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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.

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 Association (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,

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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

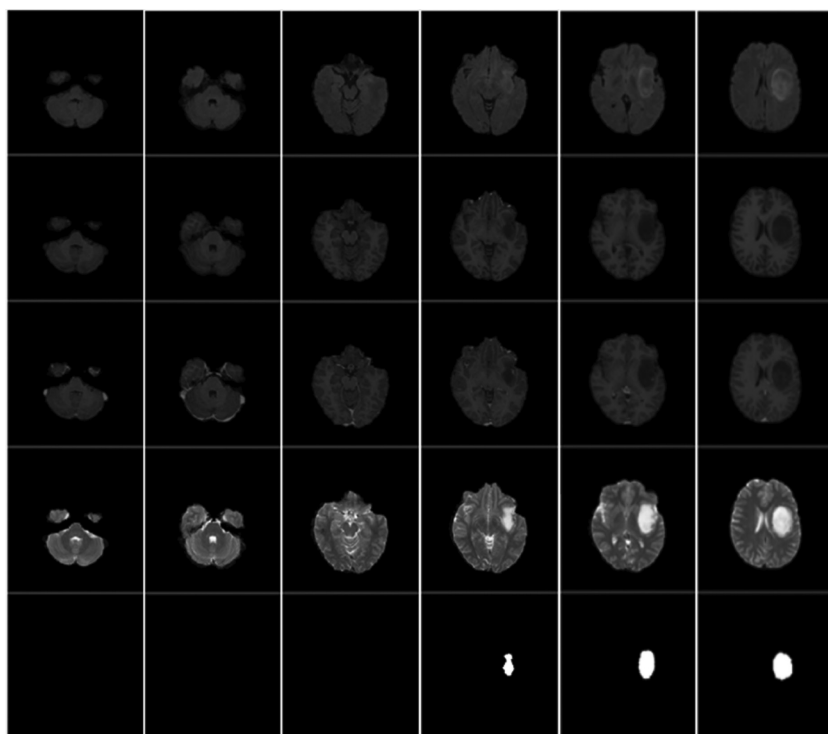


Figure 1: Brain tumor MRI scans: top to bottom: Flair, T1, T1 with contrast, T2 and ground truth (BRATS).

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.

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

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

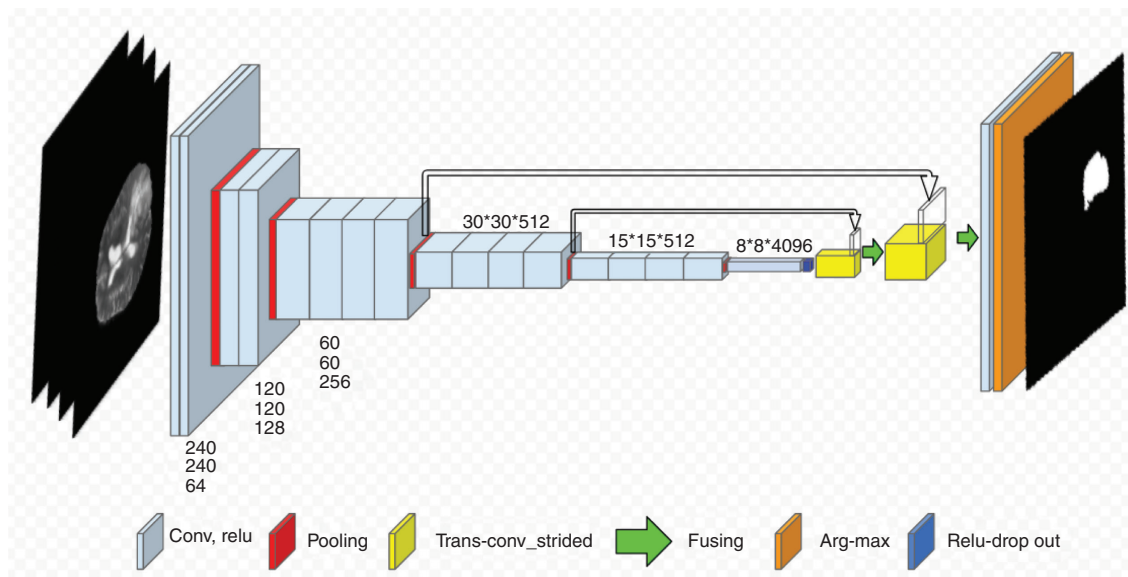


Figure 2: Original FCN for semantic segmentation.

