective method witch is taken as a weighted undirected graph. Pixel values are assigned to the nodes of graph,the graph is divided on the basis of some already stated criteria. It includes different algorithms e.g.*random walker*, *minimum cut*, *minimum spanning tree-based segmentation*, and *segmentation-based object categorization*[9].

H) **Hybrid Approach**

It combines the approach of one or more segmentation methods, morphological operations are performed on images in this last. It provides better results in comparison to its parent method[9].

2.4 Deep Learning approach

2.4.1 Artificial neural networks

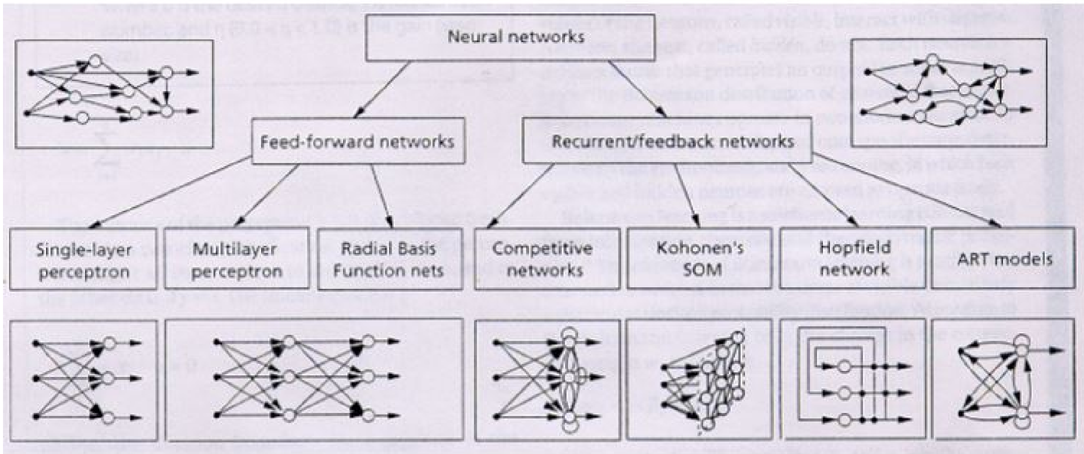


Figure 2.5: Different topology of neural networks
[13]

Learning methods

Artificial neural networks work through the optimized weight values. They are attained by the method called learning.

- The learning process try to teach the network how to produce the output when the corresponding input is presented.
- The trained neural network, with the updated optimal weights, should be able to produce the output corresponding to an input pattern within desired accuracy[14].

The learning methods are[14] :

- **Supervised learning**

  When neural network learns the correlation between labels and data this is known as **supervised learning**.

  all classification tasks depend upon labeled datasets ex:Detect faces, identify people in images, recognize facial expressions (angry,joyful). Deep learning is based on the supervised learning [15].

- **Unsupervised learning**

  Is the Learning without labels. One law of machine learning is: the more data an algorithm can train on,the more accurate it will be. Therefore, unsupervised learning has the potential to produce highly accurate models.

  Deep learning does not require labels to detect similarities(Clustering)[15].

- **Reinforced learning**

  Reinforcement learning refers to goal-oriented algorithms, which learn how to attain a complex objective (goal)or maximize along a particular dimension over many steps.

  It refers also to start from a blank slate, and under the right conditions to achieve more better performance ex:Predictive Analytics(Regressions)[15].

Artificial neural networks

Is a computational model inspired from the natural neurons. Natural neurons receive signals through synapses located on the dendrites of the neuron. When the signals received the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse,and might activate other neurons[16]. A biological neuron shown in fig.2.6

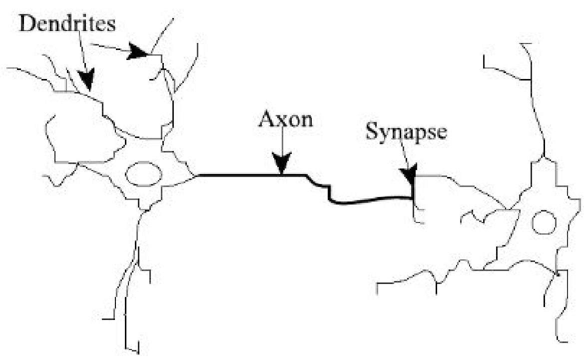


Figure 2.6: A biological neuron

When modelling artificial neurons. These basically consist of inputs(like synapses), which are multiplied by weights, and then computed by a mathematical function which activates the neuron. Compute output of the artificial neuron function(sometimes depending of a certain threshold and it may be the identity)[16]. Model of an artificial neuron shown in fig.2.7[17].

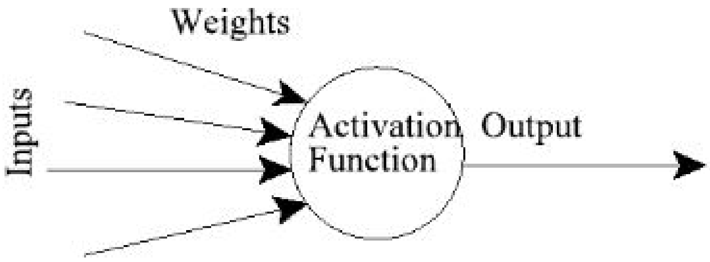


Figure 2.7: An artificial neuron

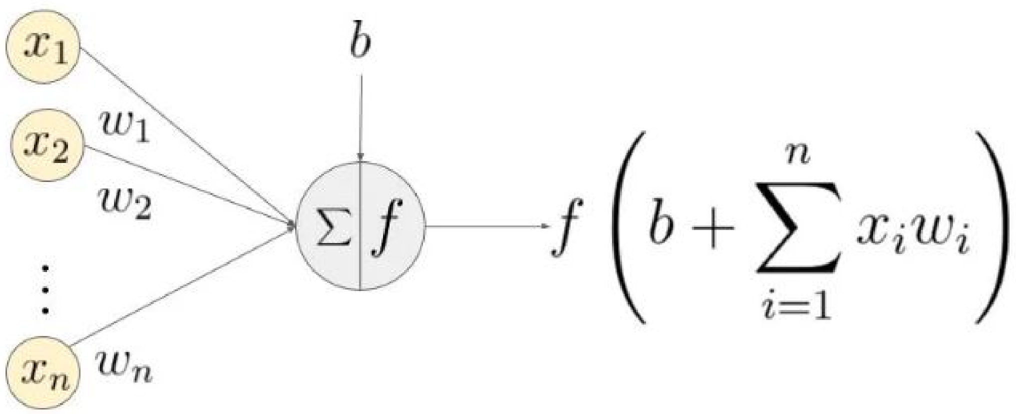


Figure 2.8: An example of a neuron showing the input (x_1.., x_n), their corresponding weights (w_1.., w_n), a bias (b) and the activation function f applied to the weighted sum of the input

- x1...xn are the inputs to the neuron.
- W0...Wn are the weights.
- Product of weight and input gives the strength of the signal.
- Sum= $\sum_{i=0}^{n} x_i W_i$

There are various functions used for activation like Sigmoid etc...shown in Table 2.2[18]

Table 2.2: Some activation functions

Name	Input/output Relation
Hard Limit	$\alpha = 0 \quad n<0$ $\alpha = 1 \quad n \geq 0$
Symmetrical Hard Limit	$\alpha = -1 \quad n<0$ $\alpha = +1 \quad n \geq 0$
Linear	$\alpha = n$
Log-Sigmoid	$\sigma(z) = \frac{1}{1+e^{-z}}$
Rectified linear activation Function	$Relu(z) = \max(z, 0)$ $Relu'(x) = \{1 \quad x>0$ $0 \quad \text{otherwise}$

Feedforward Neural Networks

Feedforward Neural Networks are artificial neural networks where the connections between units do not form a cycle[17].

- They were the first type of artificial neural network invented
- They are simpler than their recurrent neural networks.
- The word feedforward because information only travels forward in the network.
- No loops through the input nodes, the hidden nodes, and through the output nodes.
- Primarily used for supervised learning.

feedforward neural networks compute a function f on fixed size input $x$such that $f(x) \approx y$ for training pairs (x, y). On the other hand, recurrent neural networks learn sequential data, computing $g$on variable length input $X_k = \{x_1, ..., x_k\}$ such that $g(X_k) \approx y_k$ for training pairs (X_n, Y_n) for all $1 \leq k \leq n$ [19].

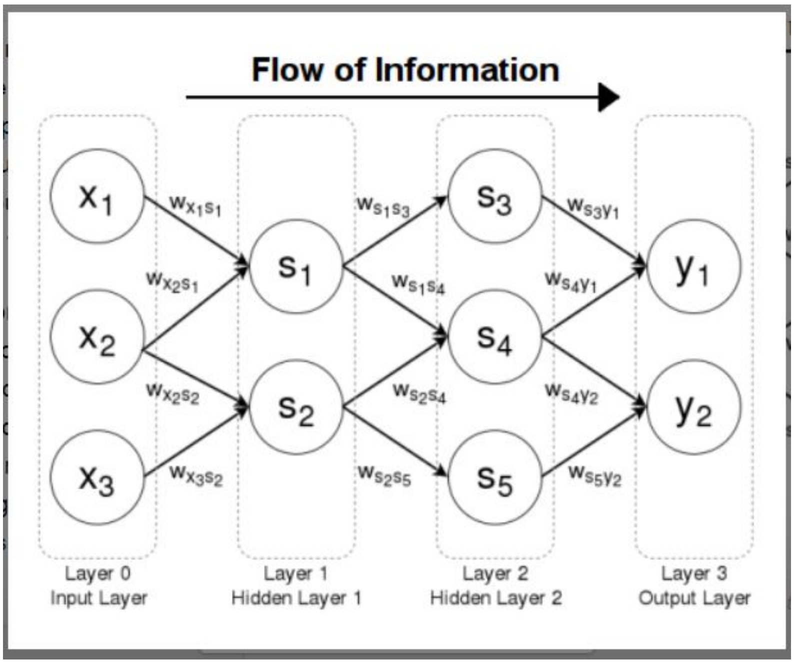


Figure 2.9: A feedforward neural network with information flowing left to right

Recurrent neural networks

The RNN is one of the foundational network architectures from which other deep learning architectures are built[20].

- It might have connections that feed back into prior layers(or into the same layer), that allows RNNs to maintain memory of previous inputs and model problems in time.

- It can be unfolded in time and trained with standard back-propagation or by using a back-propagation in time (BPTT).

