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Wavelet-enhanced convolutional neural network: a new idea in a deep learning paradigm

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Abstract

Purpose: Manual brain tumor segmentation is a challenging task that requires the use of machine learning techniques. One of the machine learning techniques that has been given much attention is the convolutional neural network (CNN). The performance of the CNN can be enhanced by combining other data analysis tools such as wavelet transform.
Materials and methods: In this study, one of the famous implementations of CNN, a fully convolutional network (FCN), was used in brain tumor segmentation and its architecture was enhanced by wavelet transform. In this combination, a wavelet transform was used as a complementary and enhancing tool for CNN in brain tumor segmentation.
Results: Comparing the performance of basic FCN architecture against the wavelet-enhanced form revealed a remarkable superiority of enhanced architecture in brain tumor segmentation tasks.
Conclusion: Using mathematical functions and enhancing tools such as wavelet transform and other mathematical functions can improve the performance of CNN in any image processing task such as segmentation and classification.

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Keywords: brain tumor; convolutional neural network; segmentation; wavelet transform.

Introduction

Brain tumor is one of the main causes of death in all age groups. According to reports by the National Brain Tumor Foundation (NBTF) and American Brain Tumor Associations (ABTA), research in developed countries indicates that the number of people with this disorder has drastically increased during the past decade [1–6].

One of the routine tests in brain tumor diagnosis is the use of magnetic resonance (MR) imaging [7] which is capable of creating the optimal contrast of soft tissues [8]. Because of its high resolution and non-ionizing nature, it is widely used in brain studies [9–14]. There are many challenges in the manual segmentation of brain tumors [12, 15–18], as one of the important steps in the processing of brain MR images [19], including differences in the size, shape, texture and intensity of tumors in the MR images. In fact, these challenges increase the manual segmentation error and lead to disagreement among experts [20]. Besides that, the large number of brain scans increases the time required for the analysis of the MR images [21]. All of the mentioned problems turn brain tumor segmentation into a complex and time-consuming process and cause misdiagnosis or delay in decision-making [22, 23]. The presence of these problems illustrates the necessity of using machine learning techniques for automatic brain tumor segmentation [20, 24, 25].

In recent years, the use of deep learning techniques has increased in the image processing as well as in the medical image processing applications [26–29]. Among techniques introduced for automatic brain tumor segmentation [2, 26, 27, 30–39], the portion of deep learning-based techniques has rapidly increased [40] and several examples of these techniques' application have been recently proposed for brain tumor segmentation [30–33, 40–53]. As a matter of fact, the best technique for exploiting the benefits of multidimensional spatial data such as image, sound and time series is a convolutional neural network (CNN) [34]. The CNN performance can be enhanced if it is combined with other data analysis tools. One of the most useful tools in signal and image analysis is the wavelet transform which is considered as a good candidate for the CNN enhancement. In the following sections, the idea of combining the CNN and wavelet transform is explained and then the application of this combination in brain tumor segmentation is investigated.

Related works

Evolution of brain tumor segmentation techniques represents a move toward achieving an automatic and accurate segmentation where three levels of algorithms were developed to achieve these goals [1, 2, 10, 14, 36–39, 54–58].

In the first generation, heuristic ideas were employed by algorithms such as the threshold level [59], area growth [60] and edge detections [10]. Simplicity of the implementation was the main feature of these algorithms; however, the big challenge was posed when they were faced with situations different from the training setting.

Techniques in the second generation were based on the probabilistic and optimization methods such as artificial neural networks [61], Bayesian models [62], fuzzy clustering [63] and support vector machines [64]. In addition, techniques like Gaussian mixture models, linear and non-linear dynamic systems, conditional random fields, maximum entropy (MaxEnt) models, logistic regression, kernel regression and extreme learning machines were in this generation too. This group of techniques was effective in solving simple or well-constrained problems [65–68], but their low modeling capacity caused some problems while dealing with complex real-world situations [69].

There are techniques in the third generation which seek to achieve the desired result using the higher levels of knowledge such as tacit knowledge, rules and models extracted directly or indirectly from data.

The significant examples of this generation's techniques include Atlas-based segmentation [70] and deep learning-based methods [40] which fascinatingly modeled the human brain information processing system. Although various versions of deep learning techniques have been proposed for image segmentation, the most successful technique in brain tumor segmentation is the CNN [30–33, 40–53].

