A Hybrid ResNet50-UNet Model for Ischemic Strokebrain Segmentation from MRI Images

[1]Fathia ABOUDI, [2]Cyrine DRISSI, [3]Tarek KRAIEM

[1]Biophysics and MedicalTechnology Laboratory ISTMT Université Tunis El Manar (UTM), Tunisia
[2]Department of Neuroradiology,National Institute of Neurology Mongi Ben Hmida,Tunisia
[3]Biophysics and MedicalTechnology Laboratory, Faculty of Medicine of Tunis,Tunisia

Abstract
Ischemic brain stroke is the most common cerebrovascular disease and one of the leading causes of death and long-term disabilities worldwide. Early detection of ischemic brain stroke helps physicians to take a precocious diagnosis whichsignificantly reduces possible cases of death or disabilities. Severalmodalities are used to detect Ischemic brain stroke in medical research; though, magnetic resonance imaging (MRI) remains themost effective modality in this field. Recently, many researchers used deep learning models to detect ischemic brain stroke inMRI images and have proven encouraging results. In this paper, we present an automated approach for segmenting ischemic stroke lesions (ISL) from MRI images using a deep learning model. The UNet used model is used as a hybrid framework with a pre-trained ResNet50 architecture. Data augmentation technique has been applied to outperform the model's accuracy. The proposed workflow has been trained and tested on a public Ischemic Stroke Lesion Segmentation challenge (ISLES) 2015 datasets. The experimental findings demonstrate the efficiency of the performance of our approach, it achieves a 99.43% average accuracy, and a 64.14% Dice Coefficient(DC). Our approach outperforms other state-of-the-art methods, more specifically, forthe accuracy values.

Keywords:

Medical image segmentation, Ischemic stroke dis- ease, UNet, ResNet50, MRI, Transfer learning, data augmentation

1. Introduction

Stroke is one of the most common causes of death and a leading factor of long-term disability and cognitive impairment worldwide [1], endangering public health but with few effective therapies [2]. The two main categories of stroke are ischemia (80%) and hemorrhage (20%). Ischemic stroke occurs when the blood supply to a part of the brain is significantly reduced, which can lead to the formation of cerebral edema and neuronal cell death. The reduction of blood flow produces tissue hypoxia, depriving brain cells of oxygen and nutrition.

Furthermore, blood flow irregularities are frequently causedby an embolism clogging a cerebral artery or arteriole, re- sulting in a severe decrease in blood supply to specific areasof the brain where outcomes crucially depend on the timingof intervention [3]. Annually, 12 million people are affectedby stroke brain in worldwide and the value is increasing [4] with six million people dying as a result [5]. The incidence.in the USA is about 800,000 patients and this number is expected to increase significantly in the next decades, dueto the aging population [6]. The World Health Organization (WHO) has declared a pandemic and forecasts a 23 millionrise in stroke cases by 2030 (16 million in 2005). Around70% of stroke patients' survivors have considerable sensory, language, and cognitive impairment, necessitating long-term special care and rehabilitation [7]. Also, the follow-up of stroke cases is important that it is can occur the recovery in chronic stages. Further, ischemic stroke lesion volume assessment isan essential end-point in clinical trials that may be utilized to enhance diagnosis, prognosis, detection, and therapeutic intervention. Management of acute stroke is a time-sensitive emergency that requires organized multidisciplinary care. The early hours after stroke onset frequently map the trajectory of subsequent neurologic disability, complications, and outcomes.

Advanced neuroimaging techniques play a critical role in resolving issues after a stroke. Magnetic Resonance Imaging (MRI) is one of the most effective methods for assessing patients with ischemic stroke. It offers a range of disease monitoring and outcome prediction. More than, such as her sequences acquisitions (Diffusion-Weighted-Images (DWI), T1, T2, and Fluid-Attenuated-Inversion-Recovery (FLAIR)), itprovides detailed information about the localization and extentof the lesion, which represents the clinical key in the early stage. It is necessary to analyze multidimensional information to make an objective, and comprehensive assessment and to reduce disabilities and death. Therefore, it is meaningful to automatically detect the infarct lesion to help the diagnosis for clinicians and to earn the timing of intervention and treatment decision-making.

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The segmentation of ischemic strokes in MRI images isa challenging issue owing to their complex structure. Consequently, Artificial Intelligence (AI) algorithms have been implemented for the automatic stroke segmentation and area crucial role in medical research field.