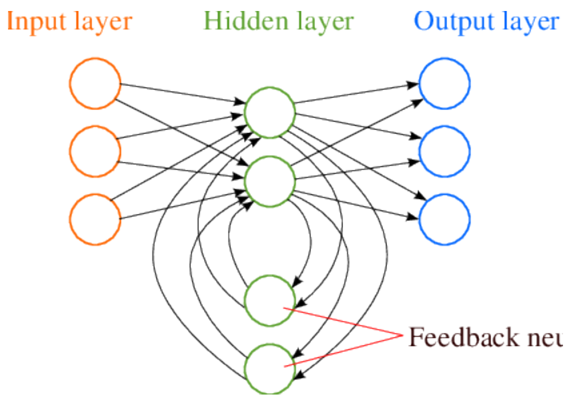


Figure 2.10: RNN exemple

2.4.2 Deep learning approach

In deep learning,a computer model learns to perform classification tasks directly from images, text, or sound. They can achieve state-of-the-art accuracy. Models are trained by using a large set of labeled data and neural network architectures with many layers[21].

Figure 2.11: Deep learning as a neural network

How Deep Learning Works

- Most deep learning methods use neural network architectures.
- The term “deep” usually refers to the number of hidden layers in the neural network,where traditional neural networks only contain 2-3 hidden layers, while deep networks can have as many as 150.
- Deep learning models are trained by using large sets of labeled data and neural network architectures that learn features directly from the data without the need for manual feature extraction[21].

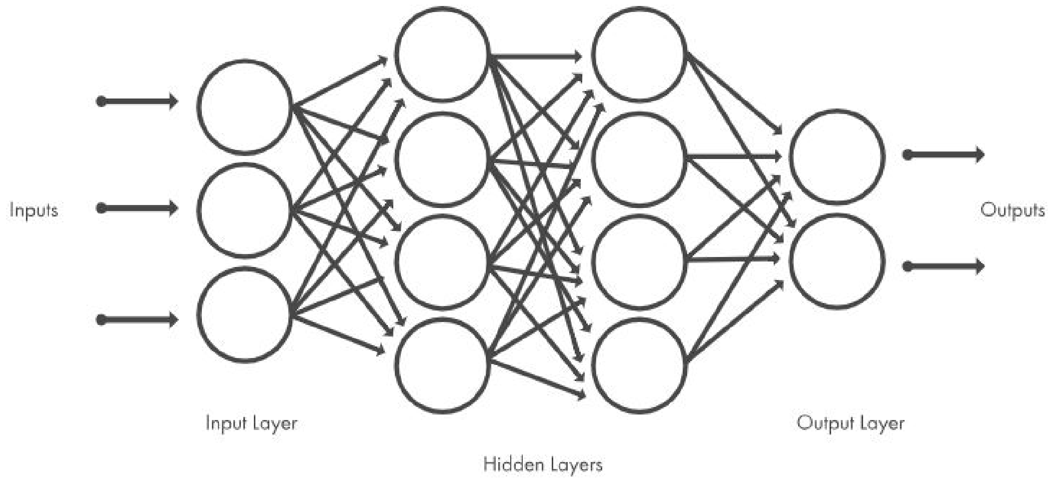


Figure 2.12: Neural networks organized in layers

why is it called “Deep” Learning?

The “deep” part of deep learning refers to creating deep neural networks with a large amount of layers with the addition of more weights and biases[22]. By the using of multiple levels of neural networks in deep learning, computers now have the capacity to see, learn to complex situations like or better than humans[23].

Deep learning architectures

One of the most popular types of deep neural networks is known as convolutional neural networks(CNN or ConvNet)[21].

- A CNN convolves learned features with input data, and uses 2D convolutional layers.
- CNNs eliminate the need for manual feature extraction to classify images.
- The CNN works by extracting features directly from images.

- They are learned while the network trains on a collection of images.
- The automated feature extraction makes deep learning models highly accurate for computer vision tasks such as object classification.
- the layers are organised in 3 dimensions: width, height and depth(three color channels R,G,B).
- the last output will be reduced to a single vector of probability scores[24].

CNNs have two components[24]:

a) The Hidden layers/Feature extraction part

   In this part, the network will perform a series of convolutions and pooling operations until the features are detected or extracted.

b) The Classification part

   Here, the fully connected layers will serve as a classifier on top of these extracted features to assign a probability for the object on the image being what the algorithm predicts it is.

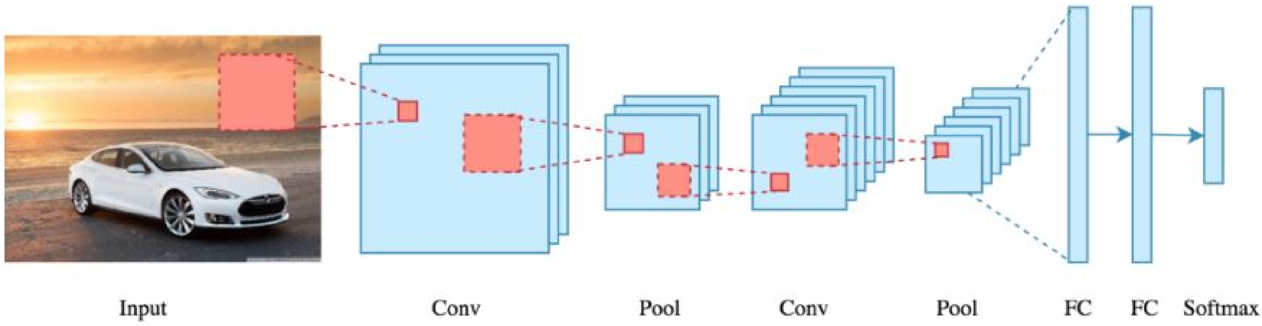


Figure 2.13: A CNN architecture

Feature extraction

Convolution is a CNN block. Witch is performed on the input data with the use of a filter or kernel to produce a feature map[24]. A filter is just a matrix of values that are trained to detect specific features. It moves over each part of the image to check if the feature to detect is present[25].

When the feature is present in part of an image, the convolution operation results a real number with a high value. If not, the resulting value is low[25].

The output of the convolution operation is summed with a bias term and passed through a non-linear activation function to introduce non-linearity into the network[25].

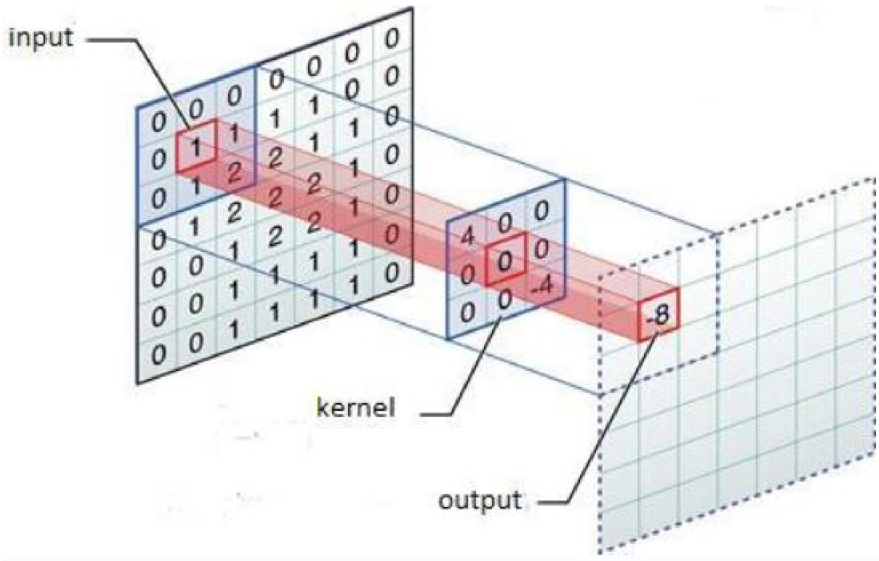


Figure 2.14: A convolution operation

Downsampling

To speed up the training process and reduce the amount of memory consumed by the network, the most common operation is: *max pooling*, witch is a window passes over an image according to a set stride (how many units to move on each pass). At each step, the maximum value within the window is pooled into an output matrix[25].

In CNN architectures, pooling is typically performed with 2x2 windows, stride 2 and no padding.While convolution is done with 3x3 windows, stride 1 and with padding[26].

Hyper parameters

A convolution layer without pooling, there are 4 important hyperparameters to decide on[26]:

- Filter size

  typically 3x3 filters, but 5x5 or 7x7 are also used depending on the application. Filters are 3D their depth is omitted because at a given layer is equal to the depth of its input.

- Filter count

  Is the most variable parameter, between 32 and 1024. Usually the use of a small number of filters at the initial layers, and progressively increase the count to go deeper into the network, to avoid overfitting.

- Stride It may kept at the default value 1.

- Padding it is generally used.

Fully-Connected Layer

In the fully-connected operation the input representation is flattened into a feature vector because it expects a 1D vector of numbers [26]and then passed through a network to predict the output probabilities[25].

Output Layer

It is to produce the probability of each class given for the input image. The final Dense layer initialized with the same number of neurons as there are classes.The output of this dense layer then passes through the activation function.

To measure the accuracy of the network a loss function assigns a real-valued number when predicting the output digit[25].

Training

CNN is trained the same way like ANN, with backpropagation, gradient descent. Due to the convolution operation it's more mathematically involved[26]. CNNs are especially useful for image classification and recognition. [24].

Deep Residual Networks(ResNets)

A ResNet consists of a number of residual modules where each module represents a layer. Each layer consists of a set of functions to be performed on the input. The depth of a ResNet can vary greatly[27].

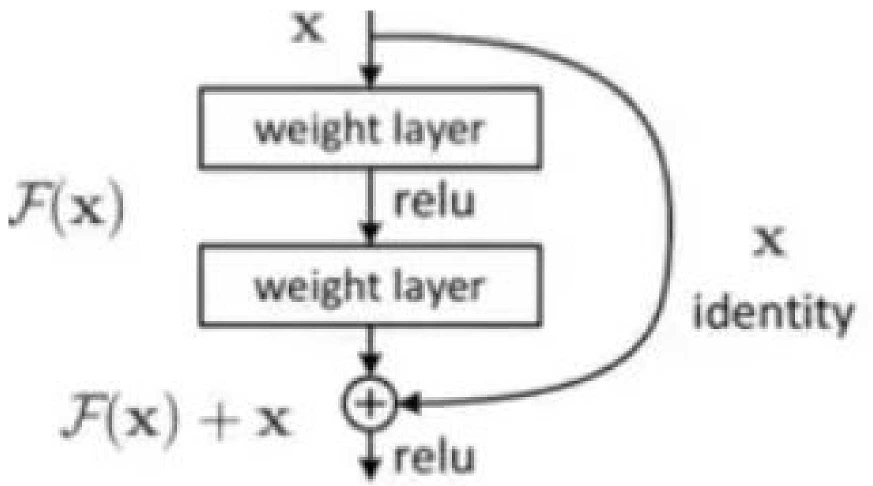


Figure 2.15: A basic building block of ResNet

- They are highly modular.Hundreds and thousands of residual layers can be added to create a network.
- ResNets can be designed to determine how deep a particular network needs to be.