Method

Idea description

The deep learning hypothesis is based on the fact that, in order to achieve a high level of representation, a hierarchy of initial and middle representations is required [71–74].

The CNN structure is based on the multilayered perceptron (MLP) [75–77], and its function is similar to the time delayed neural networks which share the intra-network weights in order to reduce the computations [78]. Employing operations like convolution, sampling and linear correction unit, the CNN is able to directly extract features from raw data [79]. In fact, the use of the convolutional operation gives CNN spatial flexibility and the use of the sampling results in higher levels of representation. The learning process occurs in the CNN using intermediate representations (known as the feature map) [80], exactly the same as the hierarchical learning in biological brains [81]. The feature maps pass through layers, so the hierarchy of learning occurs and the information becomes more meaningful by going through the layers [82, 83]. This unique ability has led the CNN to succeed in most of the image processing applications [35].

Along with the CNN properties in the hierarchical learning, a wavelet transform has interesting features that make it a candidate to enhance the CNN. The main functionality of the wavelet transform in image processing is the ability to decompose images into different scales with different levels of details [84–86]. During the decomposition, the separation of the information at different levels is repeated on the remainder part of the previous layer [79]. Therefore, it can be deduced that CNN and wavelet transform have different approaches toward image details in that CNN creates a high-level representation by upward combinations of low-level representations such as pixels, lines and object elements, whereas wavelet transform decomposes the image into its elements at different levels [75]. The difference between the viewpoints of these two data analysis tools is the basis for an idea according to which wavelet transform can be considered as an enhancing tool for the learning algorithm of CNN. In fact, according to the very idea, the compressed forms of the input image, as the result of various levels of wavelet decomposition, can be injected into the different layers of the CNN architecture and enhance its performance.

The application of this idea in brain tumor segmentation

In this section, the application of the introduced idea in brain tumor segmentation is investigated and its details are described in the form of the implementation.

Data: The Brain Tumor Segmentation (BRATS) dataset provided by the Medical Image Computing and Computer Assisted Intervention Society was used in this study. There were 220 sample MR images of patients with a high-grade glioma, and 54 samples of patients with a low-grade glioma with 155 axial scans stored in three-dimensional (3D) (mha) format for each patient. Each scan included a collection of four types of images: T1, T2, T1 with contrast (T1C) and Flair with a corresponding manually segmented (ground truth) image [76]. The provided manual segmentation was in the five-class mode: background, necrosis, edema, enhancing tumor and non-enhancing

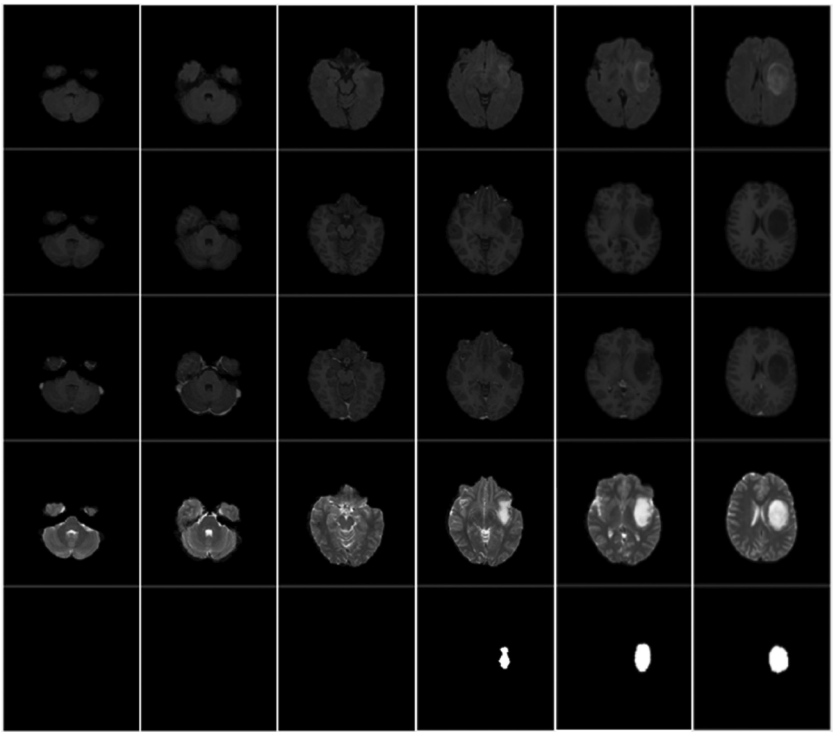

Figure 1: Brain tumor MRI scans: top to bottom: Flair, T1, T1 with contrast, T2 and ground truth (BRATS).

