Deep learning for Image segmentation—a short survey

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Abstract
Deep learning works as a discrete non-linear mapping function and has achieved great success as a powerful classification tool. However, is deep learning omnipotent? This paper gives a short survey of the accuracy achieved by deep learning so far in image segmentation. Compared to the close to 100% classification accuracy achieved by deep learning, the image segmentation accuracy achieved by deep learning is only about 80%. We analyze the possible reasons why deep learning could not achieve acceptable accuracy in image segmentation and found that deep learning only generates a prediction map and relies on other segmentation methods to complete the segmentation task. In addition, the performance of deep learning is determined by the number of outputs. Consequently, deep learning could not achieve high segmentation accuracy unless the resolution of the image is extremely small.

Introduction
Will Artificial Intelligence (AI) have a third winter after the two AI troughs in the 1970s and 1980s? According to Prof. Gary Marcus from New York University, deep learning may be approaching a wall [1]. From the successful cases of deep learning, it is seen that deep learning systems are most often used as classification system in the sense that the mission of a typical network is to decide which of a set of categories a given input belongs to. The third climax of deep learning took place around 2012 when it won several well-known speech or image recognition and classification competitions. The competitions that made deep learning resurge include, but not limited to: large-scale automatic speech recognition competition [2-3], Modified national Institute of Standards and Technology (MNIST) handwritten digits competition [4], Traffic sign competition [5], Chinese handwriting recognition competition [6], ImageNet large scale visual recognition competition [7-8], Pattern Analysis Statistical modeling and Computational Learning (PASCAL) visual object classes competition [9-10] and so on.

So far, deep learning has only achieved great success in classification of limited classes. Whether it could still make similar success in other applications remains unrevealed. However, Geoff Hinton, the grandfather of deep learning has already suggested that “entirely new methods will probably have to be invented.” Some insiders have already realized the limitations of deep learning, e.g. the inventor of AlexNet left Google in September 2017 when he lost interest in the work. The author of Keras said “For most problems where deep learning has enabled transformationally better solutions (vision, speech), we’ve entered diminishing returns territory in 2016-2017.” As surveyed among 151 chemists in [11], 45.7% chemists agree that deep learning is overhyped while 32.4% chemists disagree.

Problem statement
Most deep learning models are based on artificial neural network that is invented by simulating human brains. Although most deep learning models have various differences from the structural and functional properties of human brains, they are analogical to some extent. The neural dynamics of human brain corresponds to a form of variational EM algorithm, i.e. with approximate rather than exact posteriors [12]. For instance, the human brain could recognize an object without knowing how to calculate its exact size, height, shape or other information and just judge based on some approximated information. Similar to human brains, deep learning models classify the objects without knowing how to calculate its exact size, height, shape or other information. In nature, deep learning combines many
continuous regression units discretely and approximates a discrete non-linear mapping function without knowing its exact form. Compared to the linear regression model, deep learning has the major advantage that deep learning is more robust in estimating the discrete response variables for the linear indivisible data. Up to now, deep learning has been recognized as the most powerful classification tool. However, deep learning also has the following problems.

1. Deep learning determines a set of parameters instead of the exact mathematical functions to map the input variables into the output variables. Without the exact mathematical functions, not only deep learning could not be explained reasonably, but also the output variables could not be determined as continuous response variables. Consequently, deep learning could only map sufficient inputs into a finite number of categories. When the number of output is infinite or close to infinity, the performance of deep learning will be affected significantly.

2. Lack of the exact mathematical mapping, deep learning could not yield the ideal outputs even when it is tested with the inputs used during the training process or tested with the ground truth.

3. Lack of the exact mathematical mapping, deep learning is only powerful for the classification applications, where sufficient input variables are available while the number of output variables is comparatively limited. In information theory, there is Shannon theorem that tells the maximum rate at which information can be transmitted over the channel with the specified bandwidth in the presence of noise. In deep learning, there is no theorem about what the maximum number of the output variables is after the input variables are determined, which indicates that it might be immature.

Deep learning for image segmentation

Since deep learning is defined as a discrete non-linear mapping function, it should have some mathematical form for representation. We use the definition of linear regression to formulate deep learning. In general, the linear regression is formulated as a mapping model by the following simple equation.

\[ y \approx f(x, w) \]  \hspace{1cm} (1)

\( f \) is a continuous linear mapping function and its exact form could be determined. \( w \) denotes the coefficients to be determined by regression. \( x \) denotes the continuous input variable and \( y \) denotes the continuous output variable.

Similarly, deep learning could be formulated as:

\[ Y_i \approx F(X_j, W); i = 1, \ldots, I; j = 1, \ldots, J \]  \hspace{1cm} (2)

\( F \) is a discrete and non-linear mapping function and its exact form could not be determined exactly. \( W \) denotes the discrete mapping parameters to be determined by training. \( X_j \) denotes the discrete input variable and \( I \) denotes its total number. \( Y_i \) denotes the discrete output variable and \( J \) denotes its total number.

For image segmentation, the number of the outputs \( J \) is not fixed and it is computed as:

\[ J = L^{MN} \]  \hspace{1cm} (3)

where \( M \) is the width of the image and \( N \) is the height of the image. \( L \) denotes the total number of labeling. If the image is segmented into two classes, \( L \) equals 2. If the image is segmented into three classes, \( L \) equals 3, etc. To segment an image with a resolution of 100 × 100 into two classes, the number of outputs is close to infinity. Since deep learning is a discrete mapping function and is not capable of generating continuous (infinite) outputs, the performance of deep learning in such cases will be reduced significantly. Consequently, no good results are expected for deep learning to do the image segmentation work unless the resolution of the image is extremely small. To support this point of view, we list the competitions mentioned above in Table 1 with their critical data information and best accuracies achieved so far. As can be seen, deep learning has only achieved good performance when the number of the outputs is small or limited. Similar to Shannon theorem, a theorem about the proportion of the number of the inputs and the number of the outputs might also exist for the performance of deep learning.
Table 1. Comparisons of different competitions with their critical data information and best accuracies

|Competitions              | Number of inputs | Number of outputs | Best accuracy   |
|--------------------------|------------------|------------------|-----------------|
|Voice recognition         | 6300             | 8                | 83.5% [2]       |
|Digits recognition        | 60000            | 10               | 99.77% [4]      |
|Traffic sign recognition  | 39209            | 43               | 99.46% [5]      |
|Chinese handwriting       | 3900000          | 7356             | 97.39% [6]      |
|ImageNet image classification| 1281167         | 1000             | 93.34% [7]      |
|ImageNet image segmentation| 1281167         | ≈infinity        | 73.14% [8]      |
|PASCAL VOC image          | 8498             | ≈infinity        | 67.5 % [9]; 79.5% [10] |

The major differences between the linear regression model and deep learning include:

1. The mathematical function \( f \) of the linear regression model could be determined exactly while the exact form of \( F \) for deep learning is unknown.

2. The linear regression deals with continuous variables while deep learning deals with discrete variables.

Because of these two differences, the linear regression model based image segmentation methods should be better than deep learning based image segmentation methods. In practice, deep learning could only generate a rough prediction map instead of an accurate image segmentation result. However, there are many reported research work about the unprecedented segmentation accuracy achieved by deep learning. Let us look into the details of how these researchers made it. In [13], Ciresan who had won three international competitions [4-6] claimed that his deep neural network was trained with 3 million pixels with only 2 outputs: membrane denoted as 1 and non-membrane denoted as 0. The output is a prediction map which looks the same as the probability map generated by another competitor [14]. When deep learning generates a prediction map for image segmentation, the number of outputs is close to infinity, which will affect the performance of deep learning significantly. It is difficult for it to achieve an acceptable segmentation without further processing. As can be seen from the illustration in [15], there were serious segmentation errors in the final segmentation result by the deep learning method. However, the accuracy achieved by Ciresan in this competition is reasonable because of two reasons: (1), he divided the image into many small blocks with extremely small resolutions and conducted the segmentation work on the small blocks instead of the whole image; (2), For this special kind of images, all divided blocks are similar. In another object detection competition [16], Ciresan used his deep learning method to detect mitosis in breast cancer histology images. Although the achieved F-measure accuracy was only 78.2%, it was already significantly higher than the closest competitor who only achieved 71.8% F-measure accuracy. The low accuracy achieved at this time was caused by one major reason that the divided blocks are not similar enough. Research also shows that the method wining the competitions might not be the best method [17].

Besides international competitions, there are also many papers that adopted deep learning for prediction and then utilize other techniques to complete the segmentation task. Here, we found some contradictory results. In [18], deep learning was combined with the deformable model to segment the left ventricle in Magnetic Resonance Imaging (MRI) images and the unprecedented segmentation accuracy was reported. Its Dice measure is reported as 94%. The most contradictory part of this paper is that the inferred shape by deep learning is used as initialization contour for the deformable model evolvement. However, the accuracy of the deformable model is determined by the generated edge map instead of its initialization contour. Therefore, the final accuracy of the proposed method should be similar to that of the deformable model based methods. On the contrary, the reported accuracy was much better than those reported by
the deformable model based methods. The inferred shape by deep learning was also compared with the ground truth qualitatively in Figure 8 of reference 18, which showed that the predicted result by deep learning was far from accurate. As reported in [19], the DICE measure of the LV segmentation by deep learning was below 79%. On the other hand, there are many linear regression model based methods that could achieve DICE measure higher than 90% [20]. In addition, deep learning is combined with surface evolution to segment CT livers in [21] and is combined with graph cut to segment the CT livers in [22]. Even combined with deep learning for prediction, the reported liver segmentation accuracy was still lower than the previously reported liver segmentation accuracy by a non-deep-learning method [23-24]. For the liver tumor detection by deep learning [25], the reported accuracy computed as Dice measure is only 69% compared to 88.9% computed by a non-deep-learning method [25]. Deep learning was also used for cell segmentation [27-28]. Deep learning was combined with watershed for cell segmentation in [27] and the reported accuracy by Dice measure was only 86%. In addition, it was reported in [28] that the accuracy of cell segmentation by support vector machine was more robust than deep learning. For better comparison, we list the results mentioned above in Table 2 with their critical data information if any and their achieved accuracies. The cases described above are only the tip of the iceberg, there are also many cases in which deep learning performed very poorly or it was outperformed by other methods. However, it is usually difficult to publish these results since the linear regression model based methods may be lack of originality for publishing. In many cases, the claimed accuracy in the published paper and the reported accuracy in international competitions might make people think that it is the inability of the researcher instead of inability of deep learning for the failure of a segmentation task.

| Competitions                                | Deep learning methods       | non-deep-learning methods       |
|---------------------------------------------|------------------------------|---------------------------------|
| MRI Ventricle segmentation                  | Dice 79% [19]               | Dice 91% [20]                   |
| CT liver segmentation on 3Dircabdb database  | VOE 9.36±3.34 [22]          | VOE 9.15±1.44 [23]              |
| CT liver segmentation on MICCAI-Sliver07 test set | Score 79.3% [21]; 77.8% [22] | Score 79.6%[24]                |
| Liver tumor segmentation                     | Dice 69% [25]               | Dice 88.9% [26]                 |
| Cell segmentation                            | OR 0.83% [28]               | OR 0.69%[28]                    |

Please note: Dice, Score, the higher the better; Volumetric Overlap Error (VOE), Over-segmentation Rate (OR), the lower the better.

Conclusion

In conclusion, deep learning has only achieved good image segmentation results when the segmentation work could be conducted on small blocks of the image with extremely small resolutions and the divided blocks are similar [13], or the images could be down-sampled to extremely low-solution images without significant detail loss [9-10]. For the past several years, the overall performance of deep learning for image segmentation has been very limited. Whether deep learning could still make significant break-through in image segmentation remains unrevealed. However, we believe that there is no omnipotent method for artificial intelligence and deep learning is only a powerful tool of it. Deep learning excels in selecting the best answer from a list of choices instead of coming up with an accurate answer because it works a black box and its mathematical form could not be determined exactly and reasonably. As a result, when the number of the outputs approaches infinity, the approximating ability of deep learning will be affected significantly.

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