- The use of residual blocks, results in architectures that are easier to optimise and can gain accuracy from considerably increased depth.
- Ease backpropagation flow,improving convergence properties, learning of better fitted features[2].

U-Net

U-Net is one of the famous Fully Convolutional Networks (FCN) in biomedical image segmentation[28], considered as one of the standard CNN architectures for image classification tasks, to segment areas of an image by class.

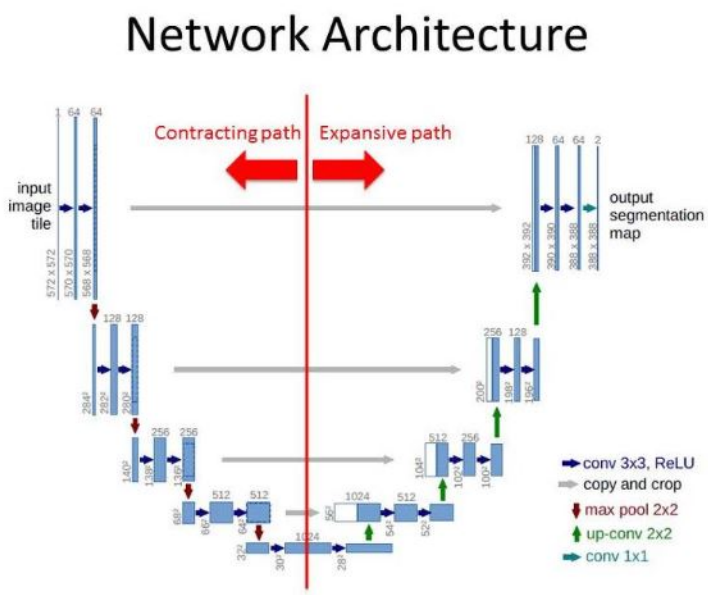


Figure 2.16: Illustration of U-Net architecture

- This architecture consists of a contracting path to capture context and a symmetric expanding path that enables precise localization.
- The network is trained in end-to-end from very few images and outperforms the prior best method higher then a sliding-window convolutional network.
- Segmentation of a 512×512 image takes less than a second on a modern GPU[29].

The U-Net architecture interesting pattern is shown in figure 2.16 [30].

Contraction path

Consecutive of two times of 3×3 Conv and 2×2 max pooling is done. This can help to extract more advanced features but it also reduce the size of feature maps[28].

Expansion path

a) Consecutive of 2×2 Up-conv and two times of 3×3 Conv is done to recover the size of segmentation map.

   the above process reduces the "where" though it increases the "what", can get advanced features, but we also loss the localization information.

b) After each up-conv, concatenation of feature maps that are with the same level is done. This helps to give the localization information from contraction path to expansion path.

c) 1×1 conv in the final level to map the feature map size from 64 to 2 since the output feature map only have tow classes, cell and membrane[28].

Interesting Implementation Details

- Data augmentation is used in the form of shifting, rotations, elastic deformations, and gray value variations.
- They only use a batch size of one image during training[30].

Autoencoders

Autoencoders apply the principle of backpropagation in an unsupervised environment. Autoencoders represent data through multiple hidden layers such that the output signal is as close to the input signal[27].

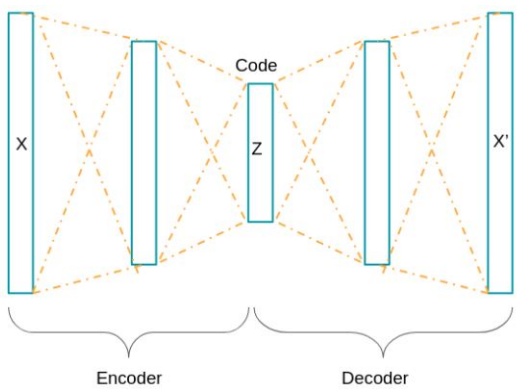


Figure 2.17: A basic representation of Autoencoder

2.5 Related work

(A Clérigue et al. 2018) proposes The 2-D Stroke convolutional network U-Net (SUNet), based on several MRI modalities designed for different acute stroke tasks such as segmentation and prediction, using Hybrid training patch sampling strategy (the balanced with offset strategy): to have a balanced representation and the same number of extracted patches from each case. The model is evaluated using DSC on the ISLES 2015 2017 and by comparison with others architectures some dice coefficient results :65.0 ,40.1 [2].

(A Pinto et al. 2018) proposes Deep learning architecture, based on the U-Net using sevral MRI images (4D PWI, perfusion and diffusion maps(DWI)) for Predicting the outcome of a stroke lesion using a temporal acquisitions window depends the needed blood dynamics to estimate the tissue at risk of infarction and data set with 75 cases. The model evaluated on ISLES 2017. Some evaluation metrics Dice,Hausdorff Distance, Precision: 0.29, 41.58, 0.23 ,0.21 by comparison with Methods from ISLES 2017[31].

(Y Wang et al 2016) Proposes a 3D convolutional neural network (ConvNet). Based on MRI T1 images of 18 samples to automatically segment stroke lesions. The ConvNet to benefit from learning ability and the Unilateral-model :voxel in one hemisphere also the Bilatearl-model: voxel with the sym property to improve localisation proprety for the voxel representation the dice coefficient is the metric of evaluation DSC = [0,63 ; 0,78][32].

(Z LIU et al. 2018) Proposes a 2D-residual (Res-FCN) network by using Multi-Spectral MRI Images (DWI, T2WI) in aim to Segment Stroke Lesion. The dataset contains 212 sample patients, the model evaluated on ISLES2015SSIS.FCN offered the whole image segmentation, reduce slices storage, processing cost and the Mult-spectral MRI to benefit with more acquisition parameters.The evaluation metric dice coefficient of 0.645 by comparing with U-NET =0.541, EDD Net =0.626.Low false negatives =1.515 when in U-NET=1.918 and EDD Net =1.753 models[33].

(R Zhang et al. 2018) proposes 3-D fully and densely connected convolutional network (3D FC-DenseNet) with Data set containing 242 subjects (90 for training, 62 for validation,and 90 for testing). Based on DWI images in order to Segment Acute Ischemic Stroke. The model evaluated on ISLES2015-SSIS data set.The Evaluation metrics [34]

- DSC=79.13%,
- FP=0.40,
- FN=1.16
- Training time=6h23m,
- Inferencing time : 0.095s.

2.6 Synthesis

In the table 2.3 we have resumed a comparative study between several Deep learning architectures from the section above of the related works.

Table 2.3: Comparison between CNN neworks using sevral evaluation metrics

Architecture	Article	DSC	False Positive(FP)	False Negative(FN)	Training time	Inferencing time	Hausdorff Distance
U-Net (SUNet).	Clérigue et al. 2018	65.0 ± 26.0 78.5 ± 14.9 40.1 ± 23.0	Non	Non	Non	Non	35.1 ± 29.7 16.0 ± 10.1 21.8 ± 17.0
CNN based on the U-Net	A Pinto et al. 2018	0.29 ± 0.21	Non	Non	Non	Non	41.58 ± 22.04
A 3D (ConvNet)	Y Wang et al 2016	0,63/0,78	Non	Non	Non	Non	Non
2D-residual (Res-FCN	Z LIU et al 2018	Non	Lower numbers	Lower numbers	Non	Non	Non
3D FC-DenseNet	R Zhang et al 2018	79.13%	0.40	1.16	6h23m	0.095s	Non

The general contribution is that the Ischemic Stroke Lesion Segmentation (ISLES), witch is a medical image segmentation challenge, started from the year of 2015 (SISS) where this challenge consisting on subacute lesion segmentation and (SPES) penumbra segmentation challenge. However the 2016 and 2017 editions focused on prediction [2],This year ISLES 2018 is depending on the segmentation of stroke lesion based on acute CT perfusion imaging and DWI (DWI maps)[35].

Chapter 3

Convolutional Neural Network for Stroke Lesion Segmentation and Implementation

3.1 Introduction

For decades automated detection of diseases based on conventional methods in medical imaging has shown significant accuracy, even more in several domains such as speech recognition, recognition , computer-aided diagnosis,Deep learning-based algorithms have shown promising as well speed performance [36], in this chapter we have discussed our Convolutional Neural Network Architecture based on the Auto-Encoder model building for Lesion Segmentation and the necessary steps to build it, even that the autoencoder has some drawbacks but we decide to choose the Conv network and to try as possible as we could to get best results,because this choice could help us to extract the features and to find a low representation of the input data and to reconstruct the results as desire as we want [37].

3.1.1 General Architecture

The figure 3.1 represent the general architecture of our model witch named by S-Net Stroke lesion segmentation network.

Figure 3.1: S-Net Stroke Network architecture

Input Data

Our input is from the public Data Set ISLES 2018 witch is for the Ischemic Stroke Lesion segmentation Challenge 2018's version, we have used as five types of MRI modalities images for every patent case. `http://www.isles-challenge.org/`

- For the first step we have reconstruct a new images from each of the forth types their original size of 256×256.
- The reason that lead to do is for the use of MRI image's multi-modalities as same input, from literature this choice will lead the model to learn more features and could converge to best results.
- Each type of these images contains two slices, that's why our Batch extraction method shown in figure (3.3), for each slice we have one Batche with the size of $256 \times 256 \times 4$.
- We Reorganize each 128×128 in the same position for the four types of each patient case and their correspondence in the output witch is the ground truth segmented by experts.