It can effectively process multidimensional medical data comparably with a trained expert such as deep learning and machine learning, which are the most popular techniques in the AI field. It has been increasingly adopted in the segmentation, diagnosis, detection, and prognosis of stroke. An automatic segmentation tool of cerebral infarction lesions from data MRI with AI would give more accurate and consistent findings. It would save time during testing, allowing the neuroradiologists to evaluate and analyze more data for their patients, which is preferred to be cost-effective.

The Computer-Aided Diagnosis (CAD) system is widely used in brain segmentation. Many studies are worth mentioning. Some techniques are supervised and others are un- supervised. There is a growing interest in convolutional neural networks (CNNs) for image classification and segmentation through their efficacity in various fields, especially in medical imaging. Several CNNs based methods combined with other statistical methods have been proposed for ischemic brain stroke segmentation from multimodal MRI. Following the increasing popularity and efficiency of deep learning algo-rithms, many patterns for automated segmentation have been developed by researchers in different laboratories worldwide.

In this paper, we propose a hybrid ResNet50-UNet model with a preprocessing step of ischemic stroke brain segmentationfrom MRI images. First, we applied data augmentation technics to overcome the problem of overfitting and unbalanced data, and to improve the model performance. Then, we used a pre-trained ResNet50 architecture with skip connections using transfer learning and fine-tuning tools. In addition, the hybrid ResNet50-UNet uses this skip-connections between the encoder and decoder which allows to stabilize parameter updates. Due to the similarity to a contracted layer of UNet and fewer parameters number, the ResNet50 presents the best choice of the building model.

The remainder of this paper is organized as follows. The section II reviewed the related works. In Section III, we describe the proposed hybrid model based on ResNet50 U- Net, and a brief description of the dataset acquisition and preprocessing. Experiments results are reported in section 11. We discuss some key issues and limitations of the proposed methods in the same section. And finally, the conclusion was discussed in section V.

II. RELATED WORK

In this section, we present the previous literature studies involving deep neural models for ischemic stroke brain segmentation using the same public benchmark dataset ISLES 2015 and we aim to address some of the shortcomings mentioned before our workflow approach. Table I illustrates a summary of the segmentation methods, applied architectures, used dataset, and performance metrics of previous works.

Yue Zhang et al. [8] proposed a multi-inputs U-Net (MI-U-Net) incorporating brain parcellation for stroke lesion segmentation using sequence T1-weighted MRI. They incorporated a 3D brain parcellation information including white matter, graymatter, and lateral ventricle. The benefit of MIU-Net was the facility to add an input channel that helps the model to adapt with any dimensions input and with various sizes.

In addition, LiangLiang Liu et al. [10] published two works for stroke MRI segmentation. Firstly, they developed a new deep convolutional neural network (Res-CNN) based on a U-shape structure to segment automatically acute ischemicstroke lesions. Data fusion and data augmentation was used to increase the number of training data. The Res-CNN achieveda DC equal to 74.20%. Secondly, A U-shape architecture and dense blocks were used to propose an end-to-end multi- kernel deep convolution neural network (DCNN). The use the underlying features to lack the information on the samplingand to improve the performance from depth and breadth of network and to alleviate the vanishing-gradient problem [12].

In other work, Y. Wang et. al. [5] presented a deep symmetry ConvNet for stroke lesion segmentation. This CNN, built with eight layers, helps detect the lesion without using anyparameters during the training process. The model performancewas assessed using unilateral and bilateral voxel descriptors. That is provided a value of DC for the unilateral voxel and bilateral equal to 63.08% and 73.07%, respectively.

Moreover, Rongzhao Zhang et al. [9] applied a 3D fully convolutional Dense Nets using DWI sequence. They integrateddense connectivity to boost information and gradient propagation within the deep 3D model and her optimization with dice loss objective function to tackle the severe class imbalance problem. This approach achieved a DC equal to 79.13% anda value precision equal to 92.67%.

More recently, Amish Kumar et al. [11] proposed a deep learning architecture based on a Classifier-Segmenter network (CSNet). That is provided a value of DC, precision, and recall equal to 63.25%, 74.23%, and 62.26% respectively.

III. PROPOSED METHOD

In this research paper, we introduce a CAD system based on hybrid deep learning model to automatic segmentation of the ischemic stroke brain lesion based on U-Net architecture. Figure 1 presents an overview of our proposed approach. The major network contributions can be summarized as follows: Firstly, a preprocessing step was applied to resize the input image to 128x128x3 pixels, along with a data augmentation technique to overcome the problem of a lack of data set and to reduce over-fitting during training. Secondly, we implemented an hybrid architecture based on ResNet50-UNet model. Then, transfer learning and fine tuning techniques were used as an alternative strategy to avoid the high cost of retraining the network. The proposed method was evaluated on a ISLES2015 dataset with four MRI sequences DWI, T1, T2, andFLAIR.