tumor. But, in terms of neurosurgery application, the existence of binary classification (tumor and non-tumor) is preferable for neurosurgeons as they are the main beneficiaries of the segmentation. Therefore, the model introduced in this study was trained based on two-class segmentation as shown in equation 1.

$$\text{NewSeg} = \begin{cases} 1, \text{ Seg class is in (Necrosis, Enhancing Tumor} \\ \quad \text{and NonEnhancing Tumor)} \\ 0, \text{ Seg class is in (Edema and Background)} \end{cases} \tag{1}$$

Equation 1: New segmentation criteria on BRATS dataset images.

Figure 1 shows examples of BRATS data with ground truth segmentation.

Implementation: In this study, a python-based implementation [87], based on [88] and adapted from vgg-net, was used for pixel-wise semantic segmentation. In order to implement the introduced idea of combination, we used the TensorFlow framework which has a great potential in designing and testing the deep learning models. In this framework, the data model is composed of multidimensional arrays, named tensors, with the operational model in graph form [77]. As the most successful model of CNN in image segmentation, a fully convolutional network (FCN) was selected to implement the wavelet-enhanced fully convolutional network (WFCN) model in brain tumor segmentation. The FCN consists of convolution, deconvolution and max-pooling layers for the image segmentation task [78]. In this regard, new paths were defined for wavelet injection. Employing Pywt as the main library of wavelet transform implementation in python, the first order of Daubechies wavelet family (db1) was used for wavelet injections [89]. Regarding the proven success of Daubechies in signal decomposition and identification of image edges, db1 was selected as the mother wavelet function, the simplest form of this family with lower computation and less wavelet filter bank coefficients [90].

Computation and hardware: To increase the generalizability and to avoid overfitting in the introduced models, the data was augmented with a 180° rotation and increased to 84,940 images. Then, it was randomly divided into two groups: 90% for training and 10% for testing. In order to evaluate the performance of WFCN, four tests were run. Each time one of the four wavelet injection paths was turned on and the remaining ones were turned off. The introduced architectures' training of 100 epochs, on Linux server CentOS release 6.8 with 128 GB shared main memory and GeForce GTX 980Ti (6 GB memory) gpu, takes about 18 h.

Results

The basic design for brain tumor segmentation was generated with a modification to the first layer of the vgg-based FCN, where the three-channel input was replaced by the four-channel input.

Figure 2 shows the basic form of segmentation with a sequence of convolution and sampling to feature compression and a reverse process to reconstruct the segmented image.

As mentioned before, the main idea behind the WFCN is to enhance the FCN using wavelet transform injections as shown in Figure 3. Given the FCN architecture, four