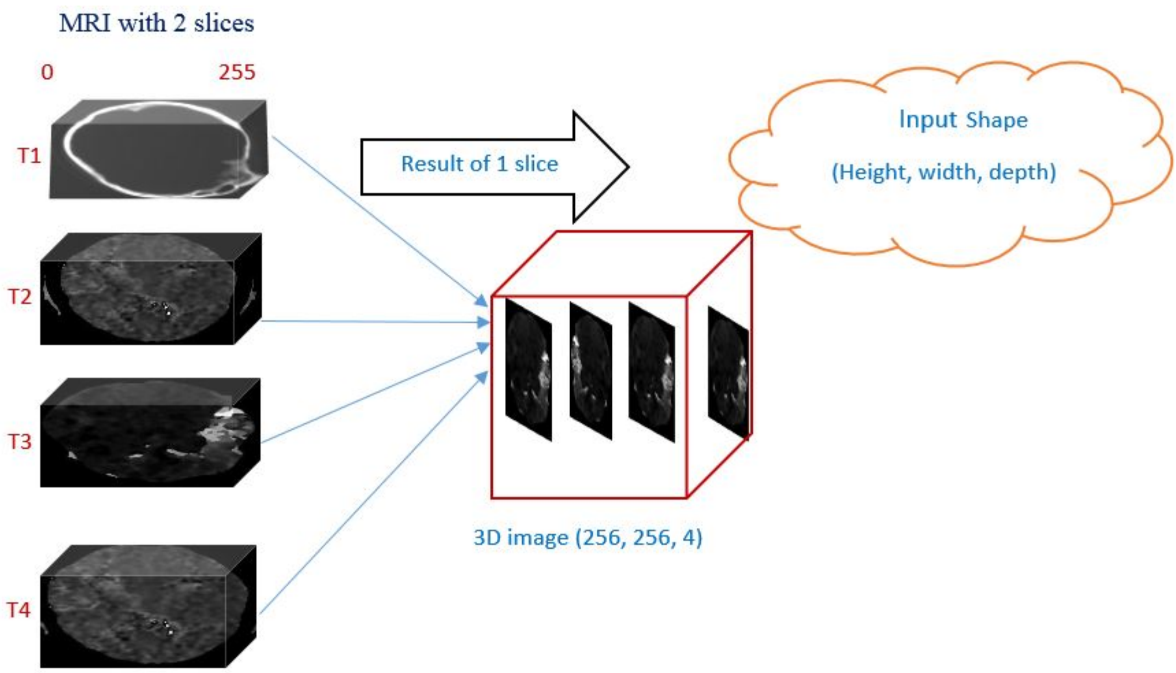


Figure 3.2: Representative example of batch extraction methods with the five MRI types

The Algorithm Batch Extraction strategy is represented in the figure coming later.

Algorithm 1 Batch Extraction Strategy

Result: Samples to train on
patientsImgs-list;
i,j,k=0;
while *i in patientsImgs-list* **do**
    while $k < 2$ **do**
        load the images.nifti in a list ;
        while $j < 4$ **do**
            - get the value of the four images types and load them in the trainable list ;
        end
        - get the value of the ground truth image and load them in the trainable list as label
    end
end

3.1.2 Model on Layers

From the literature the Auto-encoder network go deeply to pixel values and then reconstruct the result based on the features extracted from the regions of the code[38]. So based on this theory we try to use the same idea in building our model to down sample the input for the reasons of getting semantic informations and then to up-sample to reload the spatial informations. We estimate with this idea to combine between the convolutional neural network and the training strategy for the Auto-Encoder to offer flexibility and robustness and generalization to our model.

Auto-Encoder Network

Autoencoders are a type of neural networks. They compress the input into a lower-dimensional code and then reconstruct the output based on this representation. The input looks same as the output after the results[38].

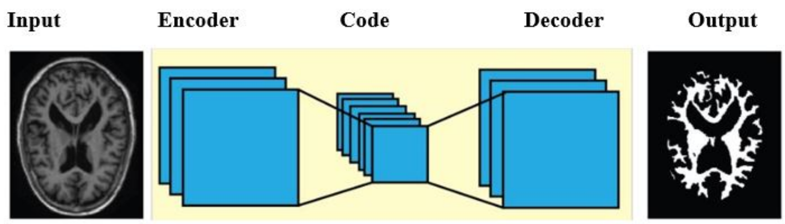


Figure 3.3: Representative architecture for the Autoencoder[39]

An autoencoder consists of 3 components[38]:

- The encoder witch compresses the input and produces the code.
- The code witch is resulting by the encoder compressor on the input.
- The decoder witch reconstructs the input only using the code.

Autoencoders are self-supervised that's why they are considered as an unsupervised learning technique because they don't need explicit labels to train on, they generate their own labels from the training data[38].

Auto-encoder details

- The encoder and decoder are fully-connected neural networks.
- Code is a single layer of an artificial neural network (ANN).
- The number of nodes in the code layer (code size) is a hyper-parameter that is setted before training the auto-encoder[38].

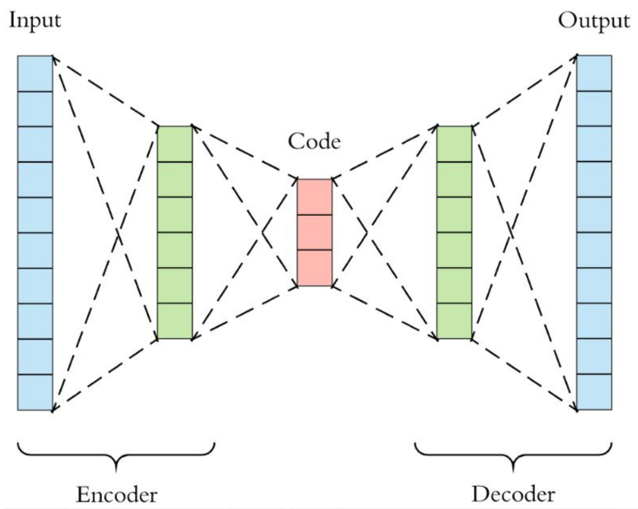


Figure 3.4: Representative architecture for the Autoencoder layers[38]

- First the input passes through the encoder, to produce the code.
- The decoder produces the output using the code.
- The decoder architecture is the mirror image of the encoder and the the dimensions of the input and output needs to be the same. That's why in this work we choose to base our architecture on this.

The main 4 hyperparameters in the autoencoder[38]:

Code size:

number of nodes in the middle layer witch is depending of the choice of the user.

Number of layers:

the auto-encoder can be as deep as desired, the number of layers is controlled by the user.
The number of nodes per layer decreases with each subsequent layer of the encoder, and increases back in the decoder.

Loss function

If the input values are in the range [0, 1] binary cross-entropy is used, otherwise the mean squared error(mse) is used depending on the desired output[38].

Convolutional Neural Network

We have introduced in the chapter State of the art the Convolutional neural network architecture from the page (14–16).

Fully Convolutional Network (FCN)

FCN model uses various blocks of**convolution** and **max pool** layers The goal of down sampling(convolution and max pooling)steps is to capture semantic/contextual information[40].

a) First decompress an image to 1/32th of its original size.

b) It then makes a class prediction at this level of granularity.

c) Finally it uses up sampling and deconvolution layers for the goal of recoving spatial information and to resize the image to its original dimensions.

d) These models typically don't have any fully connected layers.The final image is the same size as the original image so there are no limitations on image size.

e) Skip connections are used to fully recover the fine grained spatial information lost in down sampling[40].

Skip Connection

Is a connection that jumps at least one layer. In the FCN it is used to pass information from the down sampling step to the up sampling step. This is for reason of merging features from various resolution levels and helps combining context information with spatial information[40].

Our Proposal

In the previous section we have seen the Auto-encoder architecture. In this section we discuss how our own model looks like an Auto-encoder.

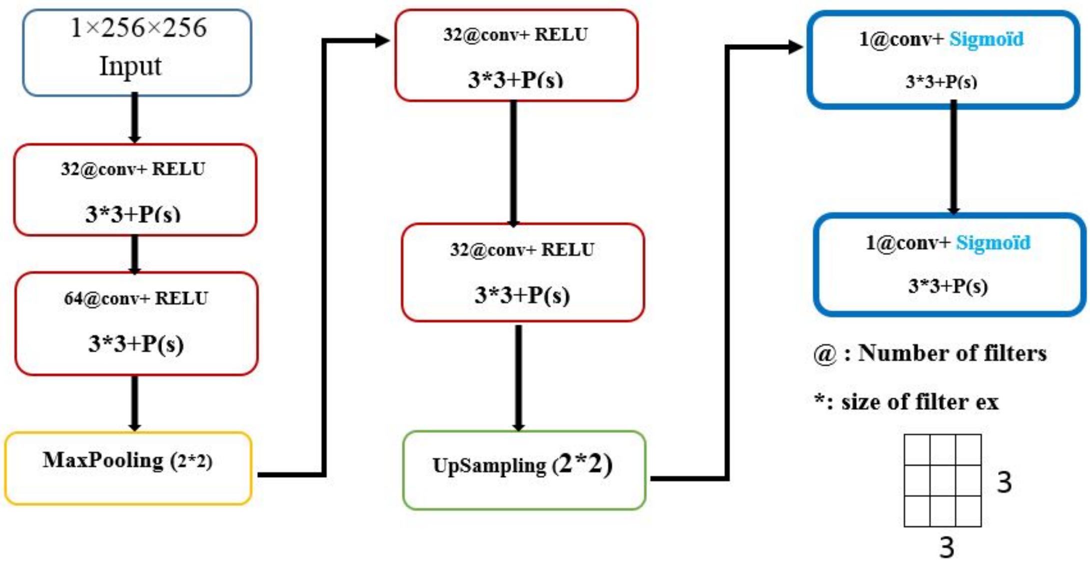


Figure 3.5: The S-Net model Layers

Data Preprocessing

The number of samples totally is 140 from 35 patient cases. Batch extraction strategy is made on the input data and few other operations such as :

- **Data Reshaping**

  We reshape the data input to get the desired correspondence with the network parameters,in our case our input shape is (256,256,4)represents the height and the length and the depth witch indicate the number of channel colors in our case we have four Mri types in grey scale (depth=1) so in total we get four. For implementation reasons we reshape our input images to (256,256,1).

- **Max-Min normalization technique**

  We have applied Max-Min data normalization technique to transfer the pixel values between [0.0,1.0], to assume that the model generalize as fast as possible and for implementation reasons by using this formula.

  images = (images - min(images)) / (max(images) - min(images)).

- **Zero Padding technique**

  This is an important step, here we pad images with zeros at the boundaries so that the dimension of the images are even and it is easier to down-sample the images while keeping their initial[1]

The Convolutional S-Net layers

Input layer

The images are of size (256,256,1) with 140 samples. We convert them to an array,rescaled between 0 and 1, reshaped so that it's of size 256 x 256 x 1,and fed

[1] P(S) means same padding as the initial

as an input to the network.