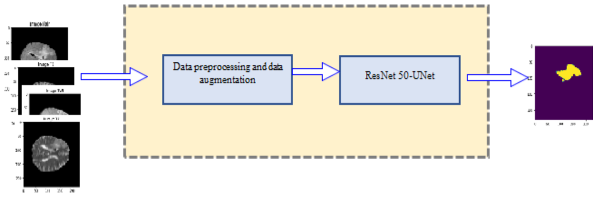

Fig. 1. Workflow of the proposed approach based on hybrid ResNet50-UNet models

TABLE I. SUMMARY OF EXISTING METHODS FOR MRI IMAGES SEGMENTATION

Authors	Methods	Dice Coefficient(%)	Accurracy(%)	Precision (%)
Rongzhao Zhang et al. [9] 2018	3D fully convolutional DenseNets	79.13	–	92.67
Liangliang Liu et al. [10] 2020	Multi Kernel DCNN : MK- DCNN	57	–	–
Yue Zhang et al. [8] 2020	Multi Input UNet : MI-UNet	56.72	–	65.45
Amish Kumat et al. [11] 2020	Classifier Segmenter network : CSNet	63	–	74

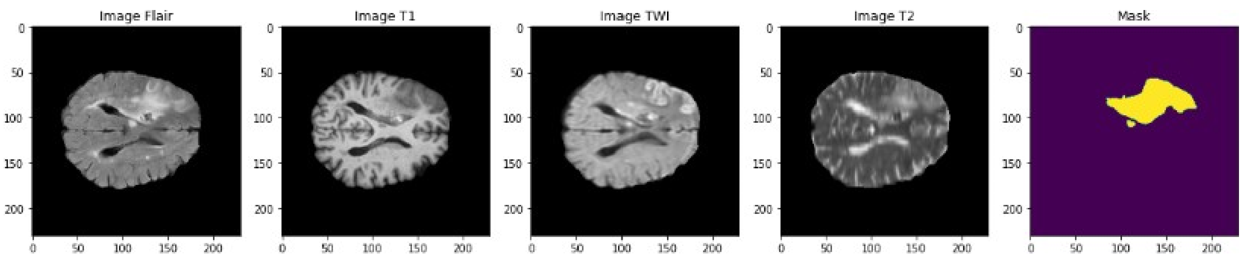

Fig. 2. Slices of the four sequence of patient (from left to right : DWI, T1, T2, FLAIR, and mask)

A. Dataset and Data Preparation

This study was performed using the multimodal Ischemic Stroke Lesion Segmentation challenge (ISLES) 2015. ISLES 2015 regrouped into sub-tasks: the first is SISS which consistedin segmenting sub-acute ischemic stroke lesions, used in our study, and the second is SPES which consists to estimate the stroke penumbra. The training dataset issue from SISS includes 28 subject cases in this model, and a ground truth that is segmented and annotated manually by experts. It is

received fromthe University Medical Center Schleswig Holstein (UKSH) Germany and the departments of Neuroradiology Hospital Rechts der Isar in Munich [13]. These data are acquired from 3T Philips systems. All cases contain a volumetric scan with a set of DWI (b = 1000), T2-weighted (T), T1- weighted (T1), and FLAIR MRI sequences. Each one of these sequences contains 57 to 154 MRI slices. Figure2 illustrates the four MRI images. DWI sequence is more sensitive to diagnose ISL in early stages and T2 to distinguish the ischemiccore and other damaged tissues.

Each sequence contains 57to 154 slices of MRI, in

NIFTI format, with a resolution equal to 230×230x3 pixels

For more specific, the acquisition parameters of DWI are slice thickness = 5 mm, echo time87 ms, and repetition time 3200 ms. The coregistration and preprocessing techniques of the subject's cases were pretreatedby the organizers including skull-stripped sequences using BET2, b-spline-resampled to an isotropic spacing of 1mm (3). An elastix toolbox was used in biais field correction and coregistration of FLAIR sequences [paper 44]. The ground truth segmented and annotated manually by expert. It coupled with this public benchmark. Furthermore, the dataset is dividedinto 70% for training, 20% for the validation, and 10% for the test, as shown in figure 3.