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 $H/2 \times W/2$, $H/4 \times W/4$, $H/8 \times W/8$ and $H/16 \times W/16$ 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.

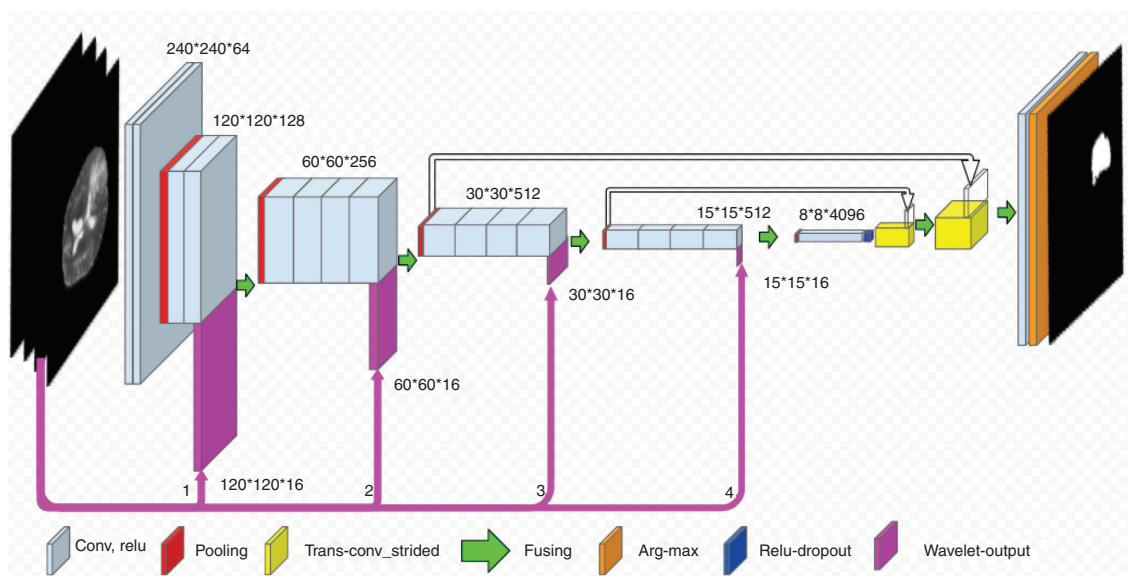


Figure 3: Wavelet-enhanced fully convolutional network (WFCN) for brain tumor segmentation.

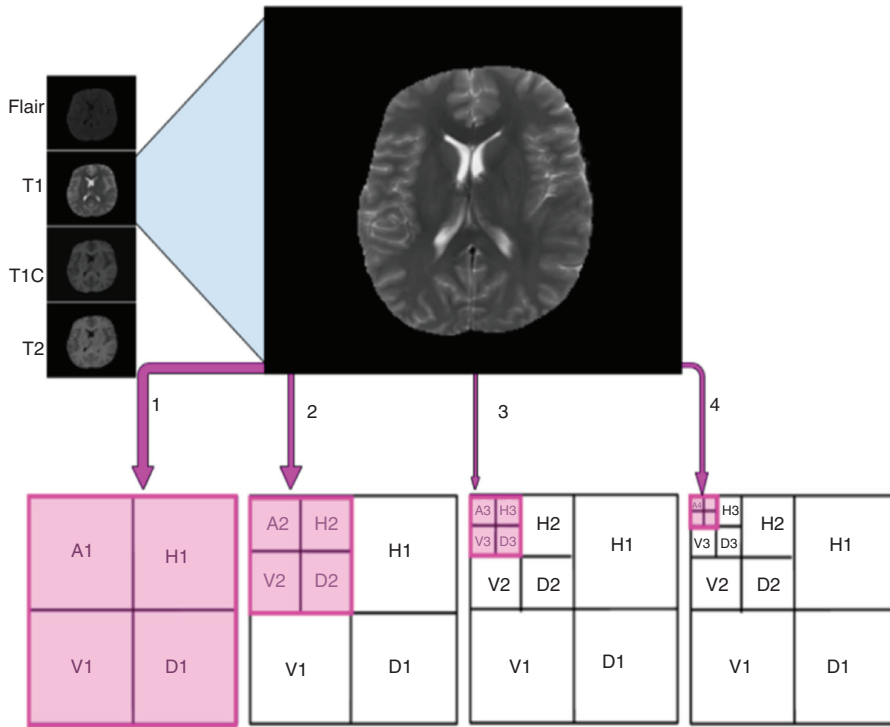


Figure 4: Wavelet compression.