The hidden layers

S-Net is based on the Auto-encoder network in this section we see how our model looks like an Auto-encoder and what are differentiation's between both of them, note that encoder decoder become DownSample-Phase and a UpSample-Phase.

DownSample-Phase:

It has one Convolution blocks, this block has a convolution layer followed by a batch normalization layer. Max-pooling layer is used after the convolution block see figure (3.5) first column.

- The convolution block has two Conv layers the first one with 32 filters in figure 3.5 (32@) of size 3 x 3, followed by a Batch normalization, the use of the batch normalization for keeping the size and for implementation necessaries, the result of the convolution operation then passed to the RELU activation function with the same padding as the input.
- The second layer has 64 filters of size 3 x 3, followed by a Batch normalization and the a Maxpooling layer. In the max pooling layer the maximum value within the window of size (2×2) is pooled into an output matrix, the image size after this step become(128,128).

In our model we use both convolutional layers followed by the max pooling layer is to don't loss the informations.

Max pooling

Is to down-sample an input representation such as image etc, by a sample-based discretization process,to reduce its dimensionality and allowing for assumptions to be made about features contained in the sub-regions binned [41].

UpSample-Phase:

It has a Convolution block, this block has two convolution layer followed by a batch normalization layer. Upsampling layer is used after the second convolution layer.

This phase consist to capture first more features. That's why we use the block with two conv layers.

From the literature as the model go deeply as more features can learned, and more generalize.

Secondly to capture the spatial information by the upsampling .

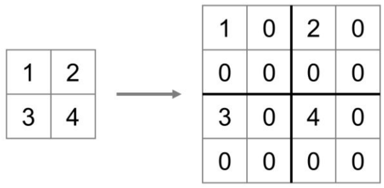
- The convolution block will have two Conv layers the first one with 32 filters of size 3 x 3, followed by a Batch normalization,
- The second layer will have 64 filters of size 3 x 3, followed by a Batch normalization and the a Upsampling of(2 x 2).
- The final two layers have one filter of size 3 x 3 to will reconstruct back the input having a single channel.

  We use two final layers because we have a binary classification that means two classes of segmentation, each layer indicate a region class such as the penumbra and the region not at risk.

What does the UpSample-Phase means?

From literature up-sampling is a technique for increasing the size of an image. In our case we want to resize or to up-sample the image from (128×128) in a new larger image of (256×256).

This is done by Nearest-Neighbor: Copies the value from the nearest pixel offered by **Keras** environment. Here is an exemple of upsampling operation using Nearest-



Neighbor technique.

a) The max-pooling layer will downsample the input by two times each time we use it.

   Results from the first downsampling phase will be a group of features learned from each of the four MRI types.

b) The upsampling layer reconstruct the final results as like as the size of the input,with features learned from the input.

   The both final layers indicate the two classes desired to segment each output is a constructed image from the four MRI modalities.

The number of filters,the filter size, the number of layers, number of epochs to train the model, are all hyper-parameters and should be decided based on the own intuition. These hyper-parameters measure the performance of the model.

Activation Function

From literature the **RELU (Rectified Linear Unit)** is the most used activation function, it is used in almost all the convolutional neural networks that achieve the actual state of the art.
RELU is one of the activation function using in the hidden layers.It actives the input just when the input is higher then certain quantity(2).
We used the **Sigmoid** as an activation function in the output level because our problem is a binary classification.

Our output layer consist of a two conv layer with one neuron for each one, the sigmoid gives reel values between [0.0,1.0] for the unique class.
This reel output is interpreted to a distribution of probabilities(1).

- $S(x) = \frac{1}{1+e^{-x}}$ ....(1)
- $R(z) = \max(0, z)$ ....(2)

Loss function

the Dice coefficient is a loss function for image segmentation tasks which is essentially a measure of overlap between two samples.This measure ranges from 0 to 1 where a Dice coefficient of 1 denotes perfect and complete overlap. It was originally developed for binary data,and can be calculated as[42]:

$$Dice = \frac{2\,|A \cap B|}{|A| + |B|} = \frac{2TP}{2TP + FP + FN}$$

where $|A \cap B|$ represents the common elements between sets A and B, and $|A|$ represents the number of elements in set A (and likewise for set B).

- True Positive (TP): The predicted is positive and it's true.
- True Negative (TN): The predicted is negative and it's true.
- False Positive (FP): (Type 1 Error) The predicted is positive and it's false.
- False Negative (fN): (Type 2 Error) The predicted is negative and it's false.

The Optimizer

The choice of optimization algorithm for the deep learning model can mean the differentiate between the results[43].

The **Adam** optimization algorithm is an extension to stochastic gradient descent to update network weights iterative based in training data.
It has recently seen broader adoption for deep learning applications [43].

Data Augmentation

The performance of deep learning neural networks often improves with the amount of data available.
This improvement offered by applying the Data augmentation technique to artificially create new training data from existing ones.
This is done with several operations for more generalization such as [44]:
shifts :

A shift to an image means moving all pixels of the image in one direction, such as horizontally or vertically.

Some of the pixels will be clipped off the image and there will be a region that new pixel values will have to be specified.
While shift the image dimensions kept the same[44].

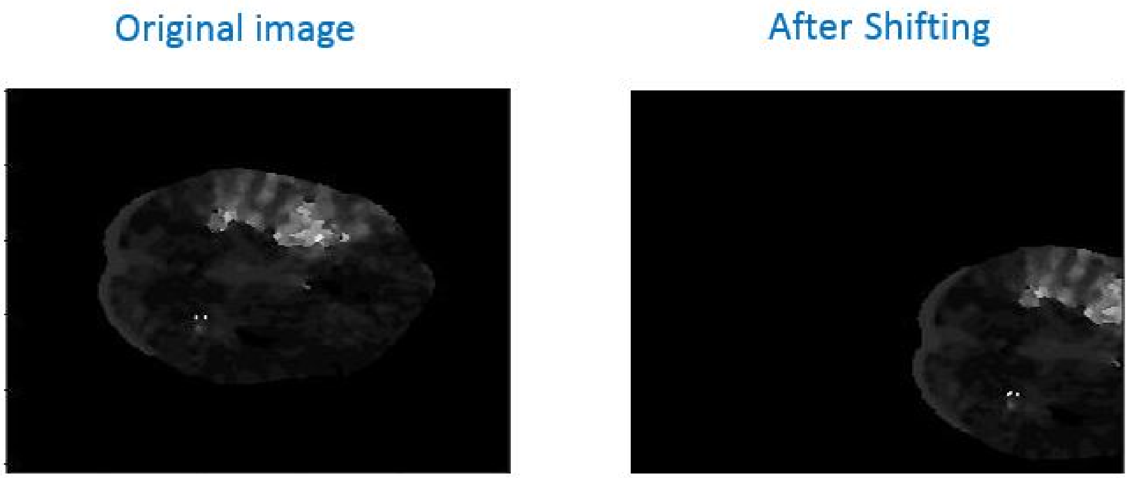


Figure 3.6: The shifts augmentation results

Random Zoom Augmentation

A zoom augmentation randomly zooms the image in and either adds new pixel values around the image or interpolates pixel values respectively[44].

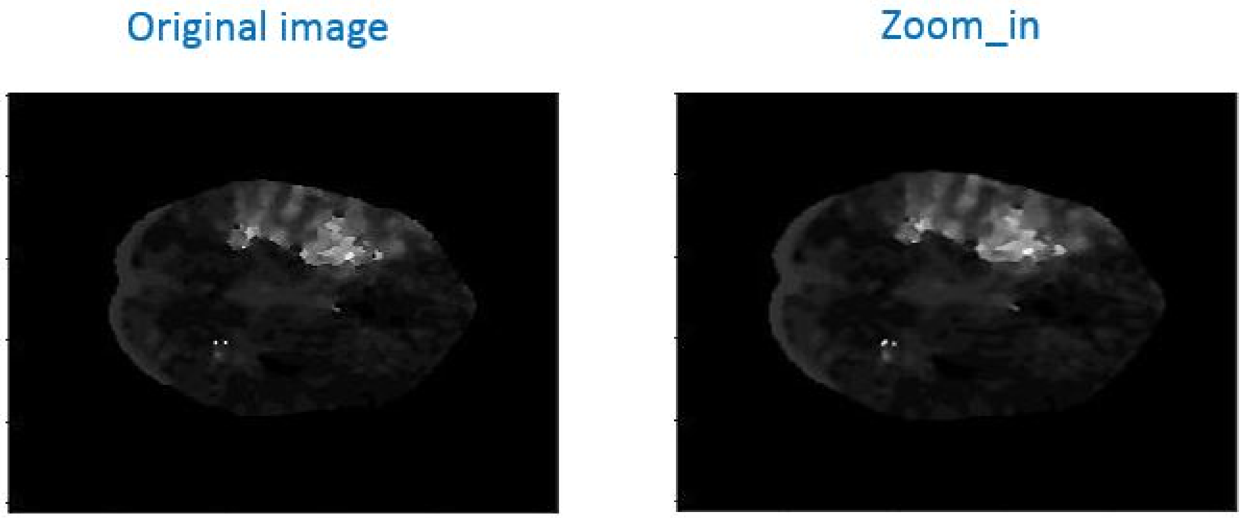


Figure 3.7: The Random Zoom augmentation results

Flip Augmentation:

An image flip means reversing the rows or columns of pixels in the case of a vertical or horizontal flip respectively[44].