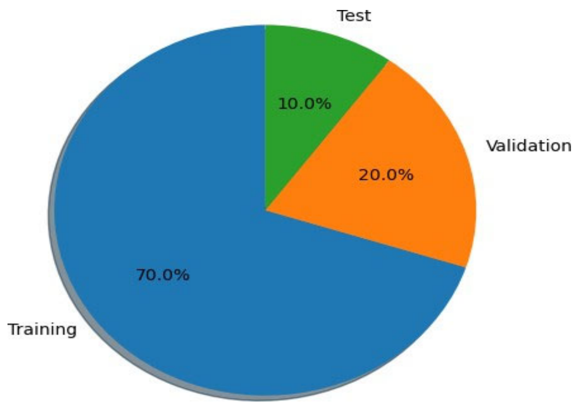

Fig. 3. Dataset repartition

B. Data augmentation

From the public available benchmark dataset ISLES 2015, we used SISS data that contained 28 brain MRI volumetric scans with four sequences. Each one contains 57 to 154 MR slices. Globally, we obtain approximately 4000 images. In mostMRI analysis tasks, the sample sizes of the MRI dataset are smaller and limited. Nevertheless, deep learning models need a large number of images for multi-parameter training model. To overcome the lack of data set, data augmentation techniques has been shown to be an efficient method to increase theaccuracy of CNN [14]. The latest allowed to increase thetraining samples due to some transformations likes flipping (horizontal and vertical) and a random rotation (-180°, +180°),from the existing training dataset to generate new patches for each image. This technique is an efficient tool to eliminatethe problem of overfitting. Then, all images were converted to (128x128x3) size to train our model.

C. Transfer learning and fine-tuning

Transfer learning (TL) and fine-tuning (FT) techniques for medical segmentation help deep learning models to achieve more accurate model performance. They are an opportunityto use a small training data set. They refer to learning skills from previous tasks to improve new similar tasks. Moreover, the lower layers of the CNN can be used in another application domain. In fact, the initialization of the CNN with pre-trained parameters achieves better performance than with random initialization [13]. Then, Fully Connected (FC) layer is replaced by a new layer from U-Net The knowledge acquired fromthis TL enables "generic global features" extraction, while the specialized network training will specialize in extracting local "specialized local features [14]. Using the model developedin this work, from ISLES 2015, we extended the acquireddata using different imaging protocols with TL and FT which benefits from the hierarchical features learned by a DL model trained on ImageNet (1000 classes). Fine-tuning adjusts lightlythe weights of the trained model. We did not only create a new dense layer and jointly retrain it with the convolutional base of U-Net but also fine-tune the convolutional base's some parameters

D. ResNet50

A Residual neural network (ResNet) is a deep CNN architecture and one of the most commonly used in image recognition architecture currently. It is proposed by He et al.[15] that taken the first place at the ImageNet Large Scale Visual Recognition Challenge (ILSVRC 2015) [16].

The implementation of multiple layer structured CNN, which including ResNet, allows for the development of approaches with greater accuracy for detecting damages in the medical field. Her architecture was inspired by VGG19, with adding a skip connections. It allows it to reduce gradient lossin deeper layers by adding residual connections between some convolutional layers [16]. In this study, we apply a ResNet 50 that is contains 50 layers deep with 26 million parameters. The learning processis performed from residuals which. A diagram of residual learning block is show in figure 4 .

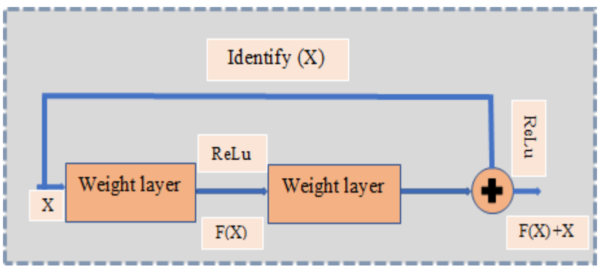

Fig. 4. A short descriptive of Residual block function

The residual connectionin a layer signifies that a layer's output is a convolution of its input. Figure 5 presents the architecture of ResNet 50 appliedin this research.