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 $H/2 \times W/2$ 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.

$$\text{Dice} = \frac{2 \cdot |S \cap G|}{|S| + |G|} \quad (2)$$

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).

$$\text{Accuracy} = \frac{Tp + Tn}{\text{All pixels}} \quad (3)$$

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.

$$\text{Sensitivity} = \frac{Tp}{Tp + Fn} \quad (4)$$

Equation 4: Sensitivity in brain tumor segmentation.

$$\text{Specificity} = \frac{Tn}{Tn + Fp} \quad (5)$$

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

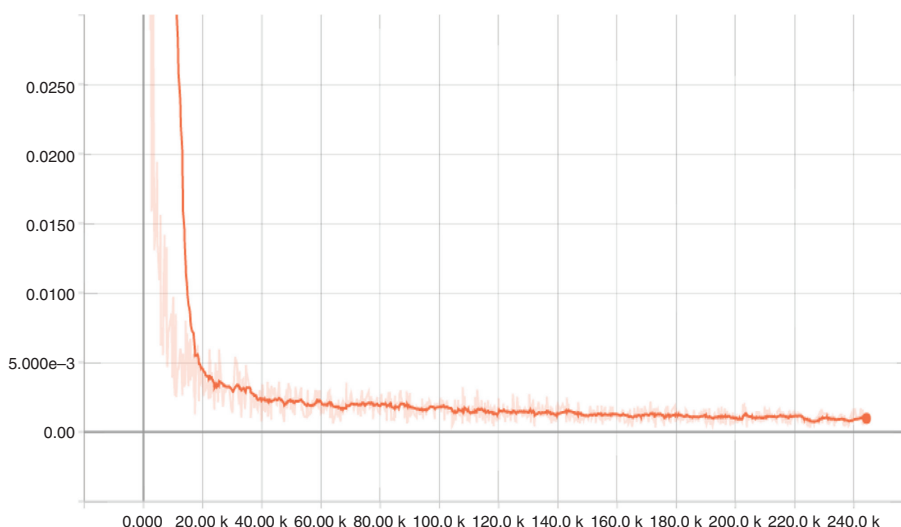
Discussion

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.