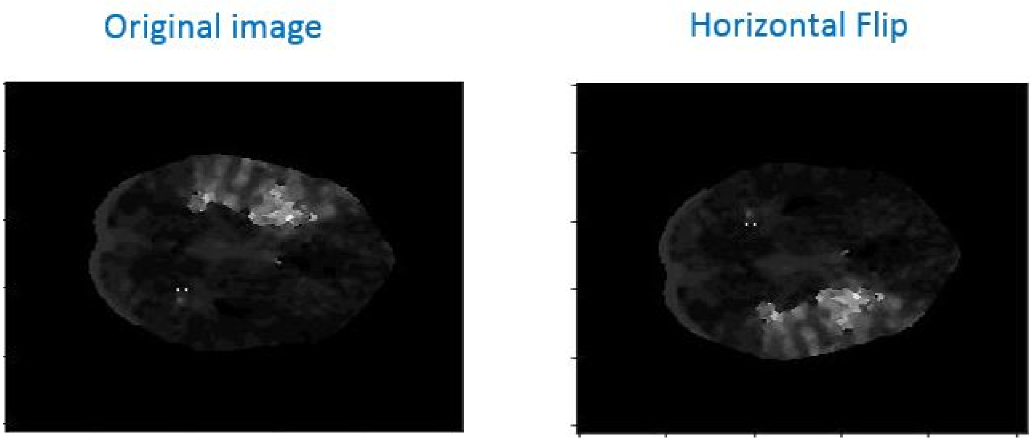


Figure 3.8: The Horizontal Flip augmentation results

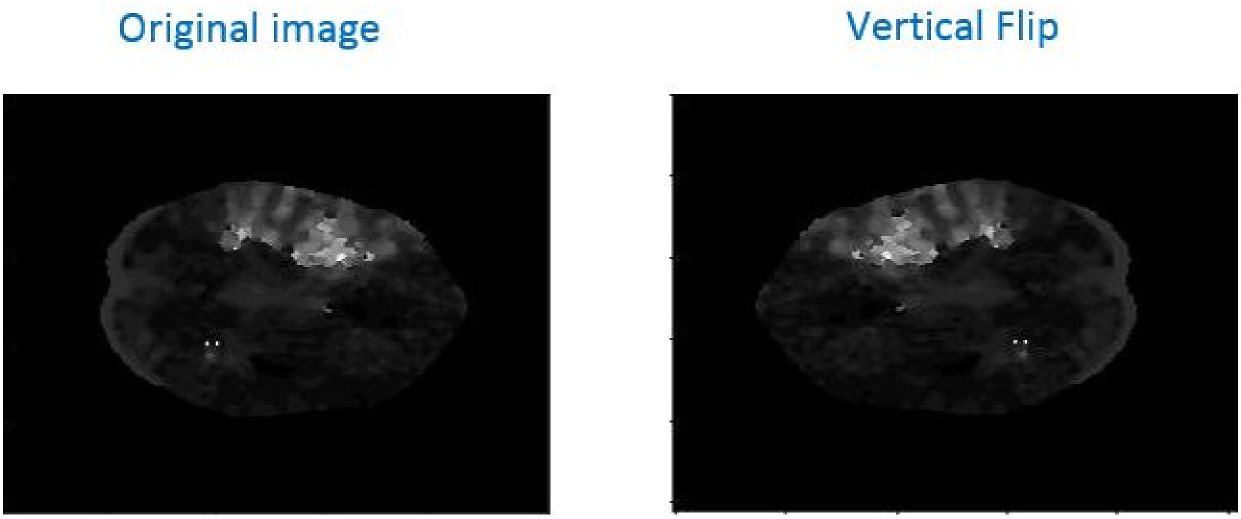


Figure 3.9: The Vertical Flip augmentation results

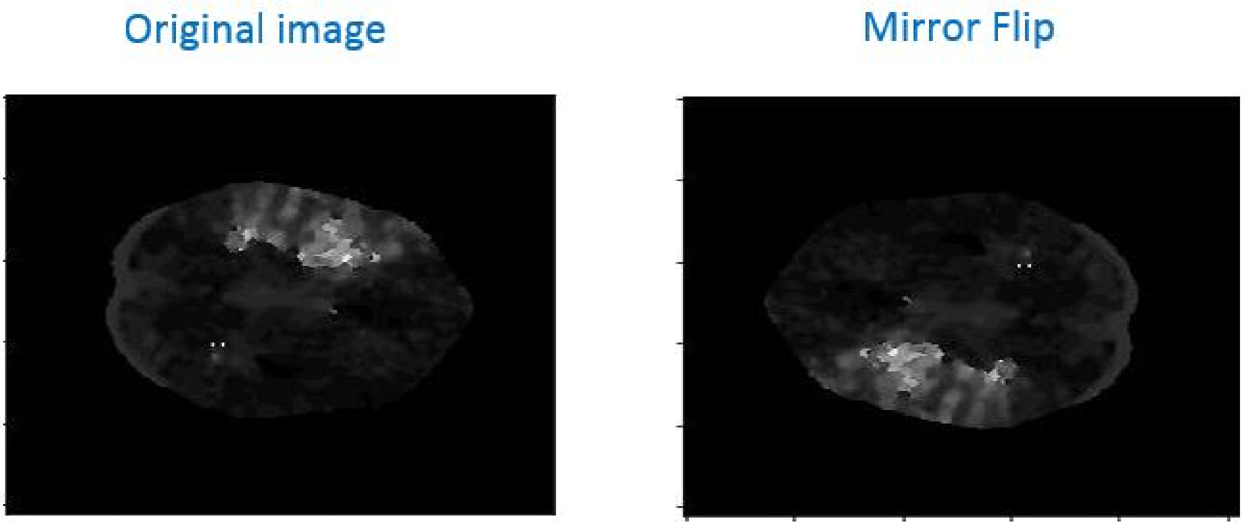


Figure 3.10: The Mirror Flip augmentation results

The Tuning

Tuning the parameters of the model it can map a particular input to some output (label). To perform for our model the best weights and to adopt their inputs with the model parameters.

Weather the parameters are tuned in the right way the model generalize better.

3.2 Implementation Details

3.2.1 Data

For evaluation of the model we use the public dataset from the Ischemic Stroke Lesion Segmentation (ISLES) web site, witch is a medical image segmentation challenge. The challenge has a different versions and a several tasks including penumbra and whole lesion segmentation, in the ISLES 2015 SISS and SPES dataset respectively, and lesion outcome prediction for the ISLES 2017 dataset, which is an extension of the 2016 with some additional cases. Our intresting case including the 2018 version [2], witch is depending on the segmentation of stroke lesion based on acute CT perfusion imaging and DWI (DWI maps) presented in next[35].

The public Data Set from the Url: `http://www.isles-challenge.org/`

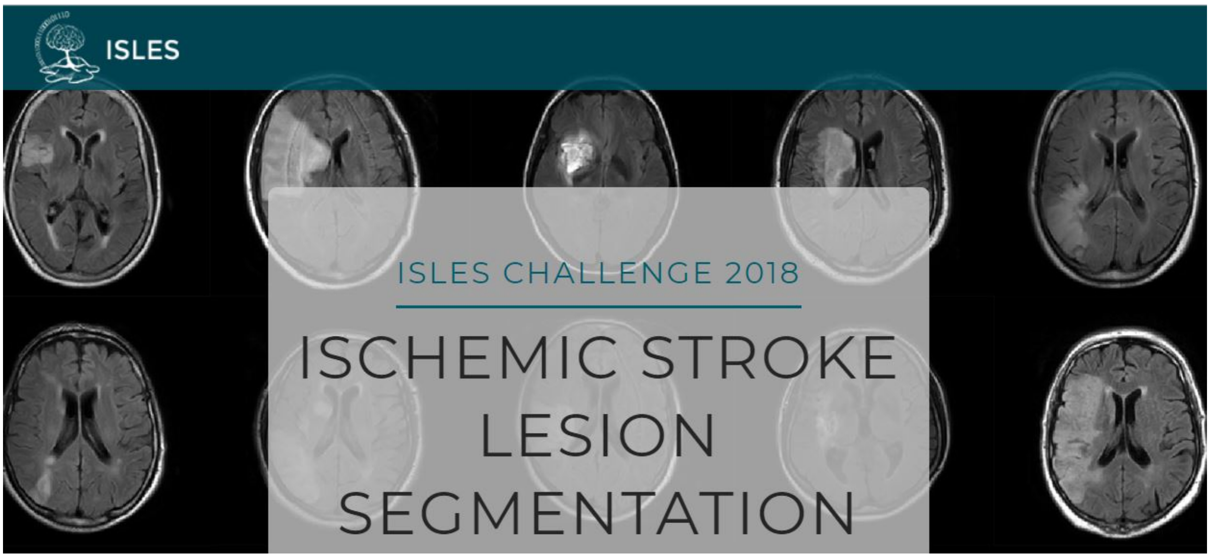


Figure 3.11: The ISLES Challenge 2018[35]

- The number of the input MRI images is equal to 35 patient's cases.
- Four MRI modalities of CT-Perfusion(CBF,CBV,TMAX,CT) in each case.
- Out put scan witch is manual segmented by the expert each type contains two slices.

PERFUSION MAPS (CBF, CBV, TMAX, CTP SOURCE DATA)

- Different maps aim to yield different information.
- The most commonly calculated maps include cerebral blood volume (CBV), cerebral blood flow (CBF), and time to peak of the residue function (Tmax). These perfusion maps are derived from the raw data for clinical interpretation.
- Data is a temporal change captured in dynamic scans acquired 1-2 sec, with the contrast agent (CA) witch is administered to the patient to assess cerebral perfusion. These perfusion maps serve as input to the algorithms[35].

CT perfusion

In the setting of acute ischemic stroke is understanding and identifying the infarct core and the ischemic penumbra,as a patient with a small core and a large penumbra is most likely to benefit from reperfusion therapies[45]. The three parameters typically used in determining these two areas are[45]:

- mean transit time (MTT) or time to peak (TTP) of the deconvolved tissue residue function (Tmax)
- cerebral blood flow (CBF)
- cerebral blood volume (CBV)

Normal perfusion parameters are:

gray matter:

- CBF: 60 ml/100 g/min
- CBV: 4 ml/100 g

white matter

- CBF: 25 ml/100 g/min
- CBV: 2 ml/100 g

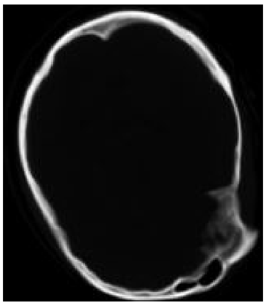


Figure 3.12: CT-Perfusion source type

Tmax

- Are measures of contrast arrival time to the tissue[46].

The Tmax perfusion parameter primarily reflects the bolus delay between the site of the arterial input function (AIF) and the tissue.This delay sensitivity seems important,as Tmax has outperformed delay-corrected perfusion parameters such as cerebral blood flow (CBF) and mean transit time for identifying critically hypoperfused tissue[47].

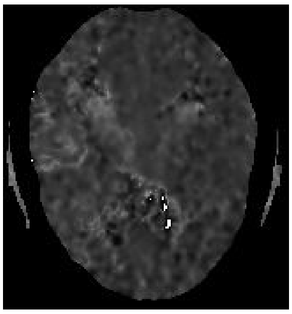


Figure 3.13: The TMax type

Cerebral blood flow (CBF)

Is one of the parameters generated by perfusion techniques (CT perfusion and MR perfusion) defined as the volume of blood passing through a given amount of brain tissue per unit of time,most commonly milliliters of blood per minute per 100g of brain tissue[45].