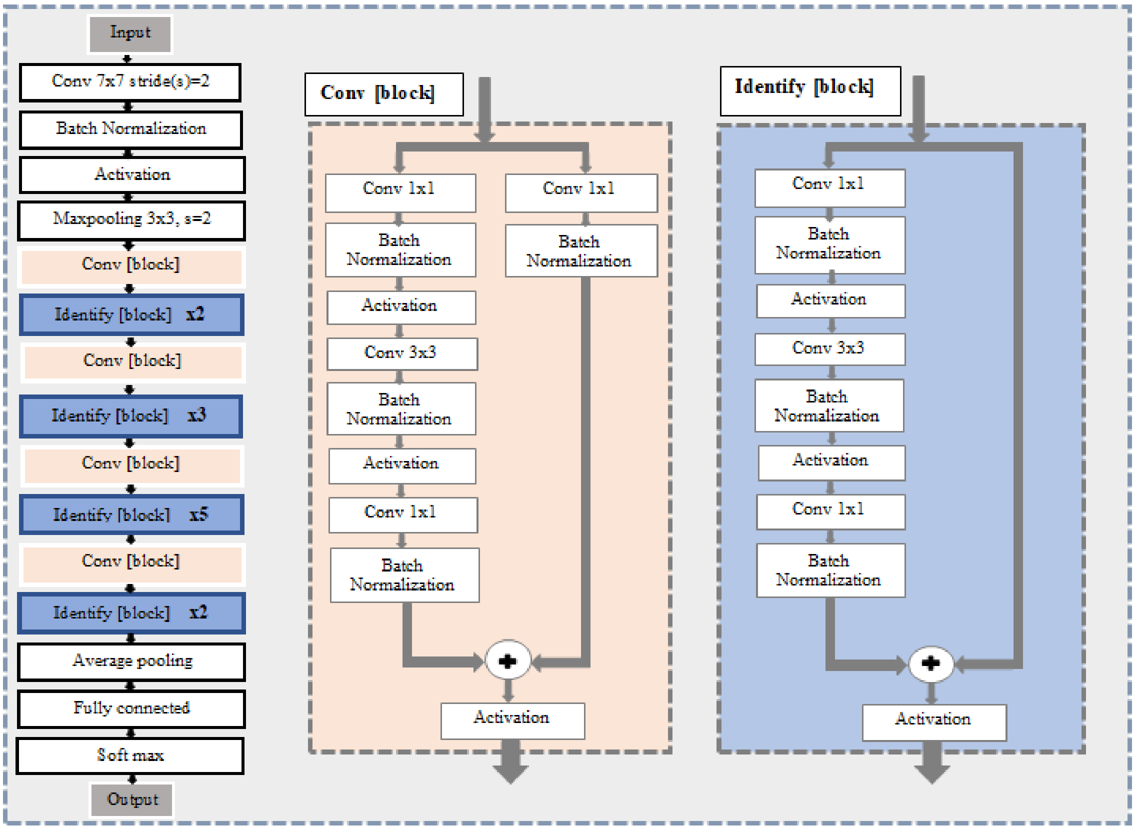

Fig. 5. The architecture of the ResNet50 model used in the proposed approach.

E. UNet architecture

Nowadays, the UNet architecture has been used for segmentation tools in 2D and 3D medical image analysis[17]. It was developed for the first time for microscopy cells segmentation and recently, it covers a variety of medical image devices used in brain tumors segmentation [18]. The configuration is built on two paths: one is the encoder or contracting path,used to extract the relevant feature of the image, and the other is the decoder or expanding path, which is used to controlthe reconstruction of the probability segmentation maps. . The encoder branch consists of a series of blocks. Each blockincludes two 3x3 convolution layers, each followed by a ReLU,and a down-sampling in each step of resolution is taken bya 2x2 max pooling operator with stride2. After each block,the number of feature maps is doubled. The encoder branch contains a 2x2 up-convolution layer for up-sampling, and two 3x3 convolution layers, each followed by a ReLU.

At the end of each block, the number of feature maps is halved to maintain symmetry [19].

F. Proposed hybrid ResNet50-Unet architecture

In this research paper, we propose a hybrid ResNet50-UNet model for ischemic stroke lesions segmentation. The backbone ResNet50 model was pre-trained on ImageNet dataset using the transfer learning and fine tuning tools. The proposed approach combines the encoder-decoder with the residual unit.In this model, the softmax fully connected layer is removed. We have retained the convolution and pooling layers only, which contain the extracted features. We tested our proposed framework on a public benchmark dataset ISLES 2015 with four MRI sequences DWI, T1, T2, and FLAIR. To over- come the lack of training data, we applied data augmentation techniques. Figure 6 presents the architecture of the hybrid ResNet50-UNet model.