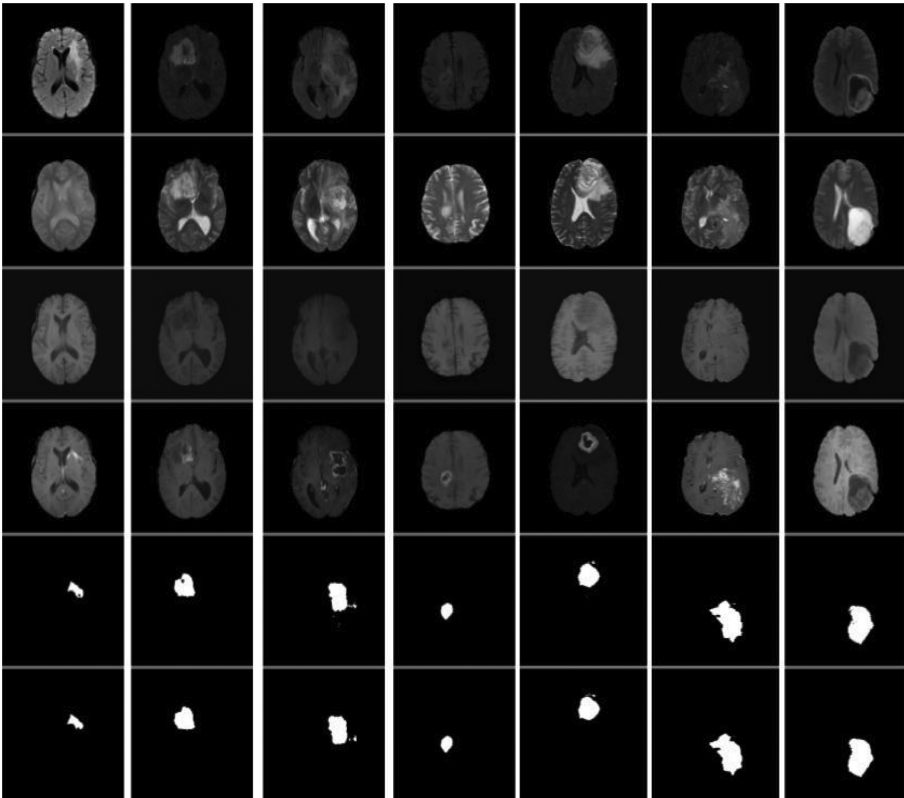


Figure 6: Brain tumor segmentation’s result for WFCN1, from top to bottom: Flair, T1, T1C, T2, manual segmentation by National Institute of Health and WFCN1 output.

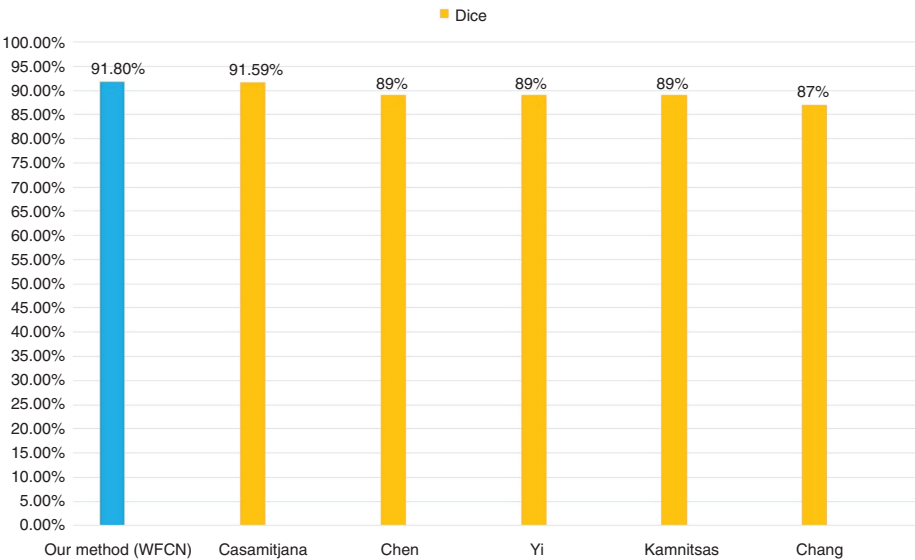


Figure 7: Comparison of the accuracy of the method presented in this study against other methods.

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 multi-level 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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Author Statement

Conflict of interest: Authors state no conflict of interest.