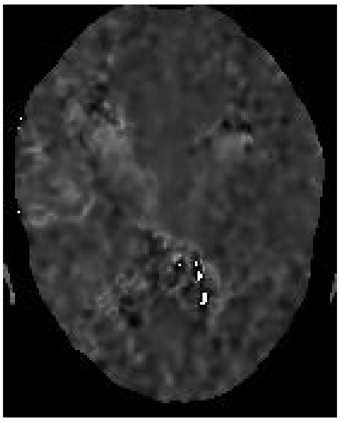


Figure 3.14: The CBF MRI type

Cerebral blood volume (CBV)

Is one of the parameters generated by perfusion techniques (CT perfusion and MR perfusion) defined as the volume of blood in a given amount of brain tissue,most commonly milliliters of blood per 100 g of brain tissue[45].

Figure 3.15: The CBV MRI type

3.3 Results and Evaluation

Neural network implementation

we choose to use the deep learning framework **Keras** for the following reasons:

- Modularity: it offers a wide range of layers types, activation functions, performance metrics... through a modular Python API.
- Efficiency and support: Keras is optimized and continuously maintained to work on both CPUs and GPUs.

Having such features makes the perfect environment for experimenting with the different possibilities and parameters. It also helped with saving the models into files, and re-using trained layers easily into a new model.

GPU	Backend google engine
Memory	12.72 GB
Programming language	Python version=3
Libraries and frameworks	Numpy Keras PyDrive Nibabel Glob2
Operating system	Online googleColab

Figure 3.16: technical details

Results

- In order for the model to generalize well,we split the data into two parts:a training and a validation set.
- We train the model on 80% of the data and validate it on 20% of the remaining training data.

This probably help in reducing the chances of overfitting.

$$\textbf{accuracy} = \frac{number \quad of \quad correctly \quad classified \quad examples}{number \quad of \quad all \quad classified \quad examples}$$

- The model was trained on 126 samples, and was validated on 14 samples with the number of epochs = 300.
- Best model weights are saved in file.h5.
- The training and the predicting time are as faster as the objective intent between the epoch and the next epoch for training 1s is spending so in total for 300 epochs we have 300s approximate to 5 minutes the big thanks to Google Collab.

Some segmented images with the input introducing.
The grey region indicate the penumbra area in figure 3.17 and 3.18 in sevral MRI modalities.

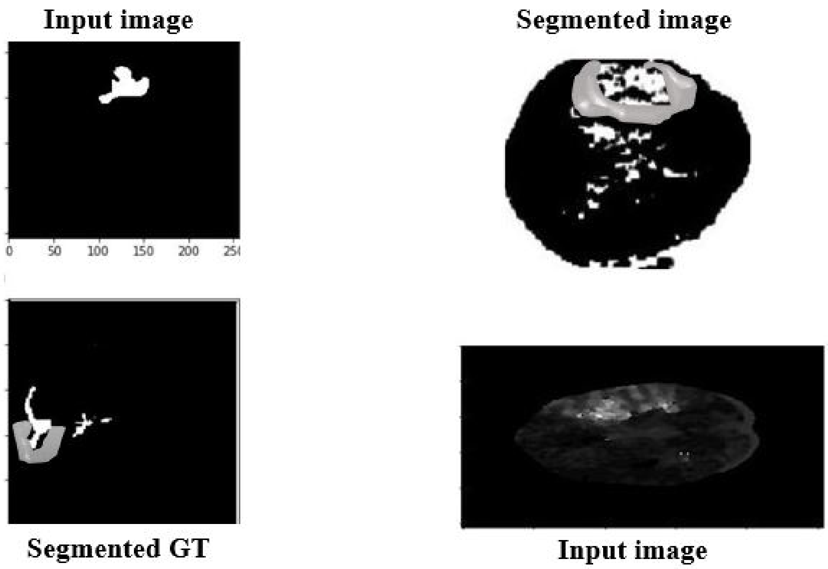


Figure 3.17: T1 image with segmentation and the ground truth output with the grey region indicate the penumbra area

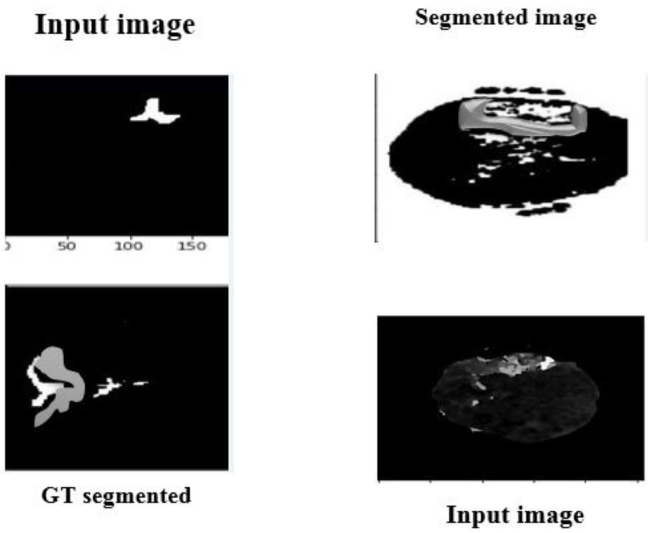


Figure 3.18: T2 image with segmentation and the ground truth output with the grey region indicate the penumbra area

The dice coefficient metric to valid on in figure 3.19.

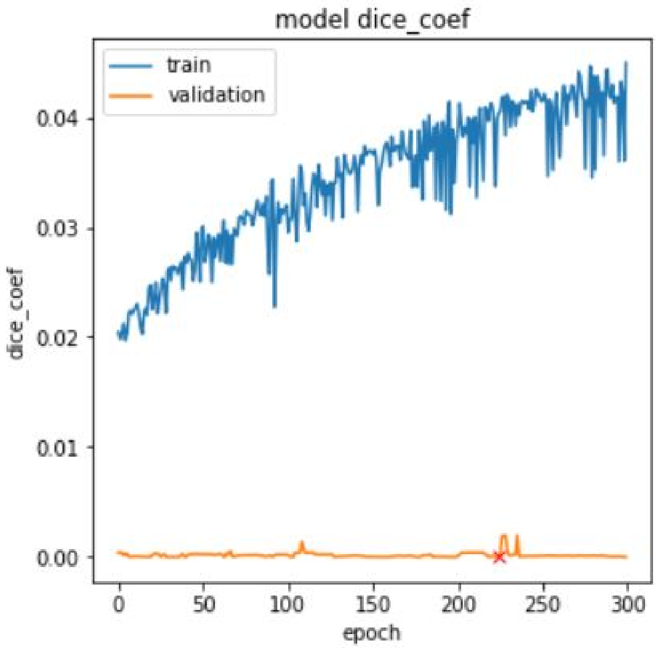


Figure 3.19: The dice coefficient history during training

The accuracy results appear in figure 3.20.

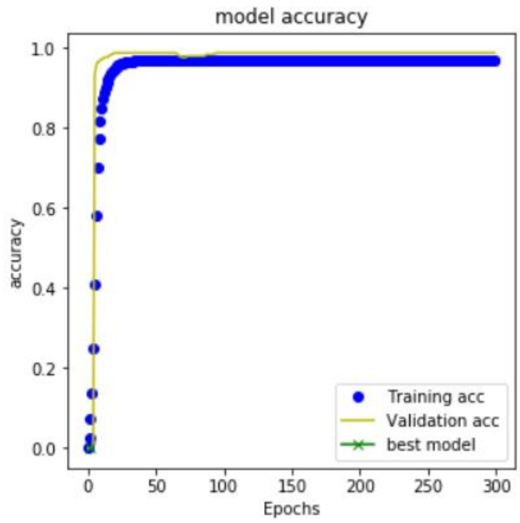


Figure 3.20: Accuracy history during training

Figure 3.21 shows the model loss.

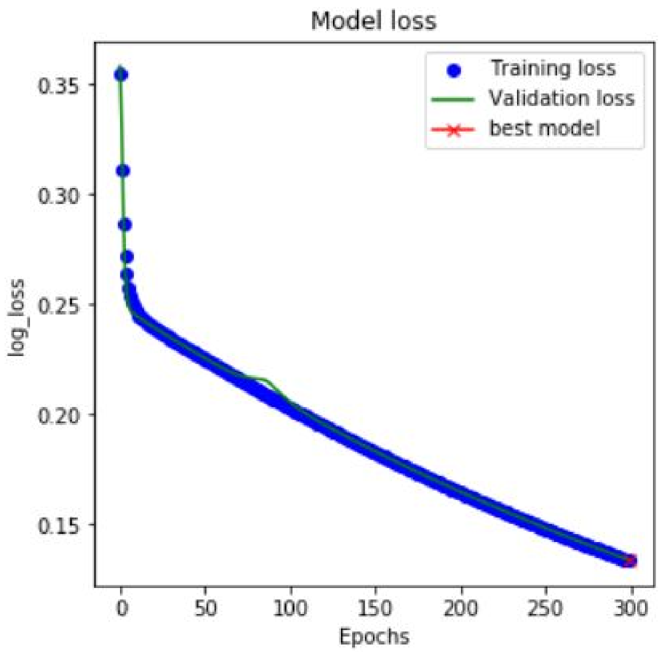


Figure 3.21: Loss history during training

3.4 Discussion

In the figure 3.22 coming later we have introduced a comparison between the results obtains in previous works and our work.

Architecture	Article	DSC	False Positive(FP)	False Negative(FN)	Training time	Inferencing time	Hausdorff Distance
U-Net (SUNet).	Clérigue et al. 2018	65.0 ± 26.0 78.5 ± 14.9 40.1 ± 23.0	Non	Non	Non	Non	35.1 ± 29.7 16.0 ± 10.1 21.8 ± 17.0
CNN based on the U-Net	A Pinto et al. 2018	0.29 ± 0.21	Non	Non	Non	Non	41.58 ± 22.04
A 3D (ConvNet)	Y Wang et al 2016	0,63/0,78	Non	Non	Non	Non	Non
2D-residual (Res-FCN	Z LIU et al 2018	Non	Lower numbers	Lower numbers	Non	Non	Non
3D FC-DenseNet	R Zhang et al 2018	79.13%	0.40	1.16	6h23m	0.095s	Non
S_net	None	0,04	None	None	5mn	0.01s	None

Figure 3.22: A Comparison results

3.5 Conclusion

In this chapter we have presented the model architecture and their components and motivate the choose of the CNN based on the Autoencoder model with multi-modal MRI images for ischemic strok lesions segmentation.