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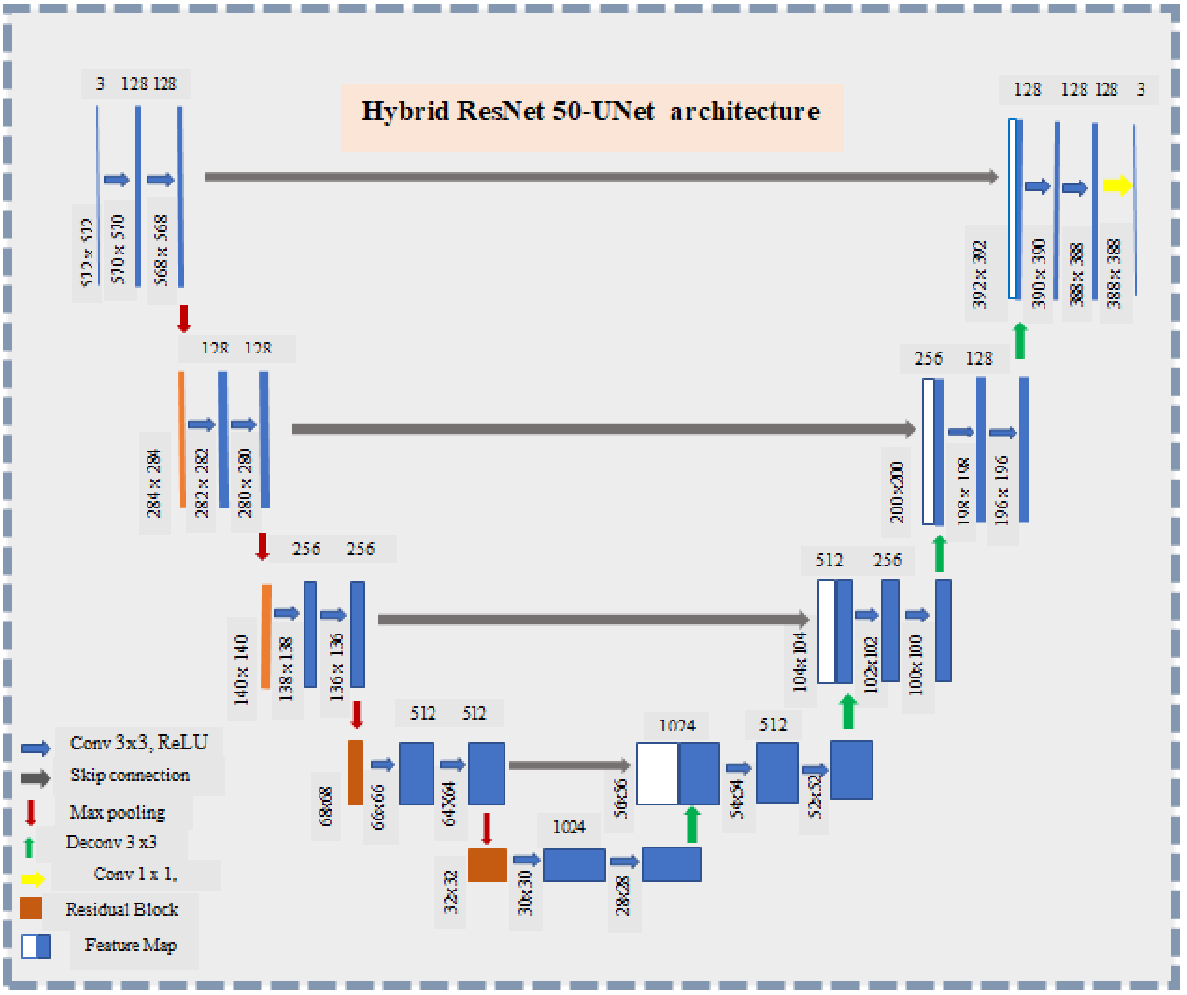

Fig. 6. The proposed hybrid ResNet50-UNet architecture

The UNet model based encoder-decoder architecture. The backbone of ResNet50 model is added into the encoder bloc only. We freeze the encoder layer using the fine-tuning and transfer learning with the pre-trained ResNet50 model on the ImageNet dataset, that it entrain the absence of update of weighted layer during the execution of training data. Instead, the weight of the convolutional layer off ResNet50 will be used. First, we modified the architecture of the ResNet50 to be similar to UNet, adding an expanding layer composed of multiple up sampling layers and convolution layers at the end of her structure. Second, this is carried out up until the model'soverall architecture will symmetric and take the form shape of a U-Net. Such as this combination the trainable parameters models will be reduced. After, we train the input data MRI using the two proposed hybrid model with a transfer learning method.