References

- [1] Charutha S, Jayashree MJ. An efficient brain tumor detection by integrating modified texture based region growing and cellular automata edge detection. In: Control, Instrumentation, Communication and Computational Technologies (ICCICCT), 2014 International Conference on, USA; 2014.
- [2] Idrissi N, Ajmi FE. A hybrid segmentation approach for brain tumor extraction and detection. In: Multimedia Computing and Systems (ICMCS), 2014 International Conference on, Morocco; 2014.
- [3] Chandra S, Bhat R, Singh H. A PSO based method for detection of brain tumors from MRI. In: Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on, India; 2009.
- [4] Logeswari T, Karnan M. An improved implementation of brain tumor detection using soft computing. In: Communication Software and Networks, 2010. ICCSN '10. Second International Conference on, Singapore; 2010.
- [5] Cancer Council Australia. Adult gliomas: a guide for patients, their families and carers. Sydney, Australia: Cancer Council Australia/Clinical Oncology Society of Australia; 2011.
- [6] Damodharan S, Raghavan D. Combining tissue segmentation and neural network for brain tumor detection. *Int Arab J Inf Technol* 2015;12:42–52.
- [7] American Brain Tumor Association. About brain tumors: a primer for patients and caregivers. Chicago, IL, USA: American Brain Tumor Association; 2015.
- [8] Bauer S. Medical Image Analysis and Image-based Modeling for Brain Tumor Studies. Switzerland: ETH Zürich; 2013.
- [9] Wein W, Brunke S, Khamene A, Callstrom MR, Navab N. Automatic CT-ultrasound registration for diagnostic imaging and image-guided intervention. *Med Image Anal* 2008;12:577–85.
- [10] Maiti I, Chakraborty M. A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV colour model. In: Computing and Communication Systems (NCCCS), 2012 National Conference on, India; 2012.
- [11] Roy S, Bandyopadhyay SK. Abnormal regions detection and quantification with accuracy estimation from MRI of brain. In: Instrumentation and Measurement, Sensor Network and Automation (IMSNA), 2013 2nd International Symposium on, Canada; 2013.
- [12] Wang G, Wang D. Segmentation of brain MRI image with GVF snake model. In: Pervasive Computing Signal Processing and Applications (PCSPA), 2010 First International Conference on, China; 2010.
- [13] Ming-Ni W, Chia-Chen L, Chin-Chen C. Brain tumor detection using color-based K-means clustering segmentation. In: Intelligent Information Hiding and Multimedia Signal Processing, 2007. IHHMSP 2007. Third International Conference on, Taiwan; 2007.
- [14] Jude Hemanth D, Selvanth D, Anitha J. Effective fuzzy clustering algorithm for abnormal MR brain image segmentation. In: IEEE International Advance Computing Conference (IACC 2009), Patiala, India; 2009;6:609–14.
- [15] Wang Y, Ma S. Automatic detection and segmentation of brain tumor using fuzzy classification and deformable models. In: Biomedical Engineering and Informatics (BMEI), 2011 4th International Conference on, China; 2011.
- [16] Heiss WD, Raab P, Lanfermann H. Multimodality assessment of brain tumors and tumor recurrence. *J Nucl Med* 2011;52:1585–600.
- [17] Moon N, Bullitt E, Van Leemput K, Gerig G. Automatic brain and tumor segmentation. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Berlin, Heidelberg: Springer; 2002:372–9.
- [18] Bara S, Maia HE, Hammouch A, Aboutajdine D. A robust approach for the detection of brain tumors by variational b-spline level-set method and brain extraction. In: Multimedia Computing and Systems (ICMCS), 2014 International Conference on, Morocco; 2014.
- [19] Costin H. Recent trends in medical image processing. *Comput Sci* 2014;22:65.
- [20] Prastawa M, Bullitt E, Ho S, Gerig G. A brain tumor segmentation framework based on outlier detection. *Med Image Anal* 2004;8:275–83.
- [21] El-Melegy MT, Mokhtar HM. Tumor segmentation in brain MRI using a fuzzy approach with class center priors. *EURASIP J Image Video Process* 2014;2014:1–14.
- [22] Amsaveni V, Singh NA. Detection of brain tumor using neural network. In: Computing, Communications and Networking Technologies (ICCCNT), 2013 Fourth International Conference on, India; 2013.
- [23] Schmidt M, Levner I, Greiner R, Murtha A, Bistriz A. Segmenting brain tumors using alignment-based features. In: Machine Learning and Applications, 2005. Proceedings. Fourth International Conference on, USA; 2005.
- [24] Prajapati SJ, Jadhav KR. Brain tumor detection by various image segmentation techniques with introduction to non negative matrix factorization. *Brain* 2015;4:600–3.
- [25] Al-Ashwal RH, Supriyanto E, Anati N. Digital processing for computed tomography images: brain tumor extraction and histogram analysis. In: Math Comput Contemp Sci. 14th International Conference on Mathematical Methods and Computational Techniques in Electrical Engineering (MMACTEE13), Singapore; 2012.
- [26] Kang J, Lu C, Cai M, Zhang W-Q, Liu J. Neuron sparseness versus connection sparseness in deep neural network for large

- vocabulary speech recognition. In: 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, Australia; 2015.
- [27] Kleč M, Koržinek D. Pre-trained deep neural network using sparse autoencoders and scattering wavelet transform for musical genre recognition. *Comput Sci* 2015;16:133–44.
 - [28] Oyallon E, Mallat S, Sifre L. Generic deep networks with wavelet scattering. *arXiv preprint arXiv:1312.5940*; 2013.
 - [29] Hassairi S, Ejbal R, Zaid M. Supervised image classification using deep convolutional wavelets network. In: *Tools with Artificial Intelligence (ICTAI)*, 2015 IEEE 27th International Conference on. IEEE, Italy; 2015.
 - [30] Casamitjana A, Puch S, Aduriz A, Sayrol E, Vilaplana V. 3D convolutional networks for brain tumor segmentation. In: *Proceedings of the MICCAI Challenge on Multimodal Brain Tumor Image Segmentation (BRATS)*, Greece; 2016:65–8.
 - [31] Rao V, Shari Sarabi M, Jaiswal A. Brain tumor segmentation with deep learning. In: *MICCAI Multimodal Brain Tumor Segmentation Challenge (BraTS)*; 2015:56–9.
 - [32] Lyksborg M, Puonti O, Agn M, Larsen R. An ensemble of 2D convolutional neural networks for tumor segmentation. In: *Scandinavian Conference on Image Analysis*. Berlin: Springer; 2015.
 - [33] Yi D, Zhou M, Chen Z, Gevaert O. 3-D convolutional neural networks for glioblastoma segmentation. *arXiv preprint arXiv:1611.04534*; 2016.
 - [34] Vo DM, Le TH. Deep generic features and SVM for facial expression recognition. In: *Information and Computer Science (NICS)*, 2016 3rd National Foundation for Science and Technology Development Conference on. Vietnam: IEEE; 2016.
 - [35] Zhou X, Zhang Y, Bai X, Zhu J, Zhu L, Quian X. Product image search with deep attribute mining and re-ranking. In: *Pacific Rim Conference on Multimedia*. China: Springer; 2016.
 - [36] Withey D, Koles Z. A review of medical image segmentation: methods and available software. *Int J Bioelectromagn* 2008;10:125–48.
 - [37] Sachin N, Khairnar V. Brain tumor detection based on symmetry information. *Int J Eng Res Appl* 2013;3:430–2.
 - [38] Constantin AA, Bajcsy BR, Nelson CS. Unsupervised segmentation of brain tissue in multivariate MRI. In: *Biomedical Imaging: From Nano to Macro*, 2010 IEEE International Symposium on, Netherlands; 2010.
 - [39] Kobashi S, Matsui M, Inoue N, Kondo K, Sawada T, Hata Y. Adaptive brain tissue classification with fuzzy spatial modeling in 3T IR-FSPGR MR images. In: *Automation Congress, 2006. WAC '06. World*; 2006.
 - [40] Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE Trans Med Imaging* 2016;35:1240–51.
 - [41] Havaei M, Davy A, Warde-Farley D, Biard A, Courville A, Bengio Y, et al. Brain tumor segmentation with deep neural networks. *Med Image Anal* 2017;35:18–31.
 - [42] Zikic D, Ioannou Y, Criminisi A, Brown M. Segmentation of brain tumor tissues with convolutional neural networks. In: *Proceedings MICCAI-BRATS*; 2014:36–9.
 - [43] Agn M, Puonti O, Law I, af Rosenschöld PM, van Leemput K. Brain tumor segmentation by a generative model with a prior on tumor shape. In: *Proceeding of the Multimodal Brain Tumor Image Segmentation Challenge*; 2015:1–4.
 - [44] Dvorak P, Menze B. Structured prediction with convolutional neural networks for multimodal brain tumor segmentation. In: *Proceeding of the Multimodal Brain Tumor Image Segmentation Challenge*; 2015:13–24.
 - [45] Rewari R. Automatic tumor segmentation from MRI scans. Available from: http://cs231n.stanford.edu/reports/2016/pdfs/328_Report.pdf.
 - [46] Zhao X, Wu Y, Song G, Li Z, Zhang Y, Fan Y. A deep learning model integrating FCNNs and CRFs for brain tumor segmentation. *arXiv preprint arXiv:1702.04528*; 2017.
 - [47] Pan Y, Huang W, Lin Z, Zhu W, Zhou J, Wong J, et al. Brain tumor grading based on neural networks and convolutional neural networks. In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. Italy: IEEE; 2015.
 - [48] Chen H, Dou C, Yu L, Heng P-A. VoxResNet: deep voxelwise residual networks for volumetric brain segmentation. *arXiv preprint arXiv:1608.05895*; 2016.
 - [49] Lun T, Hsu W. Brain tumor segmentation using deep convolutional neural network. In: *Proceedings of BRATS-MICCAI*; 2016.
 - [50] Kamnitsas K, Ferrante E, Parisot S, Ledig C, Nori AV, Criminisi A, et al. DeepMedic on Brain Tumor Segmentation. Athens, Greece Proc. BRATS-MICCAI; 2016.
 - [51] Zhao L, Jia K. Deep feature learning with discrimination mechanism for brain tumor segmentation and diagnosis. In: *2015 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP)*. Australia: IEEE; 2015.
 - [52] Chang PD. Fully convolutional deep residual neural networks for brain tumor segmentation. In: *International Workshop on Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*. Cham: Springer; 2016:108–18.
 - [53] Ghafoorian M, Karssemeijer N, Heskes T, van Uden I, Sanchez C, Litjens G, et al. Location sensitive deep convolutional neural networks for segmentation of white matter hyperintensities. *arXiv preprint arXiv:1610.04834*; 2016.
 - [54] Yu C-P, Ruppert G, Collins R, Nguyen D, Falcao A, Liu Y. 3D blob based brain tumor detection and segmentation in MR images. In: *Biomedical Imaging (ISBI)*, 2014 IEEE 11th International Symposium on, China; 2014.
 - [55] Karnan M, Selvanayagi K. Improved implementation of brain MR image segmentation using meta heuristic algorithms. In: *Computational Intelligence and Computing Research (ICCIC)*, 2010 IEEE International Conference on, India; 2010.
 - [56] Vijay J, Subhashini J. An efficient brain tumor detection methodology using K-means clustering algorithm. In: *Communications and Signal Processing (ICCSP)*, 2013 International Conference on, India; 2013.
 - [57] Fazli S, Nadirkhanlou P. A novel method for automatic segmentation of brain tumors in MRI images. *arxiv*; 2013.
 - [58] Kumar M, Mehta KK. A texture based tumor detection and automatic segmentation using seeded region growing method. *Int J Comp Tech Appl* 2011;2.
 - [59] Mustaqeem A, Javed A, Fatima T. An efficient brain tumor detection algorithm using watershed & thresholding based segmentation. *Int J Image Graph Signal Process* 2012;4:34.
 - [60] Cuadra MB, Pollo C, Bardera A, Cuisenaire O, Villemure JG, Thiran JP. Atlas-based segmentation of pathological MR brain images using a model of lesion growth. *IEEE Trans Med Imaging* 2004;23:1301–4.
 - [61] Shen S, Sandham W, Granat M, Sterr A. MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. *IEEE Trans Inf Technol Biomed* 2005;9:459–67.