Our contribution is to inspire the idea of the Autoencoder with the convoultional neural network for the reason to reconstruct segmented MRI images in same size of the input and with learnable feature from each of the MRI modalities by using the both phases such as the downsamling phase and the upsampling one.

Chapter 4

General Conclusion

In this work, we investigated the use of deep neural networks, specifically convolutional neural networks, for the problem of Stroke lesion segmentation.

In addition to the neural network architecture we proposed for this problem, witch combine the use of the convolutional neural network in term of the Autoencoder architecture we also used the technique of multispectral Mri modalities to benefice for the learning model to generalize better by reconstruting the input modalities as one to feed to model.

Experimental results also show how it affects the use of little data on the training time and on the results. So that the use of the amount dataset and other datasets it will be a priority for the future of this project.

Since the datasets used in this work were collected from the web, the future materialization of this work relies on gathering data from a sevral Stroke challenges to improve the performance of the model and to explore more.

Another possible future direction would be a further work on the transfers learning, and the implementation of the most popular deep learning architecture dedicated for medical images segmentation empirical, analysis on this approach in the future.

List of Tables

Bibliography

[1] Zeynettin Akkus et al. "Deep Learning for Brain MRI Segmentation: State of the Art and Future Directions". In: *Journal of Digital Imaging* 30.4 (Aug. 2017), pp. 449–459. ISSN: 1618-727X. DOI: 10.1007/s10278-017-9983-4. URL: https://doi.org/10.1007/s10278-017-9983-4.

[2] Clérigues Albert et al. "SUNet: a deep learning architecture for acute stroke lesion segmentation and outcome prediction in multimodal MRI". In: (Oct. 2018), p. 13. URL: https://www.semanticscholar.org/paper/SUNet%3A-a-deep-learning-architecture-for-acute-and-Cl%C3%A9rigues-Valverde/d1f29d636ef30e00026dc27ed621322225d98683.

[3] Shubham Joshi and Prof. Sonal Gore. *ISCHEMIC STROKE LESION SEGMENTATION BY ANALYZING MRI IMAGES USING DEEP CONVOLUTIONAL NEURAL NETWORKS*. URL: http://helix.dnares.in/2018/09/07/ischemic-stroke-lesion-segmentation-by-analyzing-mri-images-using-deep-convolutional-neural-networks/.

[4] Raya Dutta. "IMAGE SEGMENTATION USING THRESHOLDING". In: (2018). URL: https://www.daitm.org.in/wp-content/uploads/2019/04/15499016013_RayaDutta.pdf.

[5] Despotović Ivana, Goossens Bart, and Philips Wilfried. "MRI Segmentation of the Human Brain: Challenges, Methods, and Applications". In: *Computational and Mathematical Methods in Medicine* (2015), p. 23. URL: https://doi.org/10.1155/2015/450341.

[6] *Chapter 4 SEGMENTATION*. URL: https://www.bioss.ac.uk/people/chris/ch4.pd.

[7] *Image Segmentation*. URL: https://www.mathworks.com/discovery/image-segmentation.html.

[8] Kaur Dilpreet and Kaur Yadwinder. *Various Image Segmentation Techniques: A Review*. URL: https://ijcsmc.com/docs/papers/May2014/V3I5201499a84.pdf.

[9] Kaur Balpreet and Kaur Prabhpreet. *A Comparative Study on Image Segmentation Techniques*. URL: https://www.ijcseonline.org/pub_paper/7-IJCSE-01430.pdf.

[10] Khan Am and Srisha Ravi. *Image Segmentation Methods: A Comparative Study*. URL: http://www.academia.edu/10714033/Image_Segmentation_Methods_A_Comparative_Study.

[11] kumarV Manoj and M G Sumithra. *PERFORMANCE COMPARISON OF DIFFERENT MEDICAL IMAGE SEGMENTATION ALGORITHMS FOR NORMAL AND ABNORMAL BRAIN MRI*. URL: http://www.mnkjournals.com/ijlrst_files/Download/Vol%201%20Issue%204/15-4024%20-Manoj%20Kumar.pdf.

[12] Ahirwar Anamika. *Study of Techniques used for Medical Image Segmentation and Computation of Statistical Test for Region Classification of Brain MRI*. URL: https://pdfs.semanticscholar.org/60b8/27b6323439fb694fe96fb4d225b8e61dc9c pdf.

[13] *Introduction to Artificial Neural Networks*. URL: https://www.cse.unr.edu/~bebis/MathMethods/NNs/lecture.pdf.

[14] *Artificial Neural Network(ANN)*. URL: http://www.cs.kumamoto-u.ac.jp/epslab/ICinPS/Lecture-2.pdf.

[15] *A Beginner's Guide to Neural Networks and Deep Learning*. URL: https://skymind.ai/wiki/neural-network.

[16] Carlos Gershenson. "Artificial Neural Networks for Beginners". In: (Sept. 2003). URL: https://datajobs.com/data-science-repo/Neural-Net-[Carlos-Gershenson].pdf.

[17] *Understanding Feedforward Neural Networks*. URL: https://www.learnopencv.com/understanding-feedforward-neural-networks/.

[18] Martin T. Hagan. *Neural Network Design 2nd Edtion*. URL: http://hagan.okstate.edu/NNDesign.pdf.

[19] John McGonagle. *Feedforward Neural Networks*. URL: https://brilliant.org/wiki/feedforward-neural-networks/.

[20] M. Tim Jones. *Deep learning architectures*. URL: https://developer.ibm.com/articles/cc-machine-learning-deep-learning-architectures/.

[21] *What Is Deep Learning? 3 things you need to know*. URL: https://www.mathworks.com/discovery/deep-learning.html.

[22] *An Introduction to Deep Learning*. URL: https://towardsdatascience.com/an-introduction-to-deep-learning-af63448c122c.

[23] *What makes Deep Learning deep....and world-changing?* URL: https://readwrite.com/2017/04/28/what-is-deep-learning-il1/.

[24] Daphne Cornelisse. *An intuitive guide to Convolutional Neural Networks*. URL: https://medium.freecodecamp.org/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050.

[25] Alejandro Escontrela. *Convolutional Neural Networks from the ground up*. URL: https://towardsdatascience.com/convolutional-neural-networks-from-the-ground-up-c67bb41454e1.

[26] Arden Dertat. *Applied Deep Learning - Part 4: Convolutional Neural Networks*. URL: https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2.

[27] *Top 5 Deep Learning Architectures*. URL: https://developer.ibm.com/articles/cc-machine-learning-deep-learning-architectures/.

[28] SH Tsang. *Review: U-Net (Biomedical Image Segmentation)*. URL: https://towardsdatascience.com/review-u-net-biomedical-image-segmentation-d02bf06ca760.

[29] *U-Net: Image Segmentation Network*. URL: https://neurohive.io/en/popular-networks/u-net/.

[30] Connor Shorten. *U-Net: Convolutional Networks for Biomedical Image Segmentation*. URL: https://medium.com/@connorshorten300/u-net-convolutional-networks-for-biomedical-image-segmentation-c9140032f92.

[31] Adriano Pinto et al. "Enhancing Clinical MRI Perfusion Maps with Data-Driven Maps of Complementary Nature for Lesion Outcome Prediction". In: *MICCAI 2018* (2018), pp. 107–115. URL: https://link.springer.com/chapter/10.1007/978-3-030-00931-1_13.

[32] Yanran Wang, Aggelos K. Katsaggelos, and Todd B Parrish Xue Wang. "A DEEP SYMMETRY CONVNET FOR STROKE LESION SEGMENTATION". In: (2016), p. 5.

[33] ZHIYANG LIU et al. "Towards Clinical Diagnosis: Automated Stroke Lesion Segmentation on Multi-Spectral MR Image Using Convolutional Neural Network". In: 4 (2017), p. 12.

[34] Rongzhao Zhang et al. "Automatic Segmentation of Acute Ischemic Stroke From DWI Using 3-D Fully Convolutional DenseNets". In: 37 (Sept. 2018), pp. 107–115.

[35] *Ischemic Stroke Lesion Segmentation (ISLES) 2018*. URL: http://www.isles-challenge.org/.

[36] Muhammad Imran Razzak, Saeeda Naz, and Ahmad Zaib. "Deep Learning for Medical Image Processing: Overview, Challenges and the Future". In: *Classification in BioApps: Automation of Decision Making*. Ed. by Nilanjan Dey, Amira S. Ashour, and Surekha Borra. Cham: Springer International Publishing, 2018, pp. 323–350. ISBN: 978-3-319-65981-7. DOI: 10.1007/978-3-319-65981-7_12. URL: https://doi.org/10.1007/978-3-319-65981-7_12.

[37] *AutoEncoders are Essential in Deep Neural Nets*. URL: https://towardsdatascience.com/autoencoders-are-essential-in-deep-neural-nets-f0365b2d1d7c.

[38] Dertat Arden. *Applied Deep Learning - Part 3: Autoencoders*. URL: https://towardsdatascience.com/applied-deep-learning-part-3-autoencoders-1c083af4d798.

[39] Bandaria Jigar. *Brain MRI image segmentation using Stacked Denoising Autoencoders*. URL: https://blog.insightdatascience.com/brain-mri-image-segmentation-using-stacked-denoising-autoencoders-4e91417688f6.

[40] *Semantic Segmentation—Popular Architectures*. URL: https://towardsdatascience.com/semantic-segmentation-popular-architectures-dff0a75f39d0.

[41] *Max-pooling / Pooling*. URL: https://computersciencewiki.org/index.php/Max-pooling_/_Pooling.

[42] *An overview of semantic image segmentation*. URL: https://www.jeremyjordan.me/semantic-segmentation/.

[43] *Gentle Introduction to the Adam Optimization Algorithm for Deep Learning*. URL: https://machinelearningmastery.com/adam-optimization-algorithm-for-deep-learning/.

[44] *How to Configure Image Data Augmentation When Training Deep Learning Neural Networks*. URL: https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/.

[45] *CT perfusion in ischemic stroke*. URL: https://radiopaedia.org/articles/ct-perfusion-in-ischaemic-stroke.

[46] *Time to Dispense with the Clock and Move to Tissue-based Decision Making?* URL: https://www.medscape.com/viewarticle/742007_7.

[47] *A Comparison of Relative Time to Peak and Tmax for Mismatch-Based Patient Selection*. URL: https://www.frontiersin.org/articles/10.3389/fneur.2017.00539/full.