Furthermore, the pre-trained ResNet50 encoder receives the training input images. The ResNet50 model uses the residual blocks to assist the encoder block in extracting relevant features, that are then transmitted to the decoder block. Then,the decoder up scales the received feature maps which will be concatenated with the specific feature maps received from the backbone pre-trained encoder via skip connections. Lastly, thedecoder passed the last features maps outputs to the Softmax activation function for classification.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. *Evaluation Metrics*

To evaluate the performance of this approach, Dice Coefficient (DC) was used as the main metric. It measuresthe spatial overlap between the automatic segmentation result and the ground truth. Specificity and sensitivity evaluate the ability of a network to predict the healthy tissues andthe lesion respectively. Precision is referred to as a positive predictive value and measures the rate of relevant outcome. Accuracy has been used to evaluate the efficiency of the suggested approach. And the recall to measures the rate oftotal relevant results correctly classified by the model. These metrics are defined as [20] :

$$DC = \frac{2TP}{2TP + FP + FN}$$

$$Accuracy = \frac{TP + FP}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

where : TP = True Positive , FP = False Positive, FN = False Negative, and TN = True Negative

A. *Training and Validation of the hybrid model*

The experiments were developed using python language in Ubuntu environment, a Dell computer, Intel Core i5 8th generation, 8 GB RAM installed with NVIDIA Geforce GTX 1050, NVIDIA Driver Version 440.59 and kaggle framework. Keras and TensorFlow were used as the framework to implement the architecture. The U-Net architecture was trained using the following parameters: batch size =32, number of epochs =100, stochastic gradient descent (SGD) optimizer with learning rate =0.00001, and momentum=9. The binary cross entropy loss function was plotted with respect to the epoch number. In addition, we used categorical cross-entropy loss function. In this paper, the ischemic stroke brain is identified automatically from data MRI. Data augmentation technique was used to increase the number of test and train data set. After the training process, every image was testedand the obtained result was compared with Ground Truth (GT). Quantitative results and evaluation measures such asDC, accuracy, precision, specificity, and sensitivity were used to compare the performance of the proposed approach with existing ISL segmentation methods.

B. *Experimental results*

In this paper, we used input images obtained from four MRI sequences. Results are shown in figure that it represents the output of FLAIR sequence, figure8 that it represents the output of DWI sequence, figure9 that it represents the output of T1 sequence.

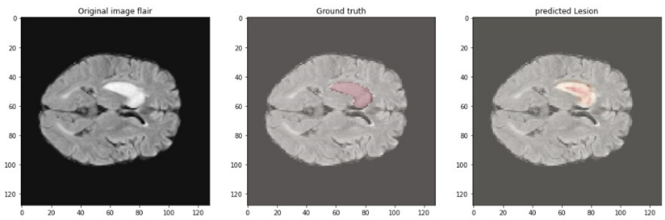

Fig. 7. Visual performance of ResNet50-UNet with FLAIR sequence

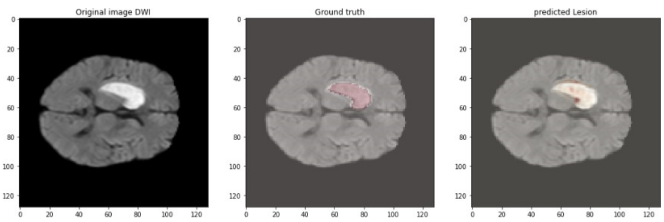

Fig. 8. Visual performance of ResNet50-UNet with DWI sequence

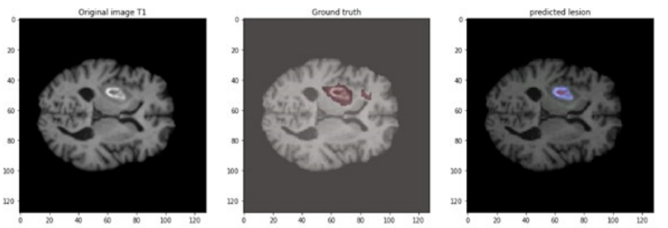

Fig. 9. Visual performance of ResNet50-UNet with T1 sequence

The detailed statistics curve of the accuracy, loss,and DC are shown in figure 10.