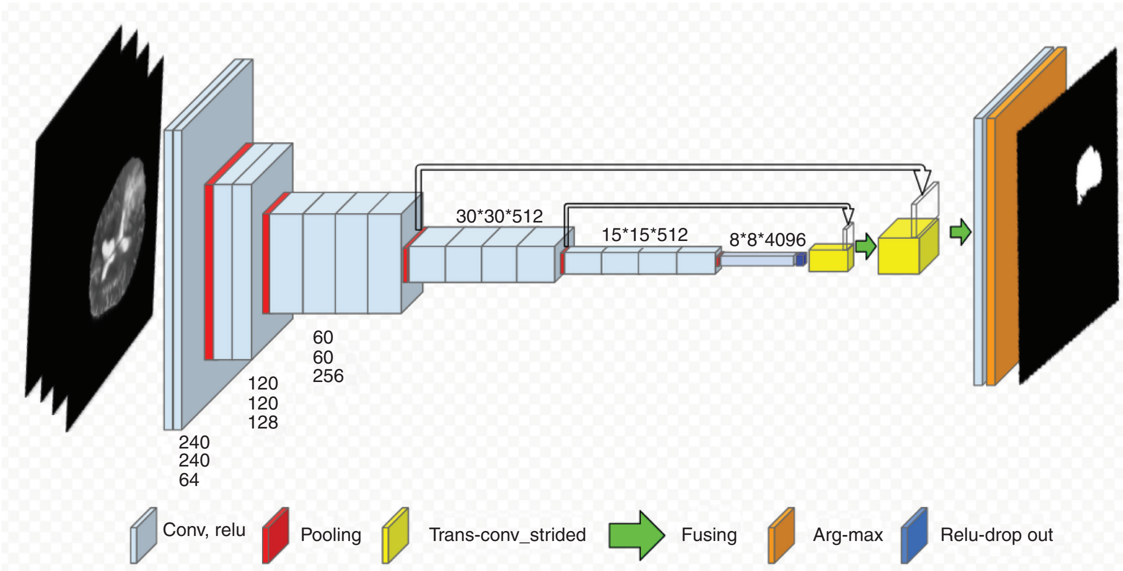

Figure 2: Original FCN for semantic segmentation.

paths were proposed for the injection. Each path transfers the compressed form of the image to an appropriate position, in terms of size, in the basic FCN architecture.

As shown in Figure 3, using four levels of the wavelet transform on input images resulted in the compression of the images to H/2*W/2, H/4*W/4, H/8*W/8 and H/16*W/16 pixel sizes.

According to Figure 4, for each input channel with 240×240-pixel size, the wavelet compression was accomplished by four (approximate, horizontal, vertical and diagonal) compressed forms. On the other hand, through four input channels, 16 compressed images were formed as $T1_A$, $T1C_A$, $T2_A$, $Flair_A$, $T1_H$, $T1C_H$, $T2_H$, $Flair_H$, $T1_V$, $T1C_V$, $T2_V$, $Flair_V$, $T1_D$, $T1C_D$, $T2_D$ and $Flair_D$ (Figure 4).

Whenever one of the paths (1–4) is activated, the injected images get concatenated with the feature maps extracted by the basic FCN architecture layers. The concatenation provides more features (FCN's feature map + wavelet injection), which can be used in the subsequent layers and consequently in creating a higher-level representation. Table 1 illustrates the results of testing different WFCN architectures in brain tumor segmentation.

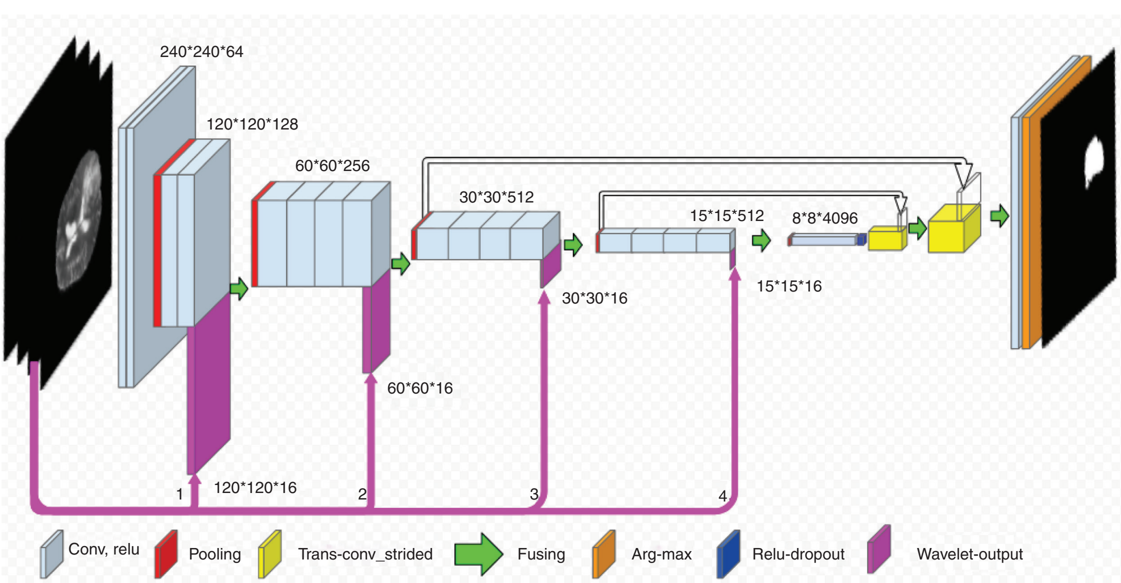

Figure 3: Wavelet-enhanced fully convolutional network (WFCN) for brain tumor segmentation.

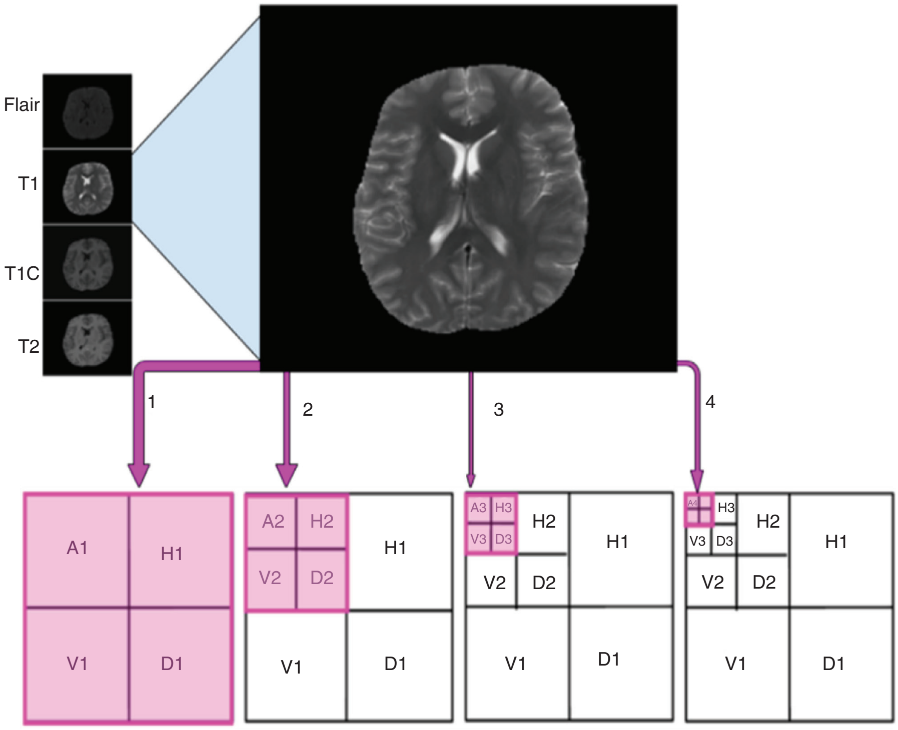

Figure 4: Wavelet compression.

Table 1: Test result of different architectures.

Architecture	Result (dice)
Basic FCN architecture (Figure 2)	77.9%
WFCN1 (1st level injection – Figure 3)	91.8%
WFCN2 (2nd level injection – Figure 3)	91.4%
WFCN3 (3rd level injection – Figure 3)	91.3%
WFCN4 (4th level injection – Figure 3)	91.3%

Dice, the most important benchmark for analyzing the performance of segmentation techniques, was used in the initial assessment of the architectures.

According to Table 1, the best performance belongs to WFCN1 in which the first path was activated and a one-step wavelet compression with H/2*W/2 size was injected into the architecture.

In order to analyze the WFCN1 performance in more detail, a set of evaluation parameters was used as shown in equations 2–5.

$$\text{Dice}=\frac{2*|S\cap G|}{|S|+|G|} \tag{2}$$

Equation 2: Dice in brain tumor segmentation.

In the above equation, S is equal to the region segmented by the algorithm and G is equal to the reference segmentation region (ground truth).

$$\text{Accuracy}=\frac{Tp+Tn}{\text{All pixels}} \tag{3}$$

Equation 3: Accuracy in brain tumor segmentation.

In the above equation, Tp denotes the number of tumor pixels which are correctly identified by the technique as tumor, and Tn refers to the number of non-tumor pixels that are correctly identified as non-tumor by the algorithm.

$$\text{Sensitivity}=\frac{Tp}{Tp+Fn} \tag{4}$$

Equation 4: Sensitivity in brain tumor segmentation.

$$\text{Specificity}=\frac{Tn}{Tn+Fp} \tag{5}$$

Equation 5: Specificity in brain tumor segmentation.

Fn denotes the number of pixels that are actually tumor but misclassified by the technique as non-tumor. On the other hand, Fp refers to the number of pixels that are not actually tumor, but they are classified as tumor. A detailed evaluation of the WFCN1 is summarized in Table 2.

Figure 5 shows the WFCN1 network entropy reduction diagram for training.

Also Figure 6 shows segmented samples as WFCN1 outputs.

Table 2: WFCN1 evaluation.

Parameter	Value
Dice	0.918
Pixel accuracy	0.99
Mean pixel accuracy	0.96
Sensitivity	0.93
Specificity	0.99

Discussion

Surveying the related studies show a large number of CNN usage in brain tumor segmentation [30–33, 40–53]. The average segmentation dice in these studies is about 84% and the standard deviation of them is around 5.5%. Figure 7 demonstrates the performance comparison between the superior ones from the surveyed studies (yellow columns) and our method (blue column).

In the present study, a total of 20 layers of convolution and deconvolution for brain tumor segmentation were used for modeling of the network. The comparison of the surveyed studies shows that the number of convolution layers in the study by Chang was nine, while this number in the study by Casamitjana et al. was 20. On the other hand, Chen et al. used 25 convolutional layers with four deconvolutional layers, which was the most number of layers in modeling. Besides that, Yi et al. used five convolutional layers and Kasamitjana et al. used a 14-layer convolutional model. There is a coincidence in the number of layers used in the modeling between the present study and the study by Casamitjana et al., as both studies are based on the vgg_net19.

Convolutional layers are considered as feature-extractors, because they look for a special pattern as the kernel in the image. Using more convolution layers implies the use of more levels of abstraction on the image analysis and leads to more modeling power in solving complex problems. Using more layers of abstraction is desired; however, increasing the number of layers in the designed model will increase the demand for more computational power. Deeper models (with more layers) require more memory usage and more power of processing. It is of great importance in the modeling to create a balance between the number of layers used in the model and the hardware capabilities.

- The WFCN dice was 91.8%. This is a better performance against all previous studies where the best of them was reported in [30] by 91.59% dice.
- This superiority can be explained according to the specific reasons and be examined from various aspects:
  - The first reason is the difference in the number of target classes in segmentation. In fact, previous studies worked with five classes, while in the present study the segmentation was based on two classes. Although the use of five classes in segmentation clearly has some advantages, it should be considered that as the neurological surgeons are the ones who make the most benefit of the segmentation of brain tumor images, binary segmentation would be more helpful for them in tumor resection. It is due to the fact that they are practically seeking to analyze tumor MR images in binary format (tumors and non-tumors).
  - The second and more important factor for the superiority of the proposed method compared

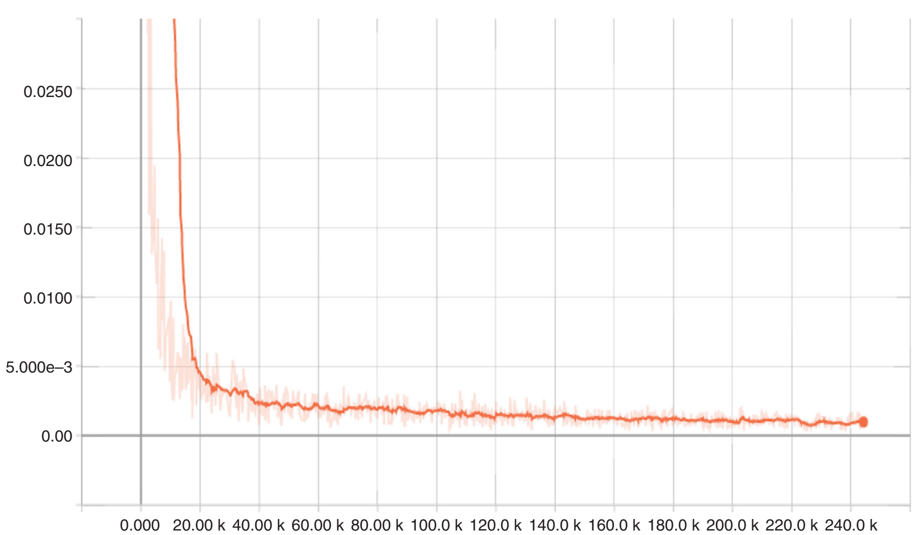

Figure 5: WFCN1 entropy reduction.

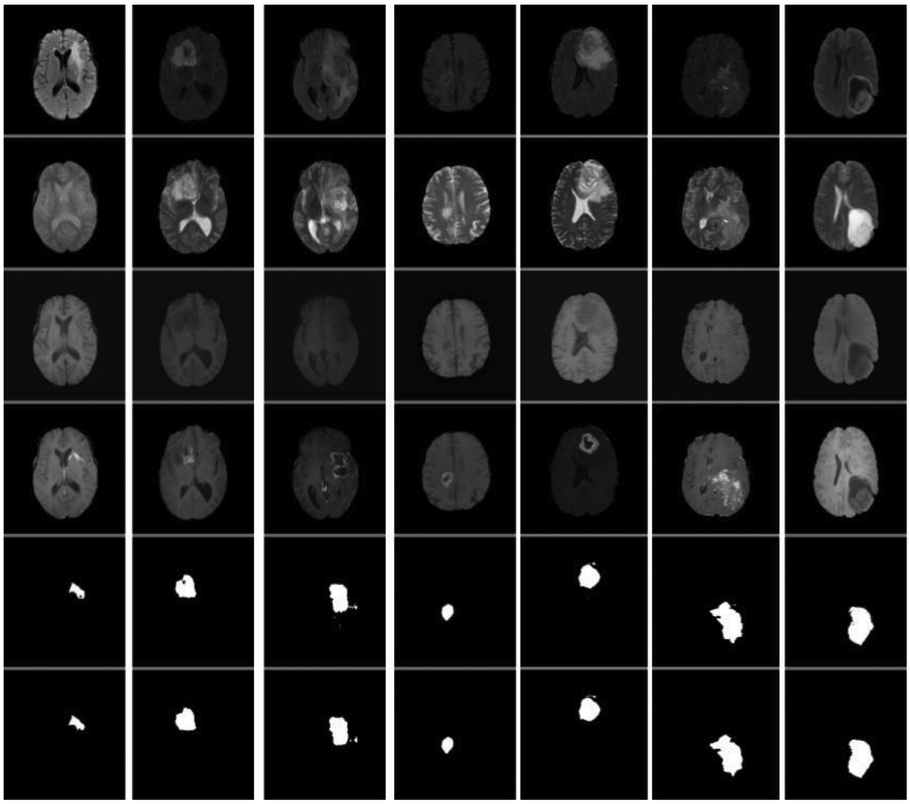

Figure 6: Brain tumor segmentation's result for WFCN1, from top to bottom: Flair, T1, T1C, T2, manual segmentation by National Institute of Health and WFCN1 output.

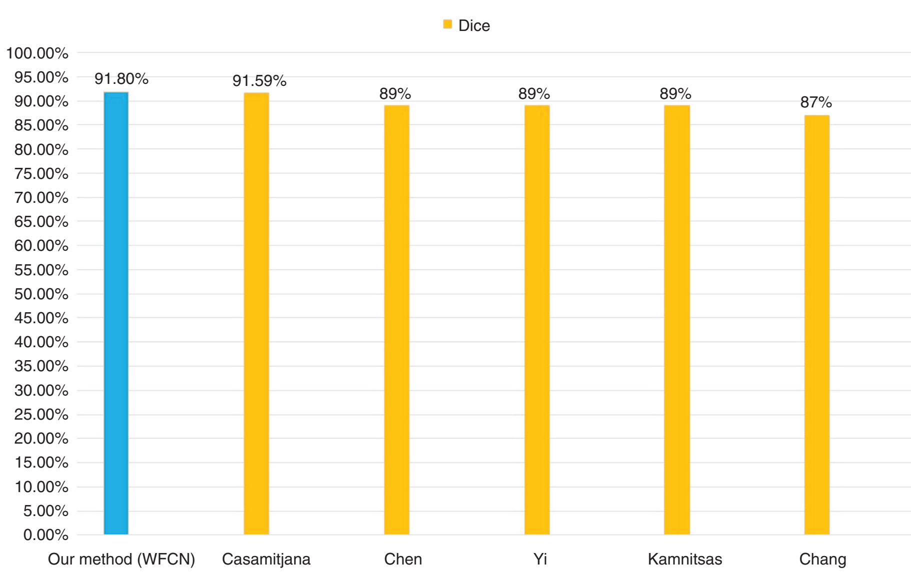

Figure 7: Comparison of the accuracy of the method presented in this study against other methods.

with the similar studies is the idea presented in this study, the combination of the wavelet and the CNN. The important thing in this combination, as mentioned earlier, is that no part of the basic FCN network has been eliminated here, and in fact its innovation is the definition and use of new paths that did not exist before. New paths add features to the structure which are derived from the wavelet transform and are different from those produced by the FCN layers itself.

This creates a variety of features that help the network to figure out the problem space better (the shape of brain tumors and their structural features) and increase the accuracy of the network. Therefore, it can be said that the composition is the main factor of the segmentation result. This claim can be easily verified by comparing the performance of WFCN with the raw FCN, where the segmentation dice for raw FCN cannot exceed over 78% for the same data.

There is a negative point in addition to the advantages of using a wavelet transform as a complementary part to the CNN. In fact, this combination increases the CNN computational burden. Although the amount of computational burden imposed by using the wavelet transform is trivial compared to the overall computation, this increase in the computational burden should be managed as much as possible. In this regard, there are some ways to reduce this computational burden:

One of the ways to reduce the computational burden is the use of low-computational wavelet functions, such as db1, which is used in this study as the simplest member of the Daubechies wavelet family. Of course, wavelet selection should be done with caution, as sometimes there may be an equilibrium between the computational burden of using a particular type of wavelet function and its ability in image decomposition and feature extraction. In the present case, the nature of the problem (like brain tumor segmentation) and, also, the time complexity can affect the selection of the desired wavelet function.

Another way to reduce the computational burden is to store the wavelet compressed images on the hard disk and reuse them in training epochs. So, in the first epoch of CNN training, the network input images are once compressed by the wavelet transform and will be used in the remaining epochs. In this study, due to the limited shared hard disk space on the server, there was no way to store wavelet compressed images. But in other cases where hard disk space is sufficient enough, it is possible to speed up the computation by storing the compressed images.

– Comparing WFCN performance with the surveyed studies leads to an interesting point. The network introduced in [30] as the most accurate CNN in brain tumor segmentation uses a dual-path architecture to combine various levels of detail into the network layers in order to build more complex representations. A fair similar idea is employed in WFCN architecture when new paths are defined for wavelet injection, in addition to the routine convolutional path in FCN. In fact, what succeeds in both architectures is the use of combining components through a variety of paths to construct higher-level concepts. But, in general, there is a significant difference between these two studies in terms of network paths and their combinations in network architecture.
– The main functionality of wavelet transform is data decomposition with different scales and levels of details that lead to the increasing success of this technique in the analysis of signal data such as images. That is why the wavelet transform, known as a multilevel analysis tool, is capable of compressing images with various details. In fact, by wavelet transform, the details of the input image are deleted in different levels. This is exactly what a CNN needs, as the main idea behind the CNN is based on the information compression into higher-level concepts by eliminating unnecessary details. Therefore, by passing information through the CNN layers, more details are removed from the input and a more compressed feature map is achieved. So, the combination of these two techniques can lead to a fantastic result as proven in this study.
– There is also another interesting point with WFCN architecture, where the performance of the WFCN1 is better than the other levels of injections (WFCN2, WFCN3 and WFCN4). The small differences between the injection levels depend on some parameters like the type of the application which is expected to be performed by the network (segmentation, classification and …), the type of the function used as the mother wavelet Daubechies, Haar, Coiflets and …) and the basic architecture used in the implementation.

As shown in this study, wavelet injections, in the first layers of the network, were somewhat more effective than its injection into the subsequent layers. This fact seems to be due to the complexity of the network analysis in the subsequent layers, as passing the feature maps through the network layers makes this analysis far more complex than the wavelet transformation, and, therefore, the wavelet injection in the first layers helps to make the CNN work better. The application of the mentioned point in the present study and other similar studies is that future studies can be developed in which the initial layers can be based on wavelet injections and more complex analyses can be used in the middle and final layers.

Conclusion

Although the deep learning paradigm emphasizes on automatic feature extraction and avoids feature engineering processes, the use of other mathematical functions, in data analysis, as an enhancing tool in the CNN architecture can improve their performance in image processing applications as proved by WFCN in this study. Employing diverse forms of mathematical functions as enhancing tools can be a turning point in the design of new CNN architectures in the future. Particularly, by increasing the computational power in the modern hardware, the advancement of deep learning optimization algorithms can also be facilitated by the development of the new combination ideas. So, in the future, new ideas can be used in order to enhance deep learning using other mathematical functions and be considered as topics for future studies.

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Conflict of interest: Authors state no conflict of interest.

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