- [62] Corso JJ, Sharon E, Dube S, El-Saden S, Sinha U, Yuille A. Efficient multilevel brain tumor segmentation with integrated bayesian model classification. *IEEE Trans Med Imaging* 2008;27:629–40.
- [63] Hall LO, Bensaid AM, Clarke LP, Velthuizen RP, Silbiger MS, Bezdek JC. A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain. *IEEE Trans Neural Netw* 1992;3:672–82.
- [64] Bauer S, Nolte L-P, Reyes M. Fully automatic segmentation of brain tumor images using support vector machine classification in combination with hierarchical conditional random field regularization. In: *Medical Image Computing and Computer-Assisted Intervention – MICCAI*, vol 11; 2011:354–61.
- [65] Aslan Ö, Cheng H, Zhang X, Schuurmans D. Convex two-layer modeling. In: *Advances in Neural Information Processing Systems*; 2013. Available from: <https://papers.nips.cc/paper/4867-convex-two-layer-modeling.pdf>.
- [66] Cho Y, Saul LK. Kernel methods for deep learning. In: *Advances in Neural Information Processing Systems*; 2009.
- [67] Deng L, Tur G, He X, Hakkani-Tur D. Use of kernel deep convex networks and end-to-end learning for spoken language understanding. In: *Spoken Language Technology Workshop (SLT)*, 2012 IEEE. USA: IEEE; 2012.
- [68] Vinyals O, Jia Y, Deng L, Darrell T. Learning with recursive perceptual representations. In: *Advances in Neural Information Processing Systems, USA*; 2012.
- [69] Huertas-Company M, Gravet R, Cabrera-Vives G, Pérez-González PG, Kartaltepe JS, Barro G, et al. A catalog of visual-like morphologies in the 5 CANDELS fields using deep-learning. *arXiv preprint arXiv:1509.05429*; 2015.
- [70] Bauer S, Seiler C, Bardyn T, Buechler P, Reyes M. Atlas-based segmentation of brain tumor images using a Markov random field-based tumor growth model and non-rigid registration. In: *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. Argentina: IEEE*; 2010.
- [71] Hinton GE, Osindero S, Teh Y-W. A fast learning algorithm for deep belief nets. *Neural Comput* 2006;18:1527–54.
- [72] Mohamed A-R, Hinton GE. Phone recognition using restricted Boltzmann machines. In: *ICASSP*; 2010.
- [73] Le QV, Zou WY, Yeung SY, Ng AY. Learning hierarchical invariant spatio-temporal features for action recognition with independent subspace analysis. In: *Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. USA: IEEE*; 2011.
- [74] Vincent P, Larochelle H, Lajoie I, Bengio Y, Manzagol P-A. Stacked denoising autoencoders: learning useful representations in a deep network with a local denoising criterion. *J Mach Learn Res* 2010;11:3371–408.
- [75] Andén J, Mallat S. Deep scattering spectrum. *IEEE Trans Signal Process* 2014;62:4114–28.
- [76] MICCAI. About MICCAI. 2016 [cited 2016]. Available from: <http://www.miccai.org/organization>.
- [77] Misale C, Drocco M, Aldinucci M, Tremblay G. A comparison of big data frameworks on a layered dataflow model. *Parallel Process Lett* 2017;27:1740003.
- [78] Zhu W, Xie X. Adversarial deep structural networks for mammographic mass segmentation. *arXiv preprint arXiv:1612.05970*; 2016.
- [79] Singh B, Singh J. Classification of brain MRI in wavelet domain. *Int J Electron Comput Sci Eng* 2011;2277–1956.
- [80] Cogswell M. Understanding Representations and Reducing their Redundancy in Deep Networks. Blacksburg, VA: Virginia Polytechnic Institute and State University; 2016.
- [81] Chen J, Kang X, Liu Y, Wang ZJ. Median filtering forensics based on convolutional neural networks. *IEEE Signal Process Lett* 2015;22:1849–53.
- [82] Arel I, Rose DC, Karnowski TP. Deep machine learning – a new frontier in artificial intelligence research [research frontier]. *IEEE Comput Intell Mag* 2010;5:13–8.
- [83] LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature* 2015;521:436–44.
- [84] Boussion N, Hatt M, Lamare F, Bizais Y, Turzo A, Cheze-Le Rest C, et al. A multiresolution image based approach for correction of partial volume effects in emission tomography. *Phys Med Biol* 2006;51:1857.
- [85] Sun J, Yao M, Xu B, Bel P. Fabric wrinkle characterization and classification using modified wavelet coefficients and support-vector-machine classifiers. *Text Res J* 2011;81:902–13.
- [86] Srivastava R. Research Developments in Computer Vision and Image Processing: Methodologies and Applications: Methodologies and Applications. Iran: IGI Global; 2013.
- [87] Shekkizhar S. Tensorflow Implementation of Fully Convolutional Networks for Semantic Segmentation. 2016 [cited 2016]. Available from: <https://github.com/shekkizh/FCN.tensorflow>.
- [88] Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, USA*; 2015.
- [89] Pu R, Gong P. Wavelet transform applied to EO-1 hyperspectral data for forest LAI and crown closure mapping. *Remote Sens Environ* 2004;91:212–24.
- [90] Satiyan M, Hariharan M, Nagarajan R. Comparison of performance using Daubechies wavelet family for facial expression recognition. In: *Signal Processing and its Applications (CSPA), 2010 6th International Colloquium on. Malaysia: IEEE*; 2010.