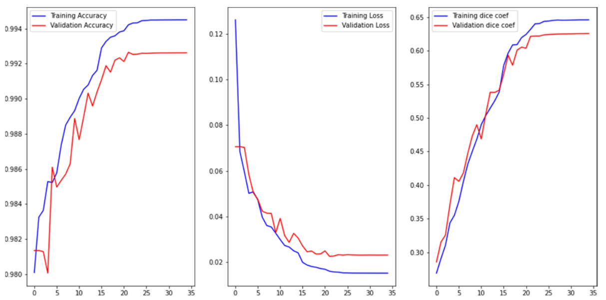

Fig. 10. Accuracy, Loss, and DC Curves performance of the proposed model

Furthermore, we comparedour method with the state-of-the-art methods for the ischemic stroke brain segmentation scenario in the ISLES 2015 databasein terms of the Dice score, accuracy, and precision as shownin Table II.

Figure 11 shows the dice coefficient and the precision metrics of the methods used in the segmentation of ISL from Isles 2015. The proposed method based on ResNet50_UNet has a higher value in terms of precision equal to 99.55%. However, the 3D FC DenseNet proposed by Rongzhao Zhang et al. [8] has the higher dice coefficient equal to 79.13%.

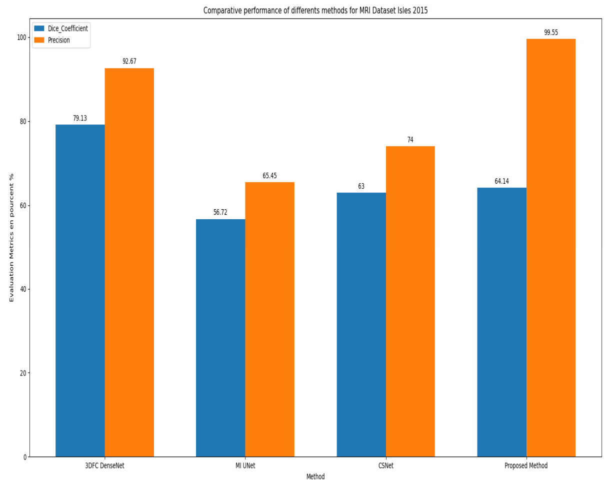

Fig. 11. Comparative performance of differents methods for MRI dataset Isles

TABLE II. COMPARATIVE PERFORMANCE OF DIFFERENT METHODS FOR MRI IMAGES SEGMENTATION

Authors	Methods	Dice Coefficient(%)	Accuracy(%)	Precision (%)
Rongzhao Zhang et al. [9] 2018	3D fully convolutional DenseNets	79.13	–	92.67
Liangliang Liu et al. [10] 2020	Multi Kernel DCNN : MK- DCNN	57	–	–
Yue Zhang et al. [8] 2020	Multi Input UNet : MI-UNet	56.72	–	65.45
Amish Kumat et al. [11] 2020	Classifier Segmenter network : CSNet	63	–	74
Proposed method	**ResNet 50-UNet**	**64.14**	**99.43**	**99.55**

C. Comparison with state of the art studies

The results of the proposed method confirm the superior performance of our method in terms of accuracy and precision compared to the reported work. We noticed that our approach had higher precision with a value equal to 99.55%. We also discovered that the DC isn't the most efficient, with 64.14%, but the fully convolutional DenseNets in sequence DWI pro- duced by Rongzhao Zhang et al. [8] had the highest DC, with 79.13% but he found a precision rate equal to 92.67%. In a brief conclusion, the evaluation metrics have been calculatedto compare the performance of the proposed architecture with some of the well-known methods, which is detailed in Table II. It can be clearly seen that the proposed method reaches a good performance in accuracy and precision metrics, but DC needs improvement

V. CONCLUSION

In this paper, we present a hybrid ResNet50-UNet based ona backbone pre-trained ResNet50 architecture and UNet modelfor ischemic stroke brain lesion segmentation. We applied a data augmentation technique to overcome the problem of imbalanced data and over-fitting. The proposed approach was tested on the ISLES2015 dataset. It achieved promising results with an average accuracy equal to 99.43%. In conclusion, our model reached higher performance than some state-of-the-art studies. The results obtained are motivating for future investigation in ischemic stroke brain lesion segmentation.

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FATHIA ABOUDI is a Ph.D. student in Biophysics and Medical Imaging at the High Institute Of Medical Technology in Tunisia (ISTMT) and a research member in the Research Laboratory of Biophysics and Medical Technology (LRBTM).In 2019, she was registered in Complementary Studies Cer- tificates (CEC) Post University Degrees In "MRI In Clinical Practice" in the Faculty of Medicine in Tunisia (FMT). She has experience in medical imaging and nuclear medicine. She is interested in the combination between the medical field and high